Econometric Modelling of the Employment Gap for the NHS Outcomes Framework

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Disclaimer

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Introduction

This work has been produced in response to a tender from the Department of Health (DH) and NHS England to develop methods for retrospective assessment against the NHS Outcomes Framework (NHSOF) to understand the contribution of the NHS and partner organisations. The objective is to explore the contribution of the health and social care system to the gap in employment rates for individuals with and without long-term physical conditions and mental health problems.

This work is the second component of a two-part study; the first part was a rapid evidence assessment (REA) to investigate the impact of health and social care systems and interventions, as well as other external drivers, on the employment outcomes of people with long-term physical conditions and mental illness (Nathwani et al., 2015). The REA found evidence that some interventions do have a positive effect on employment for those with mental health problems. However, no convincing evidence was found for physical conditions. In addition, current evidence fails to explore the reasons as to why this is the case and why certain treatments have greater influence than others.

A number of studies found in the REA also highlighted that the effectiveness of health interventions may depend on economic circumstances prevailing at the time when an initiative is introduced, such as labour market conditions and the structure and generosity of the welfare system. The employment rates of people with long-term physical conditions and mental illness are continuously lower than the rates found amongst the general population. For example, in 2012 the employment gap between people with long-term conditions and the general population was around 12 percentage points (pp), whilst the corresponding figure for mental illness was just under 40 pp.

Data and Methods

This work uses econometric methods to explore the contribution of the health and social care system to the employment gap, while controlling for other factors that may also be expected to influence this gap, such as local labour market conditions and the welfare system.

The analysis was severely constrained by the lack of available data. Ideally we would wish to estimate a predictive model by analysing trends in the employment gap over time but there are insufficient consistent data series available, largely due to changing definitions of health problems over time in household survey data sets, and the relatively recent availability of detailed NHS expenditure data.

The analysis uses labour market outcome and health status information from the quarterly Labour Force Survey (LFS) and combines this with health expenditure information from the NHS programme budgeting data and social care expenditure data from the social services departments of Council with Adult Social Services Responsibilities (CASSRs). This data is only available annually from 2007 to 2012, so we supplement variation over time with variation over space by analysing data at the level of Local Authority (LA). These data are combined with other information from standard ONS data sets, such as local unemployment rates, wages and benefits data.

Our primary model explains the employment gap (the employment rate for the total population minus the employment rate for those with a long-term health condition or mental health problem) across both LAs and years, using data on healthcare spending, social care spending, the wage ratio, the unemployment to vacancy ratio, the benefits ratios and the local population of working age. We estimate separately for the employment gap for long-term health problems, and for mental health problems. We use fixed-effects models to account for unobserved heterogeneity across LAs and we also include year effects, which reflect macroeconomic conditions.

Results

Our results find **no evidence of a statistically significant relationship between health care or social care spending and the employment gaps of people with long-term physical conditions and for people with mental health problems**, when we consider variation over the years 2007 to 2012 and across 141 LAs in England. This result is robust to a number of different model specifications and data inclusion criteria.

Further exploration reveals that the respective employment gaps are dominated by year effects, which reflect macroeconomic conditions in a time period where the UK slid rapidly into recession and then began to make a slow recovery. During this time the employment rates of people with health problems seemed to hold up whereas those for the overall population suffered, hence the employment gaps narrowed.

It is beyond the scope of this work to explore why the employment rate of people with health problems did not suffer as much during the recession as that for the overall population, but our results fail to find evidence to suggest that this was due to health or social care spending.

Discussion and Conclusion

The lack of a finding of a statistically significant relationship between health and social care spending and the employment gaps is not an unexpected result. Healthcare spending is only one potential influence on the employment gap and particularly given that most NHS healthcare interventions target health outcomes rather than employment outcomes, it is not surprising that we have been unable to detect a relationship using relatively aggregated area level data.

The work has a number of shortcomings which mean that it is not an ideal method for estimating the effect of healthcare on employment outcomes:

- lack of availability of consistent data over a long time period
- use of data from a number of different sources all subject to data manipulation which introduces noise
- a time period dominated by economic recession and subsequent slow recovery
- a time period characterised by institutional changes to the healthcare system and welfare system
- healthcare expenditure data largely reflecting resources spent on older people, not people of working age.

Recommendations for Future Work

We have a number of suggestions for future work that may help shed some more light on the relationship between health care and employment outcomes.

Firstly, we recommend an **analysis of the relationship between health care and employment outcomes at the individual level**. This would require data on health status, health care utilisation, social care utilisation, labour market outcomes and other socio-economic and demographic information, such as education levels, age, gender and ethnicity. Such data may be available from longitudinal household data sets such as Understanding Society, and there are plans in place to link the survey to the Hospital Episode Statistics data, which would provide good information on health care utilisation.

A second suggestion is to **exploit exogenous variation in specific interventions targeted at the employability of people with long-term conditions or mental health problems**. One option here for mental health is an analysis of data arising from the evaluation of the NHS Improving Access to Psychological Therapies (IAPT) programme.

Finally, there are a number of ways to improve the aggregate analysis of the employment gap such as that presented in this report. Firstly, it could be revisited when further years' data become available. This would increase power to detect relationships, and may also mean that the data might reflect a broader set of macroeconomic conditions. Secondly, it would be worth investigating with the data owners whether the NHS programme budgeting data is available by age of target population, so that we can obtain a more appropriate measure of health spending on working age people.

1. Introduction

This work has been produced in response to a tender from the Department of Health (DH) and NHS England to develop methods for retrospective assessment against the NHS Outcomes Framework (NHSOF) to understand the contribution of the NHS and partner organisations. Specifically, the objective is to explore the contribution of the health and social care system to the gap in employment between people with and without long-term conditions and mental health problems. This work is the second component of a two-part study; the first part was a rapid evidence assessment (REA) to investigate the impact of health and social care systems and interventions, as well as other external drivers, on the employment outcomes of those with long-term physical conditions and mental illness (Nathwani et al., 2015).

Long-term physical health conditions, such as diabetes and asthma, are increasing in prevalence, as a result of influences such as an ageing population and lifestyle factors, including poor diet and inactivity. NHS England (2013) suggests that the current cost of treating long-term conditions makes up more than two-thirds of health and social care expenditure. Mental health conditions such as depression and anxiety are also increasing in prevalence. The Centre for Mental Health (2010) has estimated the economic and social cost of mental health problems to the UK economy at around £105 billion, as a result of sickness absence and lower levels of labour force participation.

The NHSOF was introduced in 2010 to increase the accountability and productivity of the health care system. Long-term conditions and mental health problems are related to Domain 2 of the NHSOF. The aim of this domain is to measure the extent to which the NHS helps and supports people with long-term conditions to live as normal a life as is feasible; employment can play a part in enabling this and can also be a proxy measure of improved health outcomes.

The employment rates of people with long-term conditions and mental illness are consistently lower than the rates found amongst the general population. The difference between these rates is the employment gap. In 2012, the employment gap between people with long-term conditions and the general population was around 12 per cent, whilst the corresponding figure for mental illness was just under 40 per cent.[1] Health care and welfare provision is one way that the government can influence the employment gap. In theory, increasing employment for disadvantaged groups could lead to a fall in the dependency on health and social care services of those with health problems, since employment has been shown to have a positive impact on health and quality of life.

However, the REA (Nathwani et al., 2015) found that, whilst one may anticipate that employment will lead to better health outcomes, the evidence indicated that this may not always be the case, especially in instances of unfavourable working conditions, such as having low job control. Hence, simply helping those with long-term conditions and mental

[1] Figures taken from the Labour Force Survey

health issues into work will not be sufficient to raise their quality of life. Yet there is evidence for the impact of health on employment, with poorer health more likely to lead to an individual leaving the labour market. However, the magnitude of this relationship will be influenced by a number of other factors, only some of which can be altered by government policy, such as employment rehabilitation measures and the benefits system.

The REA found evidence that interventions, including anti-depressant medication, cognitive behavioural therapy and combinations of treatments could have a positive effect on employment for those with mental health problems. However, no convincing evidence seems to exist in this area for physical conditions. In addition, current evidence fails to explore the reasons as to why this is the case and why certain treatments have greater influence than others. One of the issues arising from the literature is the trade-off between using rigorous methodological approaches and ensuring the research takes place over a sufficient period of time for an effect to occur. For example, randomised control trials often last for no more than a few months, whereas employment outcomes can change a number of years after the original intervention. A number of studies did highlight that the effectiveness of health interventions may depend on economic circumstances prevailing at the time the initiative is introduced (see, for example, Burns et al., 2007). Labour market conditions, the structure and generosity of the welfare system as well as the implementation of employment interventions were all noted as being key determinants of employment for those with mental health conditions. Although there is currently less literature on physical conditions, the importance of working environment and reducing stigma were noted as prerequisites for successful and sustained employment for those with physical conditions and mental illnesses.

This second component of the study uses econometric methods to explore the contribution of the health and social care system to the employment gap, while controlling for other factors that may also be expected to influence this gap, such as local labour market conditions and the generosity of the welfare system. Ideally we would wish to analyse trends in the employment gap over time at an aggregate country level but there are insufficient consistent data series available to enable any meaningful time-series analysis; this is largely due to changing definitions of health problems over time in household survey data sets, and the relatively recent availability of detailed NHS expenditure data. A number of data sets were reviewed for this analysis and this review is included as Appendix 1.

The conclusion of this review was that the quarterly Labour Force Survey (LFS) was most suited to meeting the aims of this work and that variation over time could be supplemented with variation over space, by analysing data at the level of Local Authority (LA).[2] Consistent health measures are only available in the LFS from 1997 and meaningful data on health care input at a sufficiently disaggregated level is only available annually from 2003/04. Further, social expenditure data is only available from 2000/1, but is only available from 2007/8 at a sufficiently disaggregate level to be used in our analysis (see further detail below) Using the

[2] Initial discussions about this work focused on the possible use of 'age-period-cohort' (APC) modelling, since this is the method that has been used to explore trends over time for the mortality outcome domains of the NHS Outcome Framework (Domain 1). However, after reviewing the key statistical and econometric literature on this method and understanding more about data limitations we ruled out the approach; see Appendix 2 for more detail.

LA level data allows for variation across both time and area with which to model the association of the employment gap with the health and social care system, controlling for local labour market conditions and other area level variables. There are 152 (upper tier) LAs and the increased spatial variation brought about by this level of analysis adds power to the modelling exercise. In addition, local conditions in relation to health and social care, the labour market and the benefits system are likely to be much stronger drivers of the employment gap than national conditions.[3] To investigate the role of health care at this area level we use NHS programme budgeting data[4] collected at Primary Care Trust (PCT) level and converted to LA level using a geography mapping tool (see Data section). Information on social care provision obtained from reports of money spent on adult social care by the social services departments of Council with Adult Social Services Responsibilities (CASSRs) in England is used to supplement the programme budgeting expenditure. The models also include control variables at LA level, such as local labour market conditions, benefits generosity and wage ratios (see Data and Methods sections for more detail).

[3] See Manning (2003) for the classic exposition of monopsony power in local labour markets.

[4] https://www.england.nhs.uk/resources/resources-for-ccgs/prog-budgeting/

2. Theoretical Considerations

There are both microeconomic and macroeconomic theories that can help to frame our empirical modelling. Firstly, at the individual level, health is a form of human capital. Traditionally, labour economics' focus on human capital has been on education, but investment in health can also be understood via the health production function approach of Grossman (1972). Individuals will choose to invest in health capital both because it is valued for its own sake and because poorer health detracts from time available for both market and non-market activities. Thus health is one of the determinants of labour supply, but it is also an endogenous choice (Currie and Madrian, 1999).[5] It follows that on the supply side there are a number of reasons why poorer health might be expected to reduce the probability of work. Firstly, it may directly increase the disutility of work. Secondly, it can reduce the return to work via lower wages. Thirdly, it may increase the reservation wage,[6] for example, by entitling the individual to health related disability benefits (although on this point see Brown et al., 2010, discussed below). Demand side factors should be largely reflected in the wage paid to workers with health problems, which is expected to be lower than for those without health problems due to their lower productivity. However, employer discrimination may also be important. Employers may discriminate against individuals with health problems due to inherent tastes and preferences; although it is difficult to explain the continued existence of discriminating firms under profit maximising conditions. A more likely explanation for persistent discrimination is statistical discrimination (Aigner and Cain, 1977). If employers cannot perfectly observe the productivity of the individual worker, then different groups may be treated differently based on the perceived average characteristics the social services departments of CASSRs of the group; so workers with health problems may be offered lower wages because they are perceived to be less productive on average than other workers. This type of discrimination can persist even when economic agents are rational and non-prejudiced; it is rational to attribute the average characteristics of the group to each individual from that group when it is costly to gather information.[7]

The empirical work we will present is not based on individual level analysis; it is a more aggregated LA area based analysis. Nevertheless it is worth pointing out at this stage that the relationship between health and labour market outcomes, such as participation and wages, at an individual level is complex because health and work are jointly determined (Adams et al., 2003). In addition, issues such as selection into economic activity and justification bias in self-reported health measures exacerbate these problems. Considerable progress in understanding the relationship between health and the labour market has been made via both theoretical and empirical work (e.g. Bound et al. (1999), Adams et al. (2003) and Stern (1989)), and some of this work is reviewed in the Rapid Evidence Assessment produced for

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[5] It is also worth pointing out here that investment in education and health are clearly interrelated. More education should lead to better health as better educated people are more aware of the kinds of behaviours that can contribute to good health.

[6] The reservation wage is the lowest wage at which an individual is willing to work, and this concept has played an important role in labour market theory (see, for example, Mortensen, 1986).

[7] Dickinson and Oaxaca (2009) also show how statistical discrimination can extend beyond differential treatment based on average group characteristics, because risk-averse employers may offer females lower wages based not on lower average productivity but on a higher variance in productivity for certain groups.

the other component of this work (Nathwani et al., 2015). For example, Garcia-Gomez (2011) explores the relationship between health shocks (an unexpected change in one's health) and labour market outcomes in nine European countries using the European Community Household Panel survey. Garcia-Gomez finds that people who suffer a health shock are significantly more likely to move into non-employment status (i.e. unemployment, inactive or retired) than those who do not experience a health shock.

A further example of this type of micro-econometric work that is particularly pertinent for our modelling is the study by Brown et al. (2010), who have used British Household Panel Survey data for 1991 to 2004 to explore the relationship between health and reservation wages. A major contribution of the Brown et al. (2010) study is to distinguish between those who are 'attached' to the labour market (regardless of whether they are working at the time) and those who have very weak or no attachment; the former group are defined as participating in the labour market and the latter group are not. They define the economically active (participants) as those who are employed or who are unemployed but are actively seeking work, and the inactive group (non-participants) includes individuals who are long-term sick and disabled, retired before statutory retirement age, in full-time education, engaged in family care or on a government training scheme. The assumption is that this latter group has much weaker labour market attachment than the former, and is not actively seeking work. The results reveal no effect of health status on the market wages of the employed, and no evidence for the argument that has appeared in previous work (for example, Walker and Thompson (1996) and Gordon and Blinder (1980)) that those with health problems have higher reservation wages. Instead their results suggest that the main role of poor health is to weaken labour force attachment. Health is a significant determinant of attachment to the labour market but – contrary to much of the previous work – once selection into the labour market is accounted for there is no evidence that health affects the probability of being unemployed. The relevance for our analysis is that if the bulk of the people with health problems are in fact unattached to the labour market, then local labour market conditions and macroeconomic factors will have little effect on their probability of gaining employment. Instead the question is whether healthcare can improve their health sufficiently to improve their probability of becoming attached.

At a macroeconomic level there are three broad hypotheses that can be used as a basis for the expectation that people with long-term health problems might experience different employment prospects to the population without health problems, either over the business cycle, or through secular longer term changes in the labour market.

First, the *reserve army hypothesis* has its origins in Marxist analysis.[8] The reserve army is a pool of unemployed labour that can be drawn into the labour market during booms and dispensed with when the economy slumps; hence this pool of labour display pro-cyclical movement in employment rates to a greater degree than the average worker. Green (1991) explains that for any particular identifiable group to be termed a reserve army of workers, they must be available for work but "expendable and disposable" (p.194) above the average

[8] Most of Marx's work on the reserve army is found in *Capital, Volume 1*; Engels' also writes about this phenomenon in *The Origin of the Family, Private Property and the State*.

for the rest of the workforce. A number of studies have explored the role of women as a reserve army of labour due to their position in relation to domestic work and child rearing (see for example Rubery, 1988; Power 1983.) More recently, O'Brien (2010) has argued that many governments in the OECD have treated older workers as a 'reserve army', allowing early exit from the labour force by various means in periods of labour surplus and mobilising them back into the labour force during periods of labour shortage. While we can find no direct evidence on the reserve army hypothesis in relation to people with long-term health problems, the hypothesis of greater than average pro-cyclical fluctuation in employment rates for this group seems a reasonable one, since they may be viewed as more 'expendable' than the average worker. For example, there may be a perception that workers with health problems can access relatively generous health-related benefits when they are not in work. Hence employers may treat these workers as a reserve pool, and governments could manipulate benefits availability to facilitate the entry and exit of these workers to the labour market. Knapp et al. (2013) have explored the influence of the recession on the unemployment rates of those with and without mental health problems in a number of European countries. They find that the recession had a greater adverse impact on unemployment for those with mental health problems; and this was especially true for males and for those with low education.

A second hypothesis, that of labour market *substitution*, has also been applied to female employment, and this could also provide a useful way to understand the time trend in the employment gap for people with long-term health problems. The *substitution hypothesis* stresses a long-term substitution towards a particular type of labour due to secular changes in the labour market.[9] The substitution towards female employment is partly explained by the expansion of the service industries, with their need for a cheap and flexible labour force (Dex and Perry, 1984). Female labour has been cited as filling this role due to women's apparent 'willingness' to accept lower wages and more flexible terms and conditions of work than their male counterparts, for example the propensity of female workers to work part-time, or in temporary and/or flexible employment. Again, there seems to be no research suggesting that people with long-term health problems fulfil this role but it does seem reasonable to argue that if people with health problems have a weaker labour market position, and are therefore more likely to accept lower paid jobs or jobs with less security, then their employment opportunities may be increasing alongside certain secular trends in the restructuring of work.

Thirdly, related to the substitution hypothesis is the *segregation* hypothesis which states that certain groups may be segregated into certain industries or occupations, so that their experience over the economic cyclical depends on how those occupations and industries fare. Segregation can be horizontal (different jobs with the same status) and/or vertical (jobs are different levels of an occupational hierarchy). While originally proposed in relation to the segregation of female workers into a narrow range of occupations and industries (Walby, 1988), it can also be applied to the segregation of particular groups into 'types' of

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[9] Note that the 'substitution hypothesis' is distinct from the 'intertemporal substitution hypothesis' of Lucas and Rapping (1969), which states that cyclical fluctuations in employment and hours of work are optimizing labour-supply responses to short-run aggregate demand shifts.

employment. In the case of people with long-term health problems this might be, for example, flexible and/or part-time work. We could find no direct empirical evidence for this type of segregation; but Darity (2003) discusses how other forms of segregation, for example via race and ethnicity, interact with health to bring about worse socio-economic outcomes, including labour market outcomes.

Further to these theoretical hypotheses, it should be noted that it may be difficult to empirically isolate the effect of macroeconomic conditions on the employment gap because these will not only affect the gap via their effects on the labour market, but also via direct effects on health (see Ruhm, 2015). Astell-Burt and Feng (2013) explore the reporting of poor health during the 2008 recession in the UK using quarterly LFS data from 2006 to 2010. They find that the recession was associated with increasing reports of poor health status amongst both the unemployed and those who remained employed.

3. Data

Employment

The Quarterly LFS is the largest household sample survey in the UK and includes approximately 100,000 individuals in each calendar quarter. The LFS contains rich and detailed information on the employment status of individuals together with self-reported health problems. It also contains socio-demographic information. This analysis uses the Special Licence version of the LFS (Office for National Statistics, 2015) available from the UK Data Service,[10] because only this version contains the LA identifiers that we need in order to match the LFS data to the other data sources used in the analysis by area.

The first wave of data was collected in 1979. The final wave to which we have access is the first quarter of 2015. However, there are a number of changes to data collection that limit the number of waves of the LFS that can be used in this study. An important change to the health variables was introduced in spring 1997 to reflect the provisions of the Disability Discrimination Act 1995. New questions were included concerning *all* health problems, whereas previously an emphasis had been placed on problems affecting only the respondents' *work*. The changes in the questions make comparison with previous years' difficult.

The LFS data provides us with the necessary variables to define the gap in employment for individuals with and without long-term conditions (NHSOF Indicator 2.2) and mental health problems (NHSOF Indicator 2.5).[11] NHSOF Indicator 2.2 aims to capture employment of all people with a *long-term condition*. The indicator measures the difference between the percentage of people in the general working age population who are in employment, and the percentage of people of working age with a long-term condition who are in employment. The definition of someone with a long-term condition was changed in April 2013 and is now based on an answer of "Yes" for the LFS LNGLST question, which asks: *Do you have any physical or mental health conditions or illnesses lasting or expected to last 12 months or more?* Before April 2013 it was based on an answer of "Yes" for the LNGLIM variable which asked: *Do you have any health problems or disabilities that you expect will last for more than a year?* In our analysis we follow the NHSOF Indicators Specification version 1.6 and treat these questions as the same variable measured over the time period. However it is worth noting that the ONS LFS team recommend that any comparison between the new and old questions should be treated with caution as the changes to the question wording may impact on the answers given by respondents.

NHSOF Indicator 2.5 aims to capture employment of all people reporting *mental illness*. In our analysis again we follow the NHSOF Indicators Specification version 1.6 and define this on the basis of the LFS question HEAL, which asks respondents to record whether or not they suffer from any health problems chosen from a list (see Table 1 for the full list of LFS

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[10] https://www.ukdataservice.ac.uk/

[11] https://indicators.ic.nhs.uk/download/Outcomes%20Framework/Specification/NHSOF_Domain_2_S.pdf

health problems). Three of these problems relate to mental health conditions, these are: 12: depression, bad nerves or anxiety; 14: severe or specific learning difficulties; 15: mental illness or suffer from phobias, panics or other nervous disorders. Anyone who states that they have a long-term health condition (i.e. they answer "Yes" to question LNGLST (or LNGLIM) *and* who reports having either condition 12, 14 or 15, is defined as having a mental illness. In our empirical work we also consider what proportion of respondents record having more than one of these three problems.

Given the objective for this work of understanding the contribution of the NHS and partner organisations to domain 2 of the NHSOF, specifically in reducing the employment gap for people with and without long-term conditions and mental health problems, we focus solely on the NHSOF definitions 2.2. and 2.5 throughout the report. For more detail see NHSOF Indicators Specification version 1.6 for precise variable definitions in both cases.[12]

Health Care Expenditure

The English National Health Service (NHS) is a centrally-planned and publicly-funded health system, largely free at the point of use and funded through a combination of general taxation and national insurance contributions. Primary care is an important element of the system, with general practitioners acting as gatekeepers to secondary care and pharmaceuticals. The system is organised geographically, with responsibility for patient care devolved to Clinical Commissioning Groups.

Our analysis covers a period from 2006/07 to 2012/13, prior to the formation of CCGs when general practice was organised into Primary Care Trusts (PCTs). For the years 2003 to June 2006, there were 303 PCTs with average populations (lists) of 160,000. From July 2006 to March 2013 PCTs were reorganised into 152 PCTs. Through resource allocation mechanisms which aim to distribute funding on the basis of the health care needs of the population, PCTs received fixed annual budgets (targets) within which they were expected to meet expenditure on most aspects of health care, including inpatient, outpatient and community care, primary and pharmaceutical prescriptions.

To aid financial management and to help in the design and evaluation of programmes of patient care, from April 2003, PCTs were required to prepare data on expenditure disaggregated across 23 defined programmes of health care. This sought to create an accounting system that was more aligned with the distinct outputs and health outcomes of the health system. Programmes of care are defined with reference to the International Classification of Diseases (ICD) Version 10 codes, and most programme budget categories reflect ICD 10 chapter headings (e.g. 'Cancers and Tumours', 'Problems of circulation', 'Problems of the respiratory system', 'Neurological', etc.). Some categories contain sub-headings, for example expenditure on 'Mental Health Disorders' is broken down into 'Substance Misuse', 'Organic Mental Disorders' , 'Psychotic Disorders', 'Child and Adolescent Mental Health Disorders' and 'Other Mental Health Disorders'.

[12] https://indicators.ic.nhs.uk/download/Outcomes%20Framework/Specification/NHSOF_Domain_2_S.pdf

The aim of the programme budget classifications is to identify the entire volume of heath care resources assigned to broad areas of illness according to the primary diagnosis associated with an intervention. It seeks to allocate all types of PCT (now CCG) expenditure to the various programme categories, including secondary care, community care and prescribing.

The system acknowledges that a medical model of care may not always be appropriate for allocating expenditure and includes two specific non-clinical groups - 'Healthy Individuals' and 'Social Care Needs'. These are intended to capture the costs of disease prevention programmes and the costs of services that support individuals with social rather than health care needs. Where it is not possible to assign activity to a medical condition, preventative activity, or social care need, expenditure is allocated to a category entitled 'Other'. Reported expenditure relates to all public expenditure on residents of a PCT, regardless of where the provider is located.

The programme budgeting data was used by Martin et al. (2008) to investigate the relationship between health care spending and health outcomes for 295 English PCTs in 2004/5. Their results challenged the widely held view that health care has little marginal impact on health, finding instead that health care expenditure has a strong positive effect on outcomes in the two programmes of care investigated, cancer and circulatory diseases. Subsequent research has extended this work to other programmes of care (Martin et al., 2012) and to inform considerations around an appropriate cost-effectiveness threshold for health care interventions (Claxton et al. 2015).

Programme budgeting data was first collected in the financial year 2003/04 and it is only available annually.[13] Ideally data on NHS activity would be available quarterly (as per the LFS employment data) and by age-group so that we could isolate resources spent on working age people. In this work we make use of annual data collected from 2006/07. This was the first year in which sub-category information was collected which allows us to investigate in greater detail the potential impact of expenditure on mental health via the sub-categories 'Psychotic Disorders' and 'Other Mental Health Disorders'. This is also the first year in which information on sub-categories 'Diabetes' and 'Asthma' were collected. These conditions were identified in the REA as important long-term conditions that impact on the employment gap. We include Programme Budgeting Data to 2012/13.

The programme budgeting categories of greatest interest are:

- category 10: 'Problems of circulation' (and sub-categories 'Coronary Heart Disease' (10a), 'Problems of circulation'(10x));
- category 11: 'Problems of the respiratory system' (and sub-categories 'Asthma' (11b));
- category 13: 'Problems of the gastro-intestinal system';
- category 15: 'Problems of the Musculo skeletal system';

[13] https://www.england.nhs.uk/resources/resources-for-ccgs/prog-budgeting/

- category 05: ‘ Mental Health Disorders’ (and sub-categories ‘Psychotic Disorders’ (5c), and ‘Other Mental Health Disability’ (5x));
- category 22: ‘Social Care Needs’.

These categories and sub-categories have been chosen to align with the evidence presented within the REA on major long-term conditions and to align with the health problems identified in the LFS data. In the modelling exercise that follows we use two alternative measures of expenditure data; firstly, expenditure across the categories described above; for example, when modelling mental health problems, expenditure in programme budgeting category 05 is used; when modelling long-term conditions, expenditure summed across categories 10, 11, 13 and 15 is used. Secondly, overall PCT expenditure, to ensure that all expenditure that might impact people with LTC and MH problems is captured[14]. ‘Social Care Needs’ complements data on social care expenditure provided through by social services departments of CASSRs in England. In addition to these main categories and sub-categories we also include total programme budgeting expenditure. These expenditures are available across the years from 2006/07 to 2012/13.

Programme budgeting data are collected at PCT level. We convert this expenditure to LAs using the software package Geoconvert. Geoconvert is freely available software that allows data mapped to a given geography to be mapped to an alternative geography.[15] This is done through Gridlink®,[16] and attributes data between geographies on the basis of postcodes - see ONS NHS Postcode Directory User Guide.[17] This is undertaken on a year-by-year basis such that Geoconvert recognises that there were 303 PCTs prior to 2006 and 152 thereafter.

Over the period for which we use programme budgeting data the majority of PCTs were defined in terms of Local Authority Districts (LADs).[18] Of the 152 PCTs: 130 comprised of one or more LADs; 16 comprised of one or more whole LADs plus whole wards; three comprised of only wards within a single LAD; two comprised of one or more whole LADs and part wards (that is, whole parishes); one comprised of whole and part wards (that is, whole parishes) within a single LAD. This simple geographical mapping from PCTs to LADs ensures that programme budgeting data at PCT level can be reliably converted to expenditure at LA level.

Long-Term Care and Social Care

Long-term care differs from health care as conventionally defined. While the primary goal of health care services is to prevent or cure ill-health, long-term care aims to allow individuals to achieve and maintain optimal levels of personal functioning in their living circumstances and personal abilities and preferences (Fernandez et al., 2011). The US Department of Health and Human Services (2009) defined long-term care as “the range of medical and/or

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14 The main results presented in the report rely on the latter (Tables 4 and 5). Models for which expenditure on only the relevant programme budgeting categories was used are reported in Appendix 5.

15 Note that from November 2015 the PCT geography has been removed from Geoconvert.

16 The Gridlink® consortium consists of The Royal Mail Group PLC, Ordnance Survey (GB), General Register Office Scotland, Ordnance Survey Northern Ireland and the Office for National Statistics.

17 http://systems.hscic.gov.uk/data/ods/datadownloads/onsdata/pdfs-and-docs/userguide_v1a.pdf

18 See Appendix 3 for an explanation the LA Geographies.

social services designed to help people who have disabilities or chronic care needs.” The European Commission (2009) similarly define long-term care as “a range of medical and social services for persons who are dependent on help with basic activities of daily living, caused by chronic conditions of physical or mental disability.” While long-term care incorporates the provision of health care services, it is more synonymous with the provision of an array of non-medical inputs of care and support arrangements to assist with domestic, personal tasks and concerns that impact on an individual’s daily functioning and broader well-being associated with their mental or physical health problem. These might cover, for example, help with shopping, cleaning, preparing meals, dressing, bathing, and social engagement. Such support is provided via paid staff and family or other (usually unpaid) carers. There are many factors that influence the effectiveness of long-term care ranging from the needs-related characteristics of care recipients, to the situational factors (the context of the environment in which the recipient is located), and the inter-personal characteristics and skills of carers. The personal nature of long-term care, and the variability in recipients’ needs and preferences, means that tailoring support to an individual is a core value of effective long-term care provision.

Long-term care services are typically provided either in the community or in institutions. The former include support in an individual’s own home and services provided outside it, such as in day care centres and social clubs. Residential care and nursing care are examples of institutional services, often associated with catering for individual with higher levels of mental or physical disability. The vast majority of care support is provided in the recipient’s home or in other community settings, with residential care often seen as a last resort.

The government introduced Fair Access to Care Services (FACS) guidelines in 2003 to provide LAs with a common framework for determining individuals’ eligibility for social care services and address inconsistencies across England. Four categories of need were included – critical, severe, moderate, and low – with individuals assessed on the basis of their level of risk and potential loss of independence. Eligibility varied across LAs in terms of which of these groups were entitled to public support. Broadly, these eligibility criteria remained in place with LAs continuing to enjoy autonomy in deciding how services were allocated across the FACS spectrum according to their individual circumstances. In recent years (2011/12 onwards), local eligibility criteria have been tightened such that only individuals assessed to have critical or substantial needs are entitled to publicly-funded care across much of the country. As a result the number of people receiving state-supported social care has fallen significantly, even if levels of demand have risen (due to a combination of an ageing population and a fall in the availability of unpaid support from family and friends). Of individuals receiving support In 2005/06 less than 60% of all care recipients were classified as critical or substantial; between 2007/08 to 20010/11 this figures was approximately 73%; but increased to over 80% in 2011/12.[19]

The number of people receiving LA-supported social care has reduced in recent years. In 2008/09 there were just short of 1.8m individuals receiving adult LA care (approximately 1.2m aged 65 and over, and 590k aged 18 to 64) (Fernandez et al., 2013). Of particular

[19] Note less than 5% of all individuals are classified as critical across these years.

concern to this study are the group of younger adults aged 18 to 64. These are individuals of working age where for many social care is aimed, in part, at helping to support the movement into employment and maintain employment for those in work. This is particularly the case for individuals classified as moderate to low need. The provision of social care at the moderate care level may have wider benefits such as preventing more serious needs developing, or through supporting disabled people and their families to enter the labour market.

A recent report commissioned to assess the potential economic impact of providing care to working age disabled people with moderate care needs estimated that returns to social service care range from 18% to 53% (Deloitte, 2013). These estimates were largely based on case studies and were driven by a range of factors including: income generated from supporting people into employment (both for users and carers); avoidable costs of unemployment benefits; greater taxation through employment; and prevention of deterioration of individual circumstances leading to a greater reliance on health and social care services.

Data on expenditure on adult social care is taken from the information provided by the social services departments of CASSRs in England. This contains information taken from CASSR administrative systems used to record personal social services expenditure and income. The data are used by central government for public accountability, policy monitoring and national accounts, and by LAs to assess their performance in relation to their peers.

From 2000/01 onwards, social care expenditure data has been derived from returns (PSS-EX1) which CASSRs in England made to the Department of Health annually until 2003/04 and from 2004/05 to the Health and Social Care Information Centre. From 2005/06 data are available at a regional and CASSR level via the National Adult Social Care Intelligence Service (NASCIS)[20], and this data also includes LA identifiers which enables matching to our labour market data. In 2007/08 information on social services expenditure was collected separately for children's and adult social care expenditure. We make use of figures for adults under the age of 65 only to be compatible with the working age population.

The CASSR returns covers expenditure incurred and associated income for services provided to adults in different client types. The reports include gross current expenditure which represents total expenditure less capital charges and less all income except for client contributions. Gross expenditure is available from 2007/08 onwards. We also include net expenditure which excludes capital charges and total income (including client contributions). The latter is available from 2006/07 onwards and hence covers the same period for which we have programme budgeting data.

The three major categories of expenditure on adult social care by client type we include are expenditure on: 1) Adults (18 to 64) with physical disabilities; 2) Adults (18 to 64) with learning disabilities; and 3) Adults (18 to 64) with mental health needs.

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[20] https://nascis.hscic.gov.uk.

It should be noted that the majority of social care is estimated to be provided informally by friends and family, hence the data on publicly-funded social care will underestimate the social care input, and the extent of this underestimate may vary across LAs.

Both programme budgeting data and CASSR returns for social care provide total expenditure by either programme category or for the latter client type for each LA. We convert these expenditure figures into expenditure per capita in the LA. For social care expenditure via CASSR we do this by dividing expenditure by the total LA population figures for working age individuals from mid-year ONS estimates. This weighting reflects the client group (age 18 to 64) that CASSR returns cover and the employment gap outcome.

For programme budgeting data we use PCT unified weighted population figures that have been converted to LA geography. Unified weighted populations represent raw population figures for a PCT adjusted to reflect the need for health care services. Accordingly per capita expenditure is adjusted to reflect the idea that a pound spent on health care for a low need population goes further than a pound spent on health care for a high need population. The need for health care is measured through resource allocation formulae and combines the four main components of unified allocations: Hospital and Community Health Services (HCHS), prescribing, General Medical Services Non-Cash Limited and HIV/AIDs.[21] Unified population figures, however, also include an area cost adjustment to reflect the higher cost of labour and capital in certain areas of the country (largely London and the South East). This is often referred to as a market forces factor (MFF). The area cost adjustment reflects the true cost of providing health care services across geographical areas[22] by including supply and infrastructure effects; it might be argued that this should be removed from the weighted population figures so that the latter reflects only population need. Hence, expenditure data represents the per capita need weighted cost of providing health services within each of the programme categories, rather than additionally reflecting differentials in labour market and capital costs. For the purposes of this work, in the absence of a measure of the contribution of the MFF to the need weighted population, we use the unified weighted population adjusted to remove the influence of the market forces factor. Expenditure data is also deflated by the GDP deflator.

A potential alternative to the needs weighted population is the raw LAD population count in the working age population. This was used to derive per capita expenditure on social care.[23] However, unlike social care data, health care expenditure derived from Programme Budgeting data covers the whole population of users of health care, including individuals

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[21] Note, however, that the unified population figures are designed to adjust for health care needs at the PCT level, and not within each Programme Budgeting category. In principle, population needs, may well vary across Programme Budgeting categories but in the absence of a more appropriate needs adjustment at this level, we rely on the PCT unified weighted population.

[22] Input prices in London and the South East of England have been estimated to be up to 30% higher than elsewhere (Martin et al., 2008)

[23] It might also be argued that social care data could be adjusted for needs using the unified weighted population. We do not do this here, since the latter is designed to adjust for the need for health care (rather than social care) and more importantly, is an adjustment applicable to the full population and not solely those of working age (as reflected in the social care expenditure data). As a robustness check we applied the unified weighted population adjustment to the social care expenditure data and found very similar results to those reported here.

outside the working age population. Given that much of health expenditures are directed towards older people, this measure of the population would not appear appropriate. Instead, and as a sensitivity check, we consider using the total population of an LAD. This has the clear disadvantage of not adjusting population figures for health care need, but also avoids the issue around including the market forces factor.

Other Data

We condition on local labour market indicators that are available both across time and LAs. These data are available from the ONS official labour market statistics portal (NOMIS).[24] The inclusion of these data in the modelling exercise allow us to control for economic fluctuations affecting the labour market and the employment opportunities for individuals with and without long-term conditions and mental health problems. Burns et al. (2007) explore the value of individual placement support (IPS) in helping people with severe mental health problems to gain employment in six European centres, including London; using a randomised controlled trial design, they find that IPS does improve employment outcomes, but that local labour market conditions (proxied by local unemployment rates) account for much of the observed heterogeneity in IPS effectiveness.

In our study local labour conditions are proxied by two variables. Firstly, the unemployment to unfilled vacancy ratio, which provides a measure of the tightness of the local labour market. It is worth noting that in alternative specifications we also used the unemployment rate as a proxy for local labour market conditions. While related, the two measures represent different facets of the labour market. High unemployment might exist in the absence of vacancies, whereas the existence of vacancies evidences opportunities for labour market participation. These may differentially impact on people with and without long-term conditions and mental health problems. The use of the unemployment rate as an alternative variable does not substantially change the results. Secondly, we include the local wage ratio; the ratio of mean weekly wages for those with long-term health conditions (or mental health problems), to those for all people of working age. This variable is proxy for the relative productivity of workers with health problems.

We also control for variation in the generosity of the welfare state that may impact on employment participation decisions. Garcia-Gomez (2011) considers the reasons why the transition from employment to non-employment following a health shock varies across countries. Her analysis demonstrates the role of social security arrangements. Nations in Europe differ in terms of the characteristics of their benefit schemes (e.g. coverage, level of benefit etc.), as well as the employment and rehabilitation measures in place for those outside the labour market. For example, countries such as Italy with less generous unemployment benefits and quotas requiring employers to have a certain percentage of disabled people amongst their employees are more likely to see those who suffer health shocks retain employment. To control for the generosity of the welfare system we include the ratio of the mean weekly incapacity benefits payment to the mean weekly wage for those with long-term health conditions (or mental health problems). In alternative specifications we

[24] https://www.nomisweb.co.uk/

used income support payments instead of incapacity benefits payments but this makes no substantive difference. Figure 1 shows histograms of the variation in incapacity benefits payments, and the benefit to wage ratio by LA in 2007 and 2012. It is clear that there is substantial variation with the ratio as low as 0.15 in some LAs and as high as 0.45 in others.

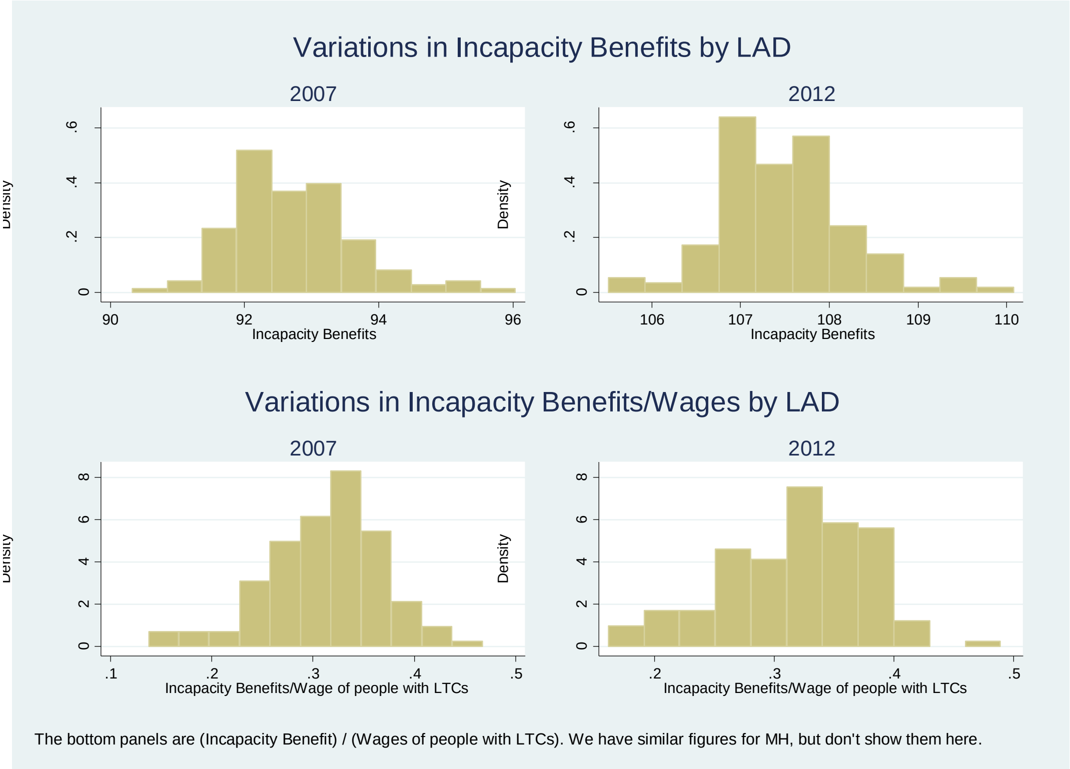

Figure 1: Variation in benefits and benefits ratio by LA. Source: NOMIS.

4. Econometric Methods

The main focus of the modelling work is an analysis of the employment gap at the LA level. The LA level model is specified as:

$$y_{it} = \beta_1 HC_{it} + \beta_2 SC_{it} + \beta_3 W_{it} + \beta_{34} L_{it} + \beta_5 B_{it} + \beta_6 LA_{it} + \alpha_i + \tau_t + v_{it} \quad (1)$$

For $i = 1, \dots, 152; \; t = 1, \dots, T$

Equation 1.

y_{it} is the employment gap is for LA i in time (year) t. The employment gap measures the difference between the percentage of people in the general working age population who are in employment, and the percentage of people of working age with a long-term condition (or mental illness) who are in employment.[25] Models are estimated separately for the long-term condition and mental health employment gaps. The overall employment gap is defined as TE_{POP} - TE_{HP}, where TE_{HP} is percentage of the sub-population of interest (those with long-term health conditions or mental health problems) who are in employment (defined as either full-time or part-time), and TE_{POP} is the equivalent percentage for all people of working age.[26]

As an alternative to all employment we also consider full-time employment only, because one hypothesis is that those with long-term physical conditions or mental health problems may be less likely to work full-time hours when compared with the general population.[27]

HC is a measure of health care input from the programme budgeting data described in the previous section. *SC* is social care input measured using the CASSR expenditure data. The per capita expenditure data is used in levels form.[28] The estimates of β_1 and β_2 provide descriptive evidence of the likely impact, if any, of the health and social care system on the observed employment gap. If the health and social care sectors help to reduce the employment gap then we would expect β_1 and β_2 to be negative.

L is a vector of local labour market conditions containing two variables; the local unemployment to vacancy ratio and the ratio of average wages for those with long-term health conditions (or mental health problems), to those for all people of working age. We

[25] Note that we have interpreted working age as 18-64 for men and 18-59 for women. In a robustness check we also included 16 and 17 year olds but this makes no substantive difference to any of the results reported here.

[26] 'In employment' is defined according to LFS variable INECAC05 where the respondent is either an employee (1), self-employed (2), on a government employment & training programmes (3), or an unpaid family worker (4). This is the International Labour Organisation (ILO) definition of basic economic activity (ref).

[27] We have not included these results in this final report because the sample sizes are relatively small, especially for mental health. In summary the results for full-time employment are largely the same as those reported for all employment.

[28] As sensitivity analysis we also used logged expenditure data to better account for non-linearity in the relationship between expenditure and outcomes (results not reported here). Using logs does not substantively change the results.

would expect the unemployment to vacancy ratio to have a positive association with the employment gap, and the wage ratio to have a negative relationship. In alternative models we use the unemployment rate instead of the unemployment to vacancy ratio, and again we expect this to have a positive association with the employment gap.

B is a measure of the generosity of the benefits system proxied by the ratio of the average incapacity benefit payment to the average wage for an individual with a long-term condition (or mental health problem). We would expect this measure to have a positive relationship with the employment gap.

LA is the local authority population, which we include in log form in the model. We expect this variable to have a negative relationship with the employment gap. A larger population may act as a proxy for large urban cities where employment prospects are greater than more sparsely populated LAs.

α_i are a set of time invariant LA dummy variables and τ_t represent a set of year dummy variables. υ_{it} is the stochastic error term. The inclusion of α_i means that our main specification is a fixed effects model that controls for time invariant unobserved heterogeneity, so that any unobserved LA factors that affect both the employment gap and the health and/or social care input do not bias our estimates of β_1 and β_2, as long as these effects vary only across LAs and not over time. As well as this fixed effects model, we also estimate random effects models and pooled OLS models. Random effects models assume time invariant unobserved LA heterogeneity is captured by a random disturbance term rather than by a fixed effect. This has the advantage of efficiency gains (via greater random variation) but can be at the expense of leading to bias in coefficient estimates (e.g. of β_1 and β_2). Pooled models do not specify LA level time invariant heterogeneity and instead assumes this is part of the overall stochastic error term, υ_{it}. The time dummies, τ_t, allow for changes over time affecting all LAs, such as in changes in macroeconomic conditions. Model estimation is weighted by the LA working age population.

For a full list of variables and sources see Table 2.

5. Results

The LFS survey contains approximately 100,000 individuals per quarter. To construct our analysis data we append all 4 quarters in a year and then collapse the data by LA code and year to produce a data set with LA as the unit of analysis. There are 152 LAs in England and our analysis sample is 141 LADs over 6 years (2007–2012) [N=846]. We do not have complete information for the full 152 LAs due to reasons of sample size,[29] miscoding[30] and missing data.[31] Our final analysis sample size is N=794 for LTCs and N=756 for MH. Further information on the cause of missing data is provided in Table 1 below.

Figure 2 shows the employment gap from 1997q1 to 2015q1 in the UK as a whole for people with long-term conditions and mental health problems. It is clear that overall the employment rates of the overall population and the groups with health problems have been rising, with some cyclical fluctuation. In addition the gap has, in both cases been narrowing i.e. the employment gap appears to be getting smaller over this time period, again with some cyclical fluctuation. What is also clear though is that the employment rates for people with mental health problems are very low, reaching only around 35% by 2015, compared to around 60% for all people with long-term health problems. This may be an indication of a greater severity of mental health problems in comparison to long-term health problems, or indicative of employment opportunities being lower for people with mental health problems. We are unable to distinguish between these hypotheses because the LFS data does not contain any information on severity of condition.

	Missing data points	Sample Size
Total LADs (152)		912
Only have information of 141 LADs (problems with mapping)	66	846
Miscoded health expenditure (footnote 27)	6	840
Missing observations on Health or SC expenditure or population in certain years	27	813
Sample size <100 for LTCs	19	**794**
Sample size <100 for MH	57	**756**

Table 1

[29] We restrict analysis to cell sizes of at least N=100.

[30] There appear to be coding errors in the health spending data for Lancashire, Staffordshire, East Sussex, Essex and Kent in 2008, and for Hertfordshire in 2012.

[31] There are missing values for the health and social care spending data for some LAs in some years.

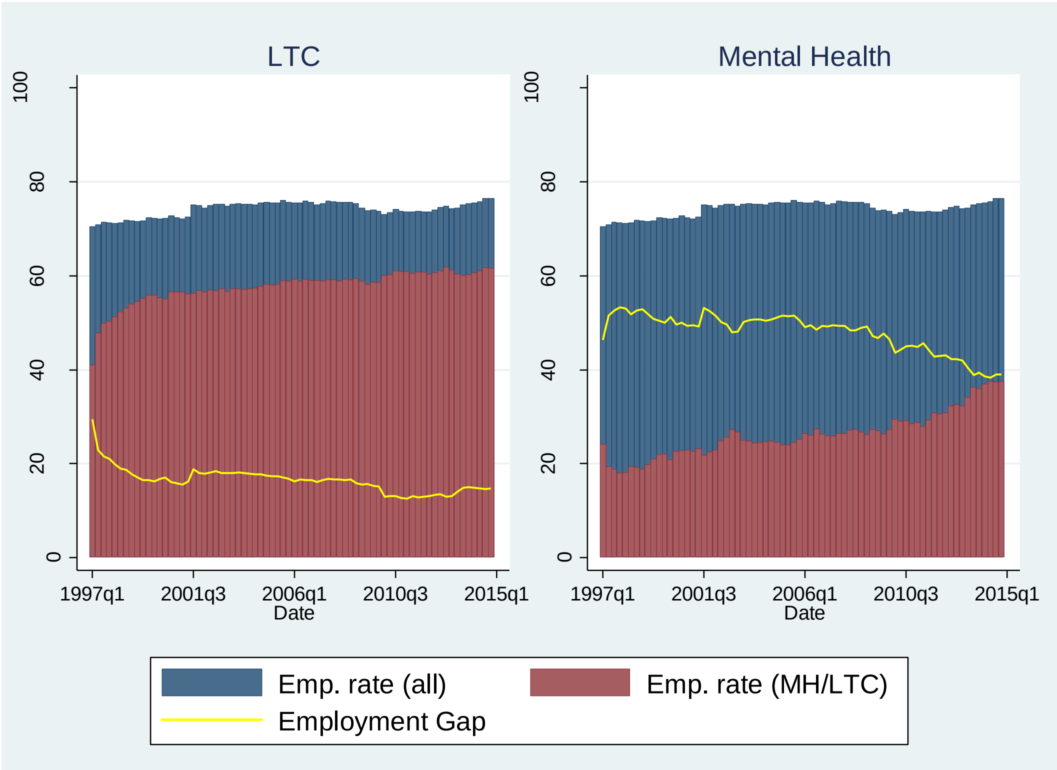

Figure 2: Employment gap for long-term conditions and mental health. Source: Labour Force Survey.

Tables 3a and 3b report descriptive statistics for our key variables. Table 3a shows statistics for the entire sample for the analysis period, 2007 to 2012. There are N = 794 observations for most variables (LA by year). The mean employment rate for the overall population of working age is just under 72%, but this is only 59% for those with long-term conditions and 29% for those with mental health problems. Real mean health care spending per capita is £1675,[32] and real mean social care spending per capita is £203. The incapacity benefit to wage ratio is higher for mental health (0.48) than for long-term conditions (0.32); and the wage ratio is higher for long-term conditions (0.96) than for mental health (0.77). Table 3b shows how these variables change year on year. The overall employment rate has decreased gradually over time from 73.1% in 2007 to 71.3% in 2012. The employment rate for those with long-term conditions has increased slightly from 58.6% to 59.7%; and that for those with mental health problems has increased more, from 27.3% to 31.3%. The changes in these rates are reflected in the narrowing of the employment gap for both groups that we see in Figure 2. Both real per capita health care spending and real per capita social care spending have increased over time. The mean unemployment to vacancy ratio increased to 2011 but reduced slightly in 2012; a similar trend is reflected in the unemployment rate. The benefits to wages ratio has been fairly constant over time for those with long-term conditions but has varied more for those with mental health problems, increasing from 0.48 to 0.56 in the first half of the period and falling to 0.45 thereafter. There has been a slight increase in the wage ratios for both groups, which, *ceteris paribus*, should make employment more attractive.

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[32] Mean health care spending per capita is needs adjusted, has the market forces factor deducted and is adjusted by the GDP deflator.

Figures 3 and 4 show scatter plots of health care spending against the employment gap for each LA, for both long-term conditions (Figure 3) and mental health (Figure 4). Both of these figures show very similar patterns. Looking at the scatter of data points with individual years (Figure 3a), a positive relationship is observed between health care spending and the employment gap for both long-term conditions and mental health; that is LAs with a higher employment gap also have higher (needs-adjusted) health spending. However, when the data is pooled (Figure 3b) there is some evidence of a negative relationship; that is higher spending is associated with a smaller gap.

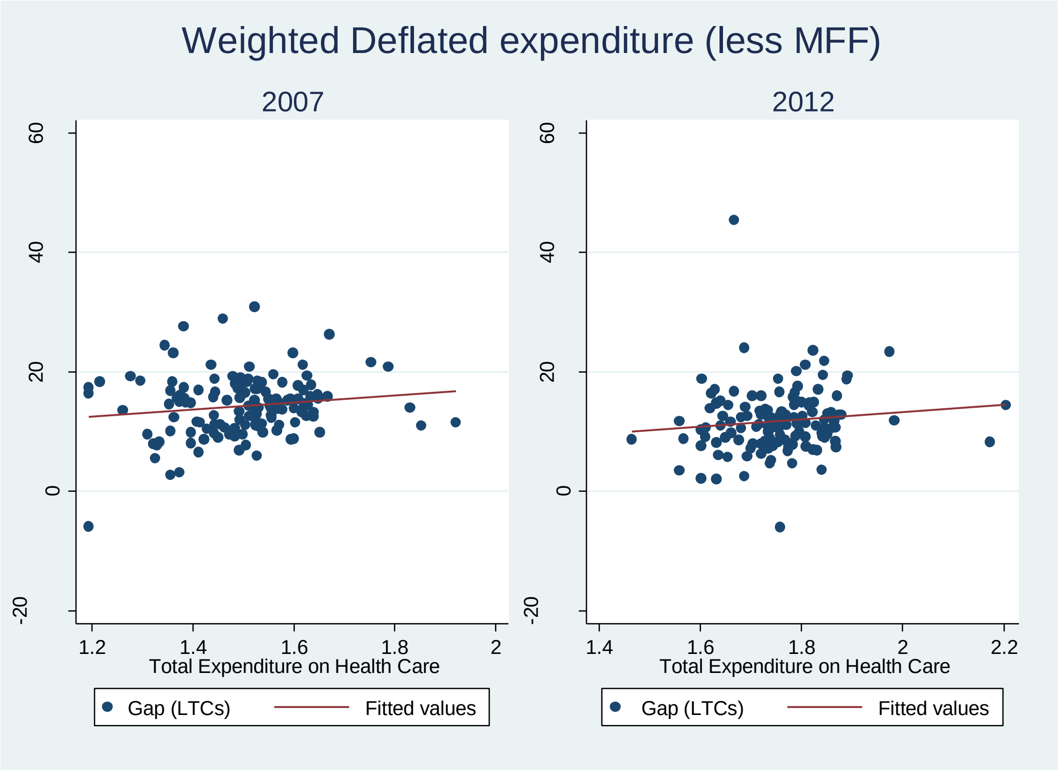

Figure 3a: Health care spending vs. employment gap, long-term conditions by LA, 2007 and 2012.

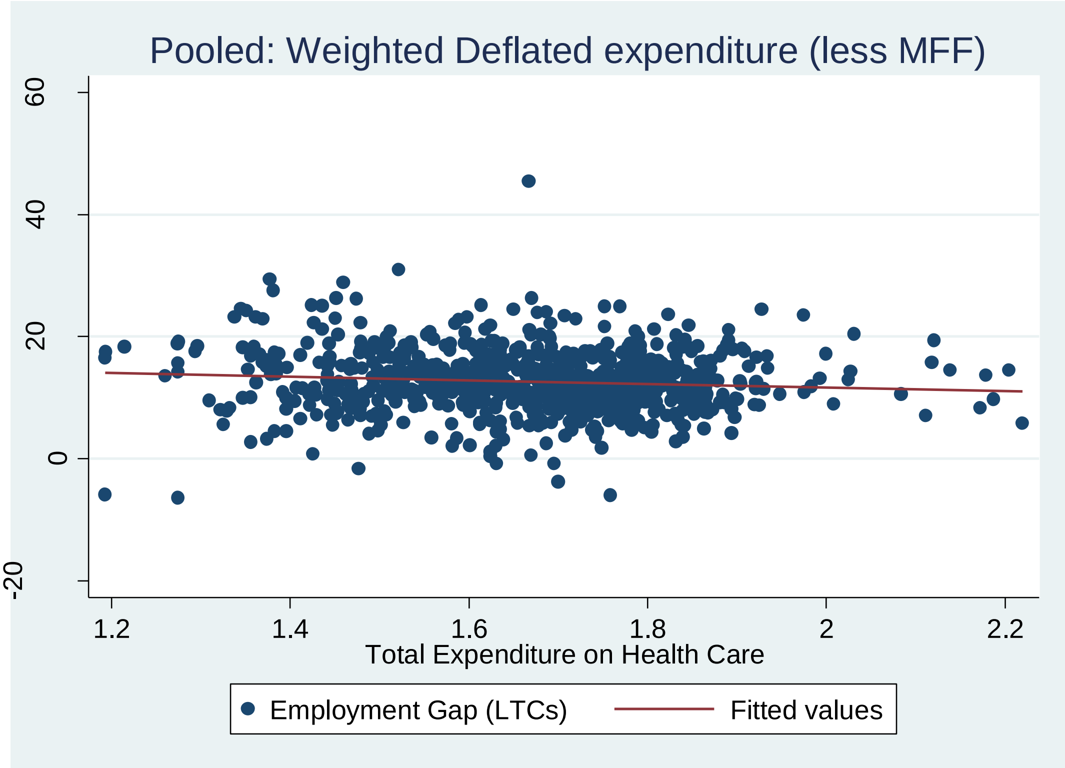

Figure 3b: Health care spending vs. employment gap, long-term conditions by LA, pooled 2007 to 2012.

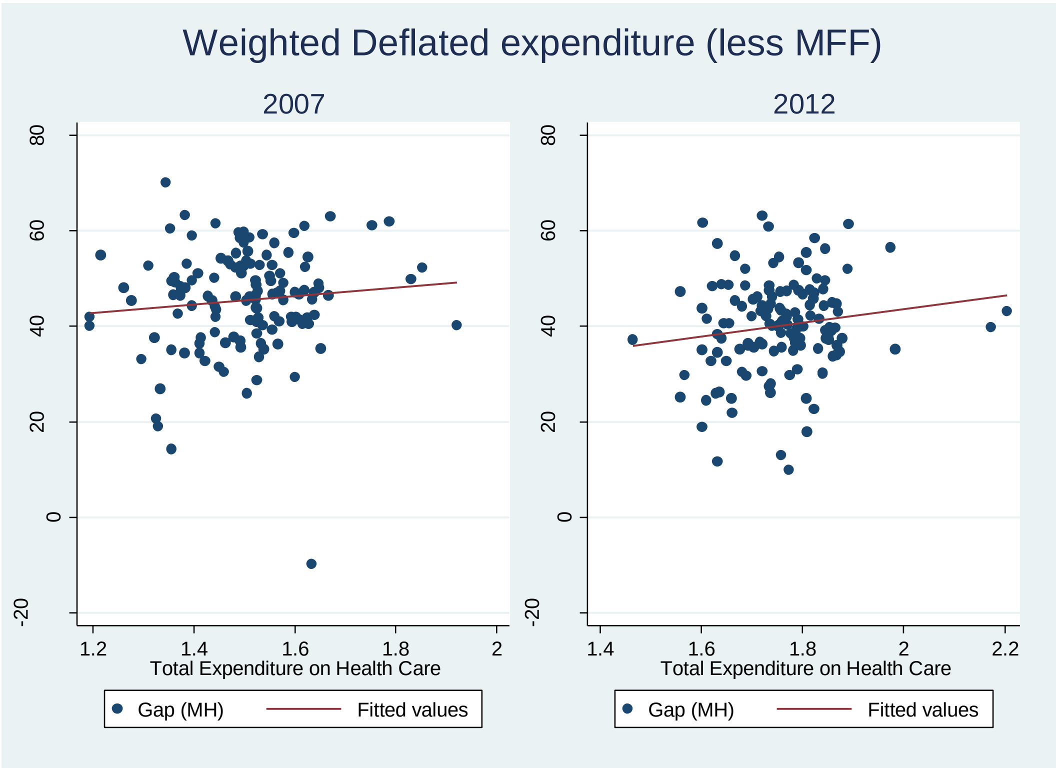

Figure 4a: Health care spending vs. employment gap, mental health by LA, 2007 and 2012.

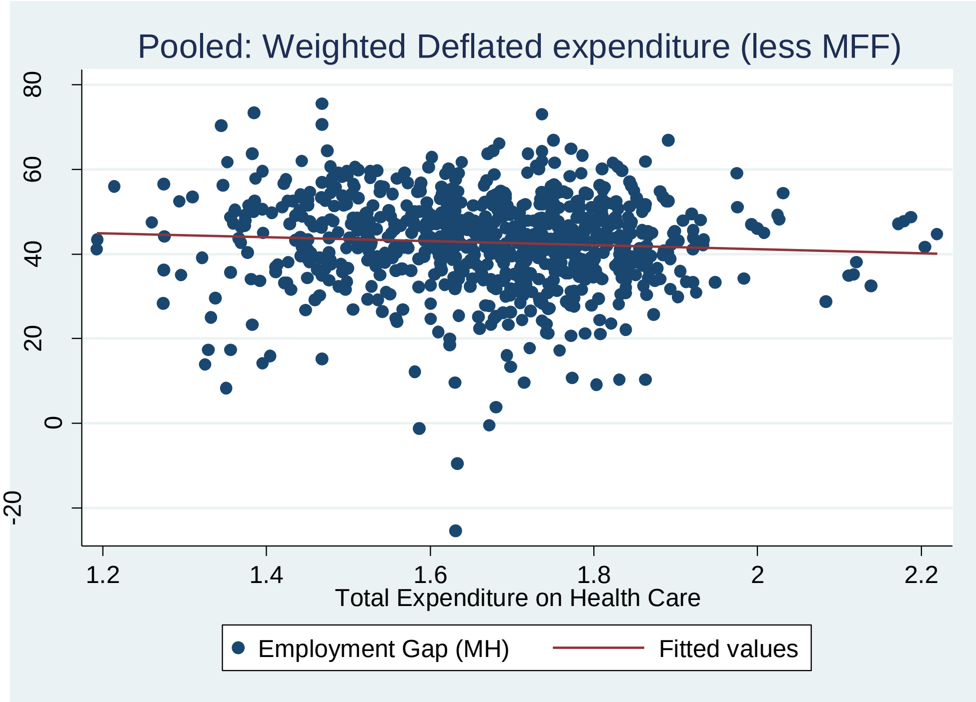

Figure 4b: Health care spending vs. employment gap, mental health by LA, pooled 2007 to 2012.

Table 4 reports the results of estimation of our main models. These are fixed effects models that include all 141 LAs. The first four columns (1) are models for long-term conditions and the last four columns (2) are the equivalent models for mental health. Considering first models (1a) and (1b); model (1a) shows the simple bivariate relationship between health care expenditure and the employment gap for people with long-term conditions. The negative and statistically significant coefficient on health care expenditure reflects the scatterplot shown in Figure 3b which pools the data across years, and implies that an increase in health care spending is associated with a smaller employment gap. Quantitatively the estimate suggests that if real needs adjusted spending per capita increased by £1000 the employment gap would decrease by 8.6 percentage points. In model (1b) the simple bivariate relationship is supplemented with the year effects, denoted τ_t in Equation 1; the inclusion of these effects reverses the relationship between health care spending and the employment gap, which is now positive and significant. This sign reversal is consistent with the scatterplots for separate years shown in Figure 3a, however in relation to any causal relationship between health spending on the employment gap this is a counter-intuitive result and we explore it further below.

It is worth stressing at this stage that we do not feel these results are due to reverse causality. If the employment gap was acting as a proxy for health care need then this may lead to two-way causation as higher need should attract higher expenditure. However, the needs adjustment we employ should preclude this possibility. This is clearly shown by Martin et al. (2008) who use the programme budgeting data to investigate the relationship between health care spending and health outcomes for 295 English PCTs in 2004/5. Without the needs adjustment there is a positive relationship between health spending and mortality outcomes (for cancer and circulatory diseases) but with the needs adjustment this relationship is reversed, suggesting that higher spending reduces mortality. In similar fashion our needs adjusted expenditure data should not reflect differential need across LAs, which may be also reflected in the employment gap.

Models (1c) and 1(d) are equivalent to (1a) and (1b) but also include the other control variables shown in equation (1). The story reflected in simpler models remains largely the same; without year effects the relationship between health care spending and the employment gap is negative, but when year effects are controlled for it is positive. Similarly social care spending has a negative association with the employment gap only if year effects are not included, and once year effects are controlled for this relationship is no longer statistically significant. The unemployment vacancy ratio has a negative relationship with the employment gap that remains statistically significant and of similar size even when year effects are included. However, the direction of this relationship is contrary to expectations because if this ratio increases this implies it is harder to find a job, and hence we would expect the employment gap to increase, unless those with health problems are finding it easier to find work (or remain in work) than the general population. To explore the robustness of this result we have also estimated models using the LA unemployment rate as the proxy for local labour market conditions rather than the unemployment to vacancy ratio.[33] Using the unemployment rate we still obtain a counterintuitive result; the coefficient on the unemployment rate is negative and significant, whereas we would expect a higher unemployment rate to have a positive association with the employment gap if it harder for people with health problems to find jobs when local unemployment is higher. Further exploration suggests that there is a significant negative association between the unemployment rate and the employment rate of the whole population, as expected. However, there is no significant association between the unemployment rate and the employment rates of people with long-term conditions or mental health problems. The result therefore is a significant negative association with the employment gap. It seems that the employment rates of people with health problems are not responding to local labour market conditions.

The benefits ratio and wage ratio have no statistically significant association with the employment gap. The log of the LA population has a negative association (whether or not year effects are included) which suggests that the employment gap is narrower in more densely populated areas.

The results for the mental health gap are very similar to those for long-term conditions; without year effects both health care spending and social care spending are negatively associated with the employment gap, but when year effects are controlled for these relationships become statistically insignificant. As for long-term conditions, the unemployment to vacancy ratio has a negative association with the mental health employment gap. The benefits to wage ratio is positively associated with the mental health employment gap, suggesting that the more generous benefits are relative to the wages that a person with mental health problems can expect to earn, the larger the employment gap will be.

[33] These results are not reported here.

In addition to fixed-effects (FE), we have also estimated all models using pooled OLS[34] and random effects (RE). In both the pooled OLS and the RE models, the coefficients on Health and Social Care Expenditure are negative and significant if we do not account for macroeconomic conditions (that is, if we do not include year effects). However, including the year effects leads to positive but insignificant effects of Health and Social care Expenditure in the pooled OLS models, but positive and significant effects in the RE models (similar to the FE specifications which we present here). However, due to the longitudinal nature of the data, we feel that either RE or FE specifications are preferred. These both allow us to account for the inherent differences between LAs (which we assume are constant over time). We then test which of RE or FE is preferred using a Hausman test (Hausman, 1978). In all cases, we find overwhelming evidence that the FE models are preferred to the RE models. For example, for the model presented in Table 4, column (1d), we get a test statistic of 44.29 (p=0.000), hence we prefer the FE models.

In addition to FE, we have estimated models using first differences (FD).[35] The results from the FD models are essentially the same as from the FE models, only the coefficient on health care expenditure is less statistically significance (and is insignificant in some cases). However, this is probably caused by reduced sample sizes (because FD models involve omission of the first year of data). Also, FE is preferred over FD if there is evidence of serial correlation in the error terms, and there is some evidence of that here. Overall, our preferred model specifications are FE.

It is also worth noting here that exploration of the raw data suggested that LAs in London and the South East could be considered as outliers in the health care spending vs. employment gap relationship as the labour market in these areas might be considered anomalous to the rest of the country. To check the robustness of our results to these potential outliers we excluded all LAs in London and the South East (leaving N = 503 observations for long-term conditions and N = 489 for mental health) and re-estimated the models reported in Table 4. These results are presented in Appendix 4 and the story is essentially the same, the main difference is that the significant positive association between health care spending and the employment gap for long-term conditions when year effects are included for all LAs is not significant when LAs in London and the South East are excluded. The wage ratio has the expected negative effect in models for the long-term conditions employment gap, but not for mental health. The unemployment to vacancy ratio has a negative effect for both long-term conditions and mental health problems, contrary to expectations. In addition the benefits ratio is negative for long-term conditions but has the expected positive effect for mental health.

In an effort to further understand the mechanisms behind the results presented in Table 4 we have also explored the association between the variables of interest and the employment

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[34] Our pooled OLS models account for the repeated nature of the data (i.e. observing the same LAs in different years) by clustering the standard errors at the local authority level. This ensures that the dependences of certain observations (i.e. the same LA in different years) is accounted for.

[35] FD models are an alternative to FE models. Instead of specifying unobserved LA level heterogeneity as a series of fixed effects (as for FE models), the data are transformed into first-differences by subtracting observation in period t-1 from observations in period t. This has the desired effect of removing unobserved heterogeneity.

rates TEPOP and TEHP, (rather than the employment gap) and these results are presented in Table 5; which includes results based on all LAs. Health and social care expenditure have no significant association with any of the employment rates. All of the models are dominated by the year effects, and in general the year effects are negative for the employment rate of the overall population and positive (or insignificant) for the employment rate of those with long-term conditions (or mental health problems), compared to our base year of 2007. Looking more closely at the year effects, they clearly reflect the macroeconomic conditions prevalent during the period. The annual growth rate of GDP in the UK was 2.6% in 2007; in 2008 this fell to -0.3%, falling further to -4.3% during the height of the recession in 2009. Since then there has been a slow recovery to 1.9% in 2010, 1.6% in 2011 and 0.7% in 2012. The year effect coefficients for the overall employment rate reflect this trend; they are zero in 2008, but negative thereafter reflecting lower employment rates in all years compared to 2007/8. The largest negative values are 2010 and 2011, with a slight recovery in 2012. In contrast the year effects are not as strong for the employment rate of those with long-term conditions or mental health problems, but they are positive is 2011 and 2012 for long-term conditions and positive in 2012 for mental health.

In further exploration we have disaggregated the categories of health and social care spending down into their constituent parts and these results are reported in Appendix 5: Employment gap – fixed effects models, all LAs – by expenditure category. These results reveal that most of the categories of spending have no significant relationship with the employment gaps for either long-term conditions or mental health problems. However, adult social care expenditure on mental health is associated with a reduction in the gap in both cases. In addition health care expenditure on muscular-skeletal problems is associated with a reduction in the mental health employment gap. However in contrast health care expenditure on gastro-intestinal problems is associated with an increase in the gap for long-term conditions, and health care expenditure on mental health problems is associated with an increase in the gap for mental health.

In summary the year effects, which reflect macroeconomic conditions, are dominating the employment rate movements, and this is not surprising given the period in question, one in which the UK slips rapidly into recession and then begins to make a slow recovery. The overall result for the employment gap is that it is narrowing largely because the overall employment rate is falling; whereas there is no strong trend in either direction for the employment rate of those with health problems. It is beyond the scope of this analysis to explore why the employment rate of those with health problems does not suffer as much during the recession as that for the overall population, but the results in Tables 4 and 5 suggest that this is unlikely to be due to health or social care spending. There is some evidence from Table 4 model (2d) that the benefit ratio is positively associated with the employment gap for those with mental health problems and so the reduction in this ratio that has been experienced over the period (see Table 3b) may be partly responsible for closing the gap. However, it should also be noted that while the benefit ratio has a negative association with the employment rate for those with mental health problems (Table 5 model 2b) this is not statistically significant. In addition evidence suggests that the employment rates of people with health problems are not responding to local labour market conditions.

6. Discussion

Our results find no evidence to reject the null hypothesis that there is no relationship between health care spending and the two employment gaps studied (for people with long-term conditions and for people with mental health problems), when we consider variation over the years 2007 to 2012 and across 141 LAs in England. This result is robust to a number of different model specifications and data inclusion criteria. Further exploration reveals that the results are dominated by year effects, which reflect macroeconomic conditions in a time period where the UK slipped rapidly into recession and then began to make a slow recovery. During this time the employment rates of those with health problems seemed to hold up whereas those for the overall population suffered, hence the employment gaps narrowed. It is beyond the scope of this work to explore why the employment rate of those with health problems did not suffer as much during the recession as that for the overall population, but our results do suggest that this is not down to health or social care spending. This is not an unexpected result; health care spending is only one potential influence on the employment gap and given that most NHS health care interventions target health outcomes rather than employment outcomes, it is not surprising that we have not been able to detect a relationship in this relatively aggregated area level data.

There are a number of shortcomings with this analysis which mean it is not an ideal method for estimating the effect of health care on employment outcomes. Firstly, we have been unable to obtain consistent data for a long time period and as a result our results are dominated by a very distinct macroeconomic set of conditions. A number of studies highlighted by the REA (Nathwani et al., 2015) pointed to the importance of macroeconomic conditions and local labour market circumstances in moderating the effectiveness of interventions designed to get those with health problems into employment; and our results are consistent with this.

Secondly, and related to the first shortcoming, we have had to draw on a number of data sources, all of which had to be manipulated in a number of ways in order to make them suitable for our analysis. For example, we have had to map between different geographies, we have made a number of adjustments to expenditure data to account for spatial and time variation needs and resource costs, and we have had to weight our estimates to account for sample sizes across our different geographies. All of these manipulations introduce noise into our data which compromise our ability to detect any relationship between health care spending and the employment gap.

Thirdly, on top of the fact that the period of analysis was characterised by distinct macroeconomic conditions, other institutional changes to the health care system and welfare system have also been going on at the same time (for example, the introduction of 'fit notes' in April 2010, and the transfer from Incapacity Benefit to Employment Support Allowance from January 2011, as well as other changes to carer allowances and the Disability Living Allowance), and these may also affect the employment gap. We have attempted to measure changes to the benefits system using benefits to wages ratio, and there is some evidence that a less generous benefits system is associated with a reduction in the employment gap for those with mental health problems, but this evidence is not consistent. It should be noted that our benefits to wage variable is a very rough proxy for changes to the welfare system and will not reflect all of the changes that have occurred and their differential effects on different groups of people.

Fourthly, the health care expenditure data used in this work is not an ideal measure of health care resource spent on working age people. The NHS programme budgeting data is not readily available for different age groups. Most health care spending goes on the very young and old; estimates suggest that people over 65 years of age account for 51% of gross spending on adult social care (Health and Social Care Information Centre, 2013) and two-thirds of the primary care prescribing budget (Department of Health, 2013), but these older people only account for about 17% of the population. So the majority of the expenditure that we identify is not spent on people of working age i.e. not on those people who constitute the employment gap. Furthermore, although the aim of Domain 2 is to measure the extent to which the NHS helps people with long-term conditions to live as normal a life as possible and employment can play a part in enabling this, health care expenditure is not spent on interventions that directly target employment outcomes; our result is therefore not surprising. Our social care data is better in this regard since it is disaggregated by age groups and we are able to identify social care expenditure on people of working age. However, a further shortcoming of the social care data is that the expenditure represents formal social care, whereas the majority of social care is informal, provided by friends and family, or privately provided.

Finally, our data on health conditions from the LFS self-report questions provides no information about severity of condition. It is likely that some of the people who respond to the survey have conditions that are so severe that they are unlikely to ever work in the labour market. Ideally we would want a measure of those who are able to work, in order to accurately identify our target population.

7. Conclusion and Recommendations

This work has attempted to explore the contribution of the health and social care system to the gap in employment for individuals with and without long-term conditions and mental health problems. Ideally we would have analysed aggregate country-level time series variation in the employment gap over a relatively long time period but this was not possible due to data limitations. Instead we have exploited time and spatial variation using LFS data by LA on employment outcomes and health status and combining this with NHS programme budgeting data on health care spending, as well as a number of other data sources. Our models controlled for other potential influences on the employment gap such as local labour market conditions and the generosity of the welfare system.

Our results provide no evidence to reject the null hypothesis that there is no relationship between health care spending and the employment gap for long-term conditions or mental health problems. Variation in the employment gap is dominated by year effects, which reflect specific macroeconomic conditions – a recession followed by a slow recovery. During this time the employment rates of those with health problems seemed to hold up whereas those for the overall population suffered, hence the employment gaps narrowed. However, it is beyond the scope of this work to explore why the employment rate of those with health problems did not suffer as much during the recession as that for the overall population, but our results do suggest that this is not down to health or social care spending.

Our results are not unexpected because health care spending is only one potential influence on the employment gap and particularly given that most NHS health care interventions target health outcomes rather than employment outcomes, it is not surprising that we have not been able to detect a relationship in this relatively aggregated area level data. Ideally to explore the influence of the NHS on employment we would need individual level data over time, with detailed information on health status, health care utilisation, social care utilisation, labour market outcomes and other socio-economic and demographic information, such as education levels, age, gender and ethnicity. In an ideal world we would also be able to exploit some exogenous variation in health or health care to overcome the simultaneous relationship between employment and health.

Recommendations for Future Work

We have a number of suggestions for future work that may help shed some more light on the relationship between health care and employment outcomes.

Firstly, we would recommend an analysis of the relationship between health care and employment outcomes at the individual level. The rapid evidence assessment (Nathwani et al., 2015) showed that there was some evidence for interventions having a positive effect on employment for those with mental health problems. However, no convincing evidence was found for physical conditions. In addition, current evidence fails to explore the reasons as to why this is the case and why certain treatments have greater influence than others. These questions can be explored in individual level analysis which includes detailed information on health status, health care utilisation, social care utilisation, labour market outcomes and other socio-economic and demographic information, such as education levels, age, gender and ethnicity. Such data may be available from longitudinal household data sets such as Understanding Society. Understanding Society includes good self-reported health information in all waves and also nurse visit data, with detailed health status information, in some waves; further there are plans in place to link the survey to the Hospital Episode Statistics data, which would provide good information on health care utilisation.

A second suggestion is to exploit exogenous variation in specific interventions targeted at the employability of people with long-term conditions or mental health problems. One option here for mental health is an analysis of data arising from the evaluation of the NHS Improving Access to Psychological Therapies (IAPT) programme. IAPT was introduced to improve outcomes in mental health by offering NICE-approved interventions to people with depression and anxiety disorders. It started with demonstration sites in 2006 and was gradually rolled out across the country between 2010 and 2015; initially IAPT had a specific focus on people of working age. Analysis of health outcomes data from IAPT and longer term employment outcomes, would be a potentially useful method for estimating the causal effect of health care interventions on labour market outcomes.

Finally, aggregate analysis of the employment gap such as that presented in this report could be revisited when further years of data become available. As well the obvious statistical advantage that this would increase our degrees of freedom and therefore our power to detect relationships, it also means that the data may reflect a broader set of macroeconomic conditions, and thus year effects may not be as dominant as they have proven in our time period. Further, more years of data would also enable us to introduce measures of lagged expenditure, which would improve model speciation. Second, at this same aggregate level of analysis, it would be worth investigating with the data owners whether the NHS programme budgeting data is available by age of target population, so that we can obtain a more appropriate measure of health spending on working age people.

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Table 1: Health problems (LFS variable "health")

1	problems or disabilities (including arthritis or rheumatism) connected with your arms or hands?
2	…legs or feet?
3	…back or neck?
4	difficulty in seeing (while wearing spectacles or contact lenses)?
5	difficulty in hearing?
6	a speech impediment?
7	severe disfigurements, skin conditions, allergies?
8	chest or breathing problems, asthma, bronchitis?
9	heart, blood pressure or blood circulation problems?
10	stomach, liver, kidney or digestive problems?
11	Diabetes?
12	**depression, bad nerves or anxiety?**
13	Epilepsy?
14	**severe or specific learning difficulties?**
15	**mental illness or suffer from phobias, panics or other nervous disorders?**
16	progressive illness not included elsewhere (eg cancer not included elsewhere, multiple sclerosis, symptomatic HIV, Parkinson's disease, Muscular Dystrophy)?
17	other health problems or disabilities?

Note:

Items 12, 14 and 15 in **bold** refer to NHSOF Indicator 2.5 (mental illness).

Table 2: Variable definitions and sources

Variable	Definition	Source
Employment gap	TE_{POP} - TE_{HP} where: TE_{HP} = percentage of those with long-term health conditions (or mental health problems) who are in employment (full-time or part-time) in each LA; TE_{POP} is the equivalent percentage for all people of working age.	LFS
Health care expenditure	Per capita real expenditure on long-term health conditions (and mental health problems) for each PCT. Calculated using unified weighted populations, which are adjusted to reflect the need for health care services. The market forces factor is removed and the data is deflated using GDP deflators.	NHS programme budgeting data
Social care expenditure	Real per capita expenditure on adult social care for each LA, converted using the total LA population figures for working age individuals from mid-year ONS estimates. The data is deflated using GDP deflators.	CASSR
Wage ratio	Mean weekly gross wage for workers with LTC (or MH) in each LA/ mean weekly gross wage for all workers in each LA	
Unemployment rate	Annual total unemployment rate in each LA	NOMIS
Unemployment/vacancy ratio	Unemployment count in each LA/vacancy count (all unfilled vacancies) in each LA	NOMIS
Income support/wage ratio	Average weekly income support payment (all claimants) in each LA /mean weekly gross wage for workers with LTC (or MH) in each LA	NOMIS
Incapacity benefit/wage ratio	Average weekly incapacity benefit long-term payment (all claimants) in each LA/mean weekly gross wage for workers with LTC (or MH) in each LA	NOMIS
Population	Total population in each LA from mid-year ONS estimates	NOMIS

Notes:

LTC is long-term conditions; MH is mental health. NOMIS is the ONS official labour market statistics portal https://www.nomisweb.co.uk/

Table 3a: Descriptive statistics – Full sample

Variable	Obs	Mean	Std. Dev.	Min	Max
Employment Rate %	794	71.639	5.733	51.503	87.725
Employment Rate (LTC) %	794	58.974	8.479	26.863	82.640
Employment Rate (MH) %	794	28.838	12.493	0.000	86.536
Employment Gap (LTC)	794	12.665	4.734	-1.939	31.410
Employment Gap (MH)	794	42.801	10.425	-1.274	75.496
Health Care Expenditure[1]	794	1.675	0.158	1.194	2.219
Social Care Expenditure[2]	794	0.203	0.071	0.000	0.784
log(Population aged 16-65)	794	12.156	0.566	10.984	13.753
Unemployment to Vacancy Ratio	794	5.696	3.156	0.440	19.975
Unemployment Rate %	794	7.806	2.792	2.000	16.500
Incapacity Benefit / Wages (LTC)	794	0.315	0.057	0.125	0.503
Incapacity Benefit / Wages (MH)	760	0.475	0.440	0.107	8.224
LTC wages / All wages	794	0.964	0.098	0.617	1.579
MH wages / All wages	760	0.771	0.274	0.028	2.359

Notes:

1. Health expenditure is mean per capita, deflated for GDP, weighted by population need, and has the market forces factor stripped out.

2. Social care expenditure is mean per capita, deflated for GDP and weighted by the population aged 16 to 65. LTC is long-term conditions; MH is mental health.

Table 3b: Descriptive statistics – by year

Variable	2007 Mean (s.d.)	2008 Mean (s.d.)	2009 Mean (s.d.)	2010 Mean (s.d.)	2011 Mean (s.d.)	2012 Mean (s.d.)
Employment Rate %	73.140	72.856	71.077	70.808	70.663	71.371
	(5.840)	(5.904)	(5.857)	(5.707)	(5.373)	(5.310)
Employment Rate (LTCs) %	58.601	58.221	57.919	59.769	59.567	59.713
	(9.161)	(9.369)	(8.368)	(7.996)	(7.782)	(8.090)
Employment Rate (MH) %	27.304	27.110	27.790	30.799	28.638	31.264
	(12.626)	(13.682)	(10.949)	(12.682)	(11.996)	(12.508)
Health Care Expenditure[1]	1.502	1.593	1.626	1.757	1.807	1.757
	(0.121)	(0.134)	(0.132)	(0.098)	(0.097)	(0.104)
Social Care Expenditure[2]	0.187	0.190	0.198	0.204	0.212	0.228
	(0.062)	(0.063)	(0.065)	(0.068)	(0.077)	(0.081)
Unemployment/Vacancies	3.554	4.062	7.415	6.246	7.027	5.768
	(2.207)	(1.918)	(3.073)	(2.874)	(3.477)	(3.038)
Unemployment Rate %	5.738	6.398	8.668	8.392	8.846	8.695
	(2.134)	(2.160)	(2.606)	(2.487)	(2.787)	(2.789)
Incapacity Benefit/Wages (LTC)	0.319	0.311	0.318	0.309	0.315	0.321
	(0.053)	(0.059)	(0.055)	(0.057)	(0.058)	(0.059)
Incapacity Benefit/Wages (MH)	0.481	0.510	0.563	0.411	0.428	0.458
	(0.402)	(0.371)	(0.837)	(0.150)	(0.167)	(0.315)
LTC wages / All wages	0.948	0.954	0.954	0.981	0.973	0.970
	(0.090)	(0.111)	(0.897)	(0.096)	(0.109)	(0.089)
MH wages / All wages	0.777	0.709	0.731	0.804	0.785	0.812
	(0.299)	(0.250)	(0.237)	(0.250)	(0.246)	(0.311)

Notes:

1. Health expenditure is mean per capita, deflated for GDP, weighted by population need, and has the market forces factor stripped out.

2. Social care expenditure is mean per capita, deflated for GDP and weighted by the population aged 16 to 65. LTC is long-term conditions; MH is mental health.

Table 4: Employment gap – fixed effects models, all LAs

	Long-term conditions				Mental health			
	(1a)	**(1b)**	**(1c)**	**(1d)**	**(2a)**	**(2b)**	**(2c)**	**(2d)**
Health care expenditure	-8.661***	3.409**	-4.866***	4.030**	-13.12***	3.021	-6.149**	4.186
	(0.951)	(1.731)	(1.149)	(1.741)	(2.476)	(4.678)	(2.945)	(4.648)
Social care expenditure			-16.48***	-6.538			-39.82***	-17.09
			(4.605)	(4.893)			(11.776)	(12.875)
Wage ratio			-3.661	-2.814			-0.408	0.533
			(2.688)	(2.621)			(1.754)	(1.751)
Unemployment Vacancy Ratio			-0.300***	-0.252**			-0.394*	-0.545*
			(0.077)	(0.109)			(0.202)	(0.293)
Benefits ratio			-9.481	-10.01			2.907*	3.111**
			(7.866)	(7.724)			(1.538)	(1.523)
Log Population			-7.621***	-4.578**			-12.06**	-5.052
			(2.125)	(2.143)			(5.421)	(5.625)
Year effects	No	Yes	No	Yes	No	Yes	No	Yes
Observations			**794**	**794**	**756**	**756**	**756**	**756**

Notes: Standard errors in parentheses.

***denotes significance at $p < 0.01$; ** $p < 0.05$; * $p < 0.10$.

Table 5: Employment rates – fixed effects models, all LAs

	Long-term conditions		Mental health	
	(1a)	(1b)	(2a)	(2b)
	All	LTC	All	MH
Health care expenditure	0.554	-3.476	0.689	-3.498
	(1.178)	(2.250)	(1.179)	(4.788)
Social care expenditure	1.955	8.493	1.184	18.28
	(3.311)	(6.323)	(3.267)	(13.265)
Wage ratio	-0.652	2.162	1.277***	0.744
	(1.773)	(3.386)	(0.444)	(1.804)
Unemployment to vacancy ratio	-0.0374	0.215	-0.0746	0.470
	(0.074)	(0.141)	(0.074)	(0.302)
Benefits ratio	0.132	10.14	0.817**	-2.294
	(5.227)	(9.981)	(0.386)	(1.569)
log(Population)	2.948**	7.526***	2.520*	7.572
	(1.451)	(2.770)	(1.427)	(5.796)
2008	0.0851	0.284	0.0690	-0.346
	(0.281)	(0.536)	(0.281)	(1.139)
2009	-1.243***	-0.702	-1.052***	-1.395
	(0.379)	(0.724)	(0.380)	(1.544)
2010	-1.816***	1.631**	-1.825***	1.255
	(0.420)	(0.802)	(0.418)	(1.696)
2011	-1.708***	1.429	-1.686***	0.691
	(0.477)	(0.911)	(0.474)	(1.926)
2012	-1.114***	1.863**	-1.130***	3.562**
	(0.422)	(0.807)	(0.421)	(1.709)
Year effects	Yes	Yes	Yes	Yes
Observations	794	794	756	756

Notes:

Standard errors in parentheses.

Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Appendix 1: Summary of individual survey data

List of UK Data Sets with both labour market and Health (levels and utilisation) information (excluding LFS)

Five other possible datasets were identified; these contain individual level information on both labour market outcomes, levels of health and healthcare utilisation. These are outlined below, along with relevant variables that may be of interest. The main shortcoming of all of these data sets is small numbers of individuals with the health problems of interest, and also relatively short time-series.

	BHPS	**Understanding Society**	**ELSA (50+ only)**	**Health Survey for England**	**GP Patient Survey**
Years of data	1991 - 2008	2008 – ongoing	2002 – ongoing	2000 – ongoing	2007 – ongoing
Frequency (& Data Type)	Yearly (Panel)	Yearly (Panel)	Every 2 years (Panel)	Yearly (repeated X-section)	Six monthly (repeated X-section)
Labour Mkt. Outcomes	– Income (wages) – Current economic activity – SOC codes (type of job) – In paid employment indicator (also employee or self-employed indicator) – Date current labour force status began (day, month, year) – Same for current job (as opposed to labour force status) – No. hours usually worked (+overtime)	– Income – Current economic activity – In paid employment indicator (also employee or self-employed indicator) – Date current labour force status began (day, month, year) – Same for current job (as opposed to labour force status) – No. hours usually worked (+overtime) – Full/part-time indicator	– Similar to BHPS, but labour market outcomes not main focus. – wage – hours worked – Type of employment	– Income – Current economic activity (last week) – SOC codes – Paid employment indicator – Date current labour force status began – Part/full time	Current economic activity Socioeconomic Vars: – Male/female – Banded age groups – Ethnicity

	– Full/part-time indicator – No. of people in HH in employment – Weeks in current spell – Second job information – Info on spouse's economic activity and hours worked	– No. of people in HH in employment – Second job information			
Benefit Receipt	List of benefits, including: – Sever disablement allowance – Incapacity benefit – Disability living allowance (H-R only)	List of benefits, including: – Severe disablement allowance – Incapacity benefit – Disability living allowance	more concerned with pensions, but includes disability benefit receipt etc.	Only relevant category would be 'other state benefit'. Not precisely defined.	N/A
Health Conditions and Objective Health	– GHQ – Health prohibits some types of work – Health limits type or amount of work – List of health conditions (see list A, below) – Self-assessed health	– From wave 2 onwards, some participants receive visits from nurses to get more objective health measures (blood pressure, BMI, etc.) – GHQ – Health prohibits some types of work – Health limits type or amount of work – List of health conditions (see list B, below) – Self-assessed health – SF-12 questions (hence PCS,	– Wave 2 and 4 has a nurse module (as USoc) – Detailed info on health (especially the effects of ageing on health) – Health limits type or amount of work – Onset of conditions (see list C, below) – Self-assessed health	– Self-assessed health – List of health conditions (think these change year-by-year, but there is a core of certain conditions in all) – Lots of changes in questions year-on-year	– Long-standing health condition indicator (Y/N) – EQ-5D (-5L) – Health limits activities (not specifically work) – Care plan indicator (Y/N) – List of health conditions (see list D, below) –

		MCS, SF-6D)			
Healthcare Utilisation	– Has had listed health check in past 12mths (Y/N) – Used health services in past 12mths (Y/N) – Then info on type (ie NHS vs. private, home help, etc.) – Saw consultant/was out patient (Y/N) – No. of visits to out-patients in past year (G-R; answered in banded intervals) – No. of inpatient visits (cts.) – Then info on NHS vs. private – No. of visits to a GP in past year (answered in banded intervals) – List of health checks in past year (inc. dentist, cholesterol, smears, blood tests, etc.)	– Visits as in-patient due to new condition (Y/N) – Healthcare utilisation data (similar to BHPS) is planned to be introduced from w7 onwards	– Very little, if any.	– Quite detailed (at least in the waves I have checked) – No. times talked to Dr. in last 2 weeks – What type of Dr.? – No. times in past year spoke to/visited a GP/family Dr. – Then as above for Outpatient, Inpatient (day patient), and A&E visits	– Very detailed. – When did you last see a GP – What type of appointment (ie in surgery, at home, nurse/doctor, etc.) – Quality of appointment (to see a GP) – Quality of appointment (to see a nurse) – Nothing on hospitals, however.
Health Limits Daily Life/Employment	– Series of questions about if health limits ability to do certain tasks at work, etc.	– Series of questions about if health limits ability to do certain tasks at work, etc.		– Not much detail.	–

Appendix 1 continued

List A: BHPS Health Conditions (Y/N)	List B: USoc Health Conditions (Y/N)	List C: ELSA Health Conditions (Y/N)	List D: GP – Patient (Y/N)
Arms, legs, hands	Asthma	High blood pressure or hypertension	Alzheimer's disease or dementia
Sight	Arthritis	Angina	Angina or long-term heart problem
Hearing	Congestive heart failure	Heart attack (including myocardial infarction coronary thrombosis)	Arthritis or long-term joint problem
Skin conditions	Coronary heart disease	Congestive heart failure	Asthma or long-term chest problem
Breathing/chest	Angina	A heart murmur	Blindness or severe visual impairment
Heart/blood pressure	Heart attack or MI	An abnormal heart rhythm	Cancer in the last 5 years
Stomach or digestion	Stroke	Diabetes or high blood sugar	Deafness or severe hearing impairment
Diabetes	Emphysema	A stroke (cerebral vascular disease)	Diabetes
Anxiety/depression	Hyperthyroidism –over active	High cholesterol	Epilepsy
Alcohol or drugs	Hyperthyroidism –under active	Any other heart trouble	High blood pressure
Epilepsy	Chronic bronchitis		Kidney or liver disease
Migraine	Liver condition		Learning difficulty
Cancer	Cancer/malignancy		Long-term back problem
Stroke	Diabetes		Long-term mental health problem
Other	Epilepsy		Long-term neurological problem
	High blood pressure		
	Clinical depression		

Appendix 2: Age-Period-Cohort modelling

Our tender document proposed an Age-Period-Cohort (APC) modelling strategy in an attempt to identify trends in the gap in employment between individuals with (i) long-term conditions and (ii) mental health problems, and the general population (the employment gap), and the likely contribution of the health and social care services to this gap.

The APC approach has precedent in epidemiological studies, particularly in studies describing trends in mortality rates or disease incidence over time. This makes intuitive sense since disease-specific mortality can be characterised by an age effect (the incidence of many diseases varies across the life course), a period effect (reflecting changes in prevention and treatment across time that affect all age groups simultaneously), and a cohort effect (representing different lifetime exposures for a given generation). Which of age, period, or cohort effect is important is of interest to many social phenomena where the focus is placed on understanding change over time. Similar arguments might apply to changes in labour participation decisions where age effects potentially reflect the accumulation of work experience and skills across the life course. Period effects represent variation over time in employment due to the impact of changing macro-economic circumstances and labour market environments. Differential exposure to education, training and work opportunities over time (for example the changing of the school leaving age or the introduction of equal opportunities legislation) might plausibly lead to different cohort effects for successive age groups in successive time periods on labour supply and employment rates.

The APC approach has precedent in modelling the mortality outcomes of Domain 1 of the Outcomes Framework. In particular the modelling was undertaken using annual data within 5-year age bands over the period from 1979 onwards.[36] This provides up to 36 years of observations within each age category from which to disentangle age and cohort influences on the underlying period (time) trend.

We have undertaken a review of the key research papers underpinning the APC approach.[37] A popular approach to estimating APC models is provided by Yang, Fu and Land (2004). This is based on modelling the outcome of interest (the employment gap) within pre-defined age groups. Generally these tend to be 5-yearly intervals. The approach regresses the outcome on a set of age dummy variables (one for each 5-year grouping, minus the baseline), a set of period dummy variables and a set of cohort dummy variables representing the year of birth of the individual. Both period and cohort effects are generally also grouped into year bands.

A fundamental problem in the APC approach is model identification due to a mathematical dependence across the three terms. In principle, the cohort year is a linear function of age and period (cohort = period – age). In many applications the cohort effect (year of birth) is

[36] P6 Invitation to Tender (2014). Developing Methods for Retrospective Assessment Against the NHS Outcomes Framework to Understand the Contribution of the NHS and Partner Organisations. DH Policy Research Programme and NHS England.

[37] Note this is not a systematic review of the literature in this area, but a review of key studies.

computed directly from age at interview and date of interview (period) so the mathematical dependence strictly holds. However, even where date of birth is available in a given dataset removing the strict mathematical dependence, identification may remain an issue for modelling. This fundamental problem of identification is well known and there have been numerous proposed solutions to estimate the independent impact of the three APC terms. All solutions, however, are assumption based and all attract criticism. Indeed, some have argued that the separation of the three APC effects is a futile exercise (see, for example, Glenn, 1976; Goldstein, 1979).

APC estimation

Classically, APC models have been estimated by specifying the effects of age, period and cohort as factors via dummy variables. It is common practice to group age and periods into 5-year intervals which correspond to over-lapping 10-year intervals for cohort effects. The model can be estimated using generalized linear models, but due to the fundamental problem of identification, the model is over-parameterized and consequently will result in the arbitrary exclusion of one of the factors. Yang, Fu and Land (2004) suggest placing restrictions on the model, in the form of constraining the effects of, say, age in two of the 5-year categories to be equivalent. This removes the strict dependence implied by cohort being a linear function of period and age, and estimation can proceed. Where the constraint is placed, however, is relevant and importantly can affect the results and interpretation of the model coefficients. Ideally the choice would be made on the basis of prior information, or theoretical guidance, but these are often difficult to find and justify. Moreover, all 'just-identified' models irrespective of where the constraint is placed will produce the same level of goodness-of-fit to the data and hence as a model selection criterion is uninformative.

An alternative approach to estimation is provided by the intrinsic estimator of Yang, Fu and Land (2004). This purports to solve the identification problem by using a form of principal component analysis[38] to reduce dimensionality and derive constrained estimates for age, period and cohort effects.

The above approaches, however, are not able to incorporate covariates in their standard form without imposing further restrictions on the parameters of the model – essentially constraining additional effects for age, period or cohorts to be equivalent. Imposing many restrictions of this kind is likely to prove untenable. This is a concern for the modelling, such as that proposed here, where ideally the aim is to investigate the impact of covariates such as NHS and social care activity on the observed period trend.

Carstensen (2007) proposes estimation of APC models based on flexible cubic splines (also see Rutherford, Lambert and Thompson, 2010), moving away from specifying age, period and cohort effects as factors by analysing them as continuous variables. The approach has appeal, and in principle can accommodate covariates into the model. In practice, this works best for discrete covariates where data are available across all age groups represented. To estimate the model both the period and cohort terms require de-trending. Inference and interpretation of the resulting estimates relies on one of either the cohort or period effect

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[38] Principal Component Analysis is a statistical procedure that uses an orthogonal transformation to convert a set of observations of possibly correlated variables into a set of values of linearly uncorrelated variables called principal components.

remaining de-trended by constraining it to have zero slope and zero mean (on a log scale). If this is the cohort effect, then the period effect can be interpreted with respect to the reference period (mean period in the data).

A further approach proposed by Yang and Land (2006) involves specifying period and cohort effects as random entities and modelling via a cross-classified multilevel model (Hierarchical Age Period Cohort model: HAPC). This approach considers individuals within age groups nested (cross-classified) within period and cohorts. In this way, age is treated as a fixed effect (appearing in the conditional mean) and period and cohort effects as random effects (representing the context in which individuals are situated). It is argued that modelling age differently to the period and cohort effect resolves the identification issue. For an application to social inequalities in happiness see Yang (2008b).

The model of Yang and Land (2006) has appeal in that it can accommodate covariates in a straightforward manner and these are not restricted to be of a given form – they can be measured on a cardinal or discrete scale. The specification, however, makes a number of assumption that Jones and Bell (2014) argue are not tenable in the majority of applications. Most importantly, the period and cohort effects are assumed to represent random draws from a pre-specified distribution (usually normal) and are independent of the age effects which populate the fixed part of the model (as a series of dummy variables). Violation of this latter assumption will bias the estimates of the period and cohort effects that are derived from the model. As Jones and Bell (2014) point out this is problematic since where there is a cohort trend, with repeated cross-sectional data, the age variable will always be correlated with the cohort residual (random effect) because older cohorts will have a higher age than newer cohorts over the time period studied. Hence it is unlikely that application of the standard HAPC model will lead to consistent estimates of all trends of interest.

Bell and Jones (2015) extend the HAPC approach to a Bayesian framework. They show that the standard HAPC approach, whilst conceptually appealing, can only produce unbiased estimates of age, period and cohort effects as long as period or cohort effects are de-trended. Where interest lies in estimating say age and period trends, then the model is required to be constrained such that, in this case, the cohort effect is zero. Such restrictions are difficult to justify empirically, but might be driven by theoretical considerations. The approach of Bell and Jones (2015) is to place (strong) informative priors on one of the trends which enable the other effects to be estimated via Bayesian Monte Carlo Markov chain. For example, placing a prior on the effect of age over the life course on outcomes, allows the trends in both periods and cohorts to be estimated. This approach presents an option for estimation when one of the APC trends is known and the effects of the other two are required to be estimated. Such priors, however, need to be based on sound theoretical arguments.

While the above approaches vary in their appeal in modelling APC effects, none of them are implementable without careful consideration of the assumptions imposed (which may well prove to be untenable for any particular application). These issues arise due to the fundamental identification problem outlined above and attempts to circumvent this empirically.[39]

Modelling interest for this project is focused on attempts to define the contribution of health and social care to the employment gap. Our approach as set out in the tender document was to follow the approach used in Domain 1 of the Outcomes Framework and model the period effect using the APC approach. However, the concerns over the fundamental problem of identification raised in the above literature, together with the assumptions required to impose restrictions on the model and the limitations in the data we have to model these effects using the LFS led us to reconsider the APC approach as being suitable for our purposes. It is noted that the APC modelling implemented for Domain 1 of the NHS Outcomes Framework for mortality outcomes, had at its disposal data from 1979 onwards, providing up to 36 years of observations from which to estimate period trends. The LFS provides us with a maximum of 17 years of observations with which to explore the employment gap, hence APC modelling is not a viable approach.

[39] Theoretically the identification problem cannot be resolved.

Appendix 3: Local Authority Geography

Since 1994 England has been subdivided into nine regions. London has an elected Assembly and a Mayor, whilst others historically have a relatively minor role (Regional Development Agencies were abolished in 2012). Excluding London, below regional level England has two patterns of local government. In some areas there is a two-tier system with county councils responsible for services such as education, and several non-metropolitan district councils responsible for services such as housing. Other areas, known as unitary authorities, have only one tier of local government.

In total there are 57 single-tier authorities comprising 55 unitary authorities, The City of London Corporation, and The Council of the Isles of Scilly. There are 34 upper-tier authorities consisting of 27 non-metropolitan counties (which function as local education authorities), 6 metropolitan counties, and The Greater London Authority. Within the upper-tier authorities, there are 269 lower-tier authorities (which have the function of billing for Council Tax). These comprise 201 non-metropolitan districts, 36 metropolitan boroughs, and 32 London boroughs. The metropolitan and London boroughs also function as local education authorities.

In total there are 326 separate local authorities (57 single tier authorities plus 269 lower-tier authorities) which we refer to as local authority districts (LADs). These can be amalgamated into 152 (57 single-tier, plus 27 non-metropolitan counties, plus 36 metropolitan boroughs, plus 32 London boroughs) higher-level local authorities. We refer to the latter geography simply as local authorities (LAs).

It is common for the above two geographies (326 local authority districts or 152 local authorities) to be used for data collection purposes. Our data is no exception and we have various key variables measured across one of the two geographies. For example, social care expenditure data is collected by County Councils with responsibility for social care and available annually at the LA level. The measures of key labour market indicators representing opportunities for labour supply (via the unemployment and vacancy rates), and levels of social support were also obtained at the LA level. An exception is data on health care expenditure which is collated via Programme Budgeting Data (PBD) at the level of Primary Care Trusts (PCTs). From 2003 to 2006 there were 303 PCTs in England, and from 2006 to 2013, there were 152 PCTs. Using Geoconvert,[40] we have converted relevant expenditure data taken from Programme Budgeting Data to LAD geography.

The analysis undertaken at the LA level consists of 152 single-tier, non-metropolitan and metropolitan councils and boroughs. This level of geography ensures alignment with the variables we wish to model, but also allows for sufficient observations within LAs of people with long-term conditions for whom we can calculate the employment gap.

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[40] Geoconvert is freely available software that allows data mapped to a given geography to be mapped to an alternative geography. This is done through Gridlink™ which attributes data between geographies on the basis of postcodes.

Appendix 4: Employment gap – fixed effects models, LAs excluding London and South East

	Long-term conditions				Mental health			
	(1a)	**(1b)**	**(1c)**	**(1d)**	**(2a)**	**(2b)**	**(2c)**	**(2d)**
Health care expenditure	-11.38***	1.454	-5.623***	2.396	-17.14***	-4.301	-7.999**	-1.033
	(1.240)	(2.000)	(1.506)	(2.006)	(3.026)	(5.214)	(3.799)	(5.293)
Social care expenditure			-20.29***	-5.521			-33.10**	-2.677
			(6.185)	(6.855)			(15.382)	(17.913)
Wage ratio			-8.914**	-7.264*			3.551	4.048
			(4.137)	(4.007)			(2.652)	(2.642)
Unemployment/Vacancy Ratio			-0.417***	-0.393***			-0.491**	-0.634*
			(0.094)	(0.139)			(0.239)	(0.364)
Incapacity Benefits/Wage ratio			-17.84*	-18.86*			6.623**	6.639**
			(9.954)	(9.666)			(3.165)	(3.147)
log(Population 16-65)			-8.617***	-3.926			-9.752	-0.401
			(2.446)	(2.579)			(6.093)	(6.738)
Year effects	No	Yes	No	Yes	No	Yes	No	Yes
Observations	503	503	503	503	489	489	489	489

Notes: standard errors in parentheses. ***denotes significance at $p < 0.01$; ** $p < 0.05$; * $p < 0.10$.

Appendix 5: Employment gap – fixed effects models, all LAs – by expenditure category

	Employment Gap (long-term conditions)	Employment Gap (mental health)
HExp on Diabetes	35.06	-1.288
	(31.532)	(84.762)
HExp on Mental Health	7.496	1.736
	(5.942)	(15.975)
HExp on Circulatory Problems	2.774	10.69
	(8.961)	(24.176)
HExp on Respiratory Problems	4.628	4.788
	(20.779)	(55.222)
HExp on Gastro Intestinal System	34.69**	41.61
	(16.185)	(44.139)
HExp on Musculo Skeletal Problems	-11.88	-55.75**
	(9.231)	(25.176)
HExp on Social Care Needs	6.362	22.19*
	(4.361)	(11.502)
HExp on Other Categories	0.850	0.435
	(2.274)	(6.173)
SCExp on Physical Health	21.91	20.97
	(20.302)	(54.393)
SCExp on Learning Difficulties	-1.191	-3.843
	(7.599)	(20.127)
SCExp on Mental Health	-63.37***	-127.2**
	(23.334)	(62.438)
Wage ratio	-2.447	0.139
	(2.619)	(1.757)
Unemployment to Vacancy Ratio	-0.227**	-0.552*
	(0.110)	(0.298)
Benefits to Wage Ratio	-8.960	2.957*
	(7.702)	(1.532)
Log population	-4.410**	-4.989
	(2.141)	(5.650)

Year effects	Yes	Yes
Observations	794	756

Notes:

Standard errors in parentheses.

Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.