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ABSTRACT

Macroeconomic Conditions and Health in Britain: Aggregation, Dynamics and Local Area Heterogeneity

We estimate a model that allows for dynamic and interdependent responses of morbidity in different local areas to economic conditions at the local and national level, with statistical selection of optimal local area. We apply this approach to quarterly British data on chronic health conditions for those of working age over the period 2002-2016. We find strong and robust counter-cyclical relationships for overall chronic health, and for five broad types of health conditions. Chronic health conditions therefore increase in poor economic times. There is considerable spatial heterogeneity across local areas, with the counter-cyclical relationship being strongest in poorer local areas with more traditional industrial structures. We find that feedback effects are quantitatively important across local areas, and dynamic effects that differ by health condition. Consequently, the standard panel data model commonly used in the literature considerably under-estimates the extent of the countercyclical relationship in our context.

JEL Classification: J10, J21, C33, E32

Keywords: macroeconomic conditions, health, morbidity, dynamics, heterogeneity, aggregation

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1. Introduction

Whether population health improves or worsens with changes in macroeconomic conditions is a long-standing question. Despite a substantial literature there is no clear consensus on the answer. Some studies find evidence that recessions are good for population health (i.e. poor health is pro-cyclical), while other studies find that health worsens in response to bad economic times (i.e. poor health is counter-cyclical). In addition, results for various health outcomes differ (see Bellés-Obrero and Vall Castello, 2018, for a review).

Following Ruhm (2000), the workhorse model for almost all studies of the relationship between macroeconomic conditions and health is a linear regression with local area-fixed effects and national and local area time trends. Identification comes from co-movements in a macroeconomic indicator measured at local level such as the state unemployment rate (which is assumed to be exogenous) and a measure of health such as the state mortality rate around a (linear) trend. While this model controls for fixed and time-varying confounders and provides a useful average estimate of the relationship between local area economic changes and health outcomes, it is less informative about (1) short versus long-run dynamics, (2) the extent of area-level heterogeneity in the relationship between the economy and health, (3) the importance of spillovers between areas, and (4) the optimal level of spatial disaggregation. Since these influences have been shown to be important in studies of the effect of the business cycle on consumption (e.g. De Giorgi et al., 2019), labour market outcomes (e.g. Lee and Pesaran, 1993) and well-being (e.g. Luttmer, 2005), they may also be important for the relationship between economic conditions and health outcomes. Health conditions evolve over time, so dynamics are likely to be important. Health is affected by social interactions, which take place at both large and small spatial scales, meaning that spillovers between areas are likely. Local areas differ considerably in their demographic and industrial composition and therefore are likely to have different health responses to economics events.

Our innovation is to take a different approach and to adopt heterogenous panel methods to estimate the relationship between economic conditions and health. We estimate a Global Vector Autogressive (GVAR) model that captures the full extent of differences in the population health responses to economic changes across local areas. It accommodates feedback across areas and captures both the direct effects of economic changes on population health and those exerted indirectly through interdependent economic and population health influences. Further, rather than impose the level of spatial aggregation (e.g. state, county) *a priori* as in the standard modelling approach, we choose it based on a sequence of tests. These tests are premised on the assumption that a more disaggregated model is preferable unless the data suggest that aggregation is appropriate (Lee et al., 1990; van Garderen et al., 2003).

This approach enables us to examine the complex dynamic and interdependent responses of population health in different local areas to changes in economic circumstances. For example, we can look at how any impacts on population health develop over time and how economic changes at the national level differ in their impact from economic changes at the local level. Using statistical tests to determine the appropriate level of spatial aggregation formally addresses concerns raised by Lindo (2015) and Ruhm (2016), who both find that estimates from standard fixed effects models differ over levels of spatial aggregation in the US.

We also innovate in our focus on chronic health conditions. The majority of studies in this literature examine mortality. While mortality has the advantage of being objectively measured, studying the effect of economic changes on chronic illness is important. The rising prevalence of chronic conditions imposes a major cost on health care systems (Department of Health, 2010). Understanding how reports of chronic health conditions are affected by economic conditions is important for developing policy responses.

In an extension, we use the same modelling approach to examine chronic health conditions split into five groups: musculoskeletal, cardiovascular, respiratory, mental health and other. Our model captures any interdependence between these different types of chronic health conditions. Such interdependence is not unlikely because the underlying drivers of different chronic conditions are often similar as many are lifestyle-related. Thus, an increase in one type of chronic condition may propagate across others, contributing to the rising prevalence of multimorbidity (an individual suffering from more than one chronic condition).

Splitting chronic health conditions into major groups also allows us to estimate the impact of economic conditions on mental as well as physical health. The prevalence of mental ill-health is rising and is both an important outcome in its own right, and may be one pathway to the relationship between mortality and the business cycle (for example, Ruhm, 2000, 2003; Charles and DeCicca, 2008; Tefft, 2011; McInerney and Mellor, 2012; Golberstein et al., 2019).[1]

We examine data from Britain for 2002 to 2016. Britain is a good case study for several reasons. In common with many other countries across the world, the prevalence of chronic conditions is rising with costly implications for the public purse as well as affecting the quality

[1] We examine chronic conditions that are associated with the cardiovascular related mortality studied in earlier research (for example, Birgisdóttir et al., 2018; Colombo et al., 2018).

of individuals' lives. There is considerable geographical variation in both the prevalence of chronic conditions and in economic conditions. Our sample includes the large negative shock to the economy from the Global Financial Crisis (GFC), providing considerable time-series variation in economic conditions at national and local level. Our data are at quarterly frequency and contain 57 quarters, so we can examine dynamic responses to economic changes.

Contrary to the pro-cyclical findings of a number of recent studies of mortality, we find robust evidence that reported chronic illness responds counter-cyclically to the business cycle (i.e. chronic illness decreases as the economy picks up). Our long-run elasticity estimate implies a one percent point increase in local employment growth results in around a 2 per cent fall in the prevalence of chronic illness. We find important feedback effects from aggregate national levels of chronic illness that amplify the response to economic conditions. Models which omit such feedback effects would, on average, under-estimate the long-run elasticity by around 50%. Our estimates suggest that the long-run effects are reached only after 2 years. There is considerable heterogeneity across local areas in the response of health to economic conditions. While there is a counter-cyclical relationship in almost all local areas, the estimates are largest in areas with a higher proportion of employment in `blue collar' industries, older populations and populations in poorer long-term health. Examining conditions by major type, we find substantial counter-cyclical effects for all conditions, with the strongest relationship for mental health conditions, followed by musculoskeletal conditions. We also find that reaching the full impact takes longer for the conditions with the largest long-run elasticity estimates.

In sum, we find clear evidence that long-term health conditions get worse in recessions, that older, poorer areas with a more traditional industrial structure respond the most negatively, and that it takes over 2 years for these effects to fully manifest themselves. We also show that in our context the fixed effects panel data model commonly used in the literature substantively under-estimates the relationship between local area economic conditions and health.

The paper proceeds as follows. Section 2 provides a brief review of the extant literature, focusing on papers which address issues of modelling. Section 3 presents our modelling approach, Section 4 the data and Sections 5 and 6 the results. Section 7 concludes.

2. Background and literature

Ruhm's (2000) seminal finding that mortality moved pro-cyclically in the US over the period 1972-1991, implying that recessions are good for population health, has spurred an extensive literature following his approach. This literature provides evidence across different time periods and countries, across different age groups (infants, children, adults, the elderly), across indicators of socioeconomic status and extended to morbidities and health-related behaviours.[2] While a number of recent studies reproduce Ruhm's finding of a pro-cyclical relationship for overall mortality – which may have weakened in recent years (for example, Fuure Haaland and Telle, 2015; Granados and Ionides, 2015; Lindo, 2015; Stevens et al., 2015; Ruhm, 2016; van den Berg et al., 2017; Brüning and Thuilliez, 2019) – there is less consistent evidence across causes of death (e.g. Ruhm, 2015; Toffolutti and Suhrcke, 2019). For example, there is mounting evidence that suggests recessions are associated with more drug-related deaths and greater substance abuse (Ruhm, 2019; Hollingsworth et al., 2017; Carpenter et al., 2017; Colombo et al., 2018).[3] There is much less evidence for morbidity, as distinct from mortality, outcomes (e.g. Furre Haaland and Telle, 2015; Colombo et al., 2018; Wang et al., 2018). Within studies of morbidity, there has been relatively little focus on long term chronic health (e.g. Ruhm, 2007; Antonova et al., 2017; Colombo et al., 2018;), despite its rising importance.

So, despite the large volume of studies, recent reviews of the literature (for example, Ruhm, 2016; van den Berg et al. 2017; and Bellés-Obrero and Vall Castello, 2018) all conclude that the literature on whether and how economic conditions impact on health continues to find mixed results. Bellés-Obrero and Vall Castello (2018) go so far as to argue that the only well-established finding is that mental health deteriorates during economic slowdowns.

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[2] Examples include Dehejia and Lleras-Muney, 2004; Tapia Granados, 2005; Gerdtham and Ruhm, 2006; Fishback et al., 2007; Miller et al., 2009; Stuckler et al., 2009; Tapia Granados and Diez Roux, 2009; McInerney and Mellor, 2012; French and Gumus, 2014; Haaland and Telle, 2015; Lindo, 2015; Ruhm, 2003, 2005, 2007, 2015, 2016; Stevens et al., 2015; Carpenter et al., 2017; Hollingsworth et al., 2017; van den Berg et al., 2017; Tekin et al., 2018; Wang et al., 2018; and for children, Dehejia and Lleras-Muney, 2004; Golberstein et al., 2019; Page et al., 2019. There is a related literature looking at the effect of large economic shocks (for example, stock market crashes) on health outcomes (for examples see, McInerney et al., 2013; and Cotti et al., 2015).

[3] Some of the discussion of why the findings from the literature are mixed centres around potential explanations of the relationship between economic conditions and health. These are many and sometimes contested and reflect the fact that mortality may behave differently to morbidity and different forms of morbidity may respond differently to economic conditions. For example, risky behaviours such as binge drinking and smoking have been argued to increase in economic expansions (Ruhm and Black, 2002; Dehejia and Lleras-Muney, 2004) and in economic downturns (Dee, 2001; Sullivan and von Wachter, 2009; Eliason and Storrie, 2009; Cotti et al., 2015; Hollingsworth et al., 2017). Similarly, although individuals may have less time to invest in their health when the economy is doing well (Ruhm, 2000), other research suggests that individuals are happier and have a higher life satisfaction during economic booms (see e.g. Di Tella et al., 2003). Some argue that job-related stress increases in good economic times (Ruhm, 2000) whilst others suggest that there is more job-related stress in economic downturns (Brenner and Mooney, 1983). These mechanisms have also been argued to have differential effects on individuals of working age compared to the elderly (see, for example, Ruhm 2016).

Our focus here is on the modelling approach. After the early studies of Brenner (1971, 1979), the literature has been dismissive of the ability of simple aggregate time-series modelling techniques to shed robust light on the link between the economy and health (e.g. Gravelle et al., 1981; Wagstaff, 1985; Laporte, 2004). The 'workhorse model', following Ruhm (2000), is a panel data model in which the unit of observation is a geographical location at a time period. This model explains the health H_{jt} of area j at time t as a function of local area economic conditions EMP_{jt}, an area-fixed effect λ, an area-specific time trend λt (linear, or quadratic), and a national time trend T. Mortality rates are often used as the measure of (poor) health because they represent the most severe negative health outcome and are well measured (although there can be errors in the assigned cause of death), and diagnosis generally does not require access to detailed medical data. Unemployment or employment rates are the most common proxy for macroeconomic conditions. Lags of the macroeconomic variables are sometimes used to try and capture dynamics of the adjustment process. This approach estimates a single elasticity, implicitly assuming that there is no coefficient heterogeneity across areas or that the coefficient heterogeneity can be subsumed into the error term. The latter assumption relies on the coefficient heterogeneity being unrelated to any characteristics included in the regression. A violation of this assumption can lead to biases (see Pesaran and Smith, 1995, for details).

Within this approach, two recent papers have explicitly addressed issues of the appropriate level of aggregation at which the analysis is conducted. Van den Berg et al., (2017) focus on the use of individual versus area as the unit of analyses. They note that studies using aggregate data (data at an area level) tend to find that mortality is pro-cyclical (e.g. Ruhm, 2000; Gerdtham and Ruhm, 2006; Neumayer, 2004), whereas studies that use individual-level data tend to find the opposite (e.g. Gerdtham and Johannesson, 2005). To test whether this difference in level of aggregation drives the differences in results, they examine how accurately models using aggregate data infer effects of economic changes on mortality at the individual level. They compare results from analyses on the same underlying data estimated at both levels. Using a sample from the entire Swedish male population aged 20–64 between 1993 and 2007, they examine the relationship between transitory changes in economic conditions and individual and regional (county-level) mortality. They find evidence of pro-cyclicality at the individual level (i.e. temporary downturns in economic conditions decrease mortality). These findings are robust to the inclusion of a set of covariates. Collapsing the data to the county-level, they find estimates for the aggregate data which are of similar sign and magnitudes to those from individual level data, suggesting that aggregate data can be used to adequately infer the individual-level association between business cycles and mortality. They conclude that (at least for Sweden) estimates of the relationship between mortality and the business cycle are not sensitive to the level at which the dependent variable is measured. However, in contrast to our study, they do not examine different local area definitions, or allow for local areas to have different health reactions to changing economic conditions.

Lindo (2015) identifies issues to be considered in the *a prioiri* choice of the level of geographic area. For example, from an empirical perspective, he argues the effects of an individual's job loss should be captured by changes in economic conditions in the local area where the individual works. However, economic conditions both near and far may affect an individual's health through impacts on re-employment, migration decisions, perceptions about economic conditions, traffic congestion, levels of pollution, the quality of medical care, government policies, and through effects on the members of an individual's social network. He also identifies statistical issues to be considered, such as the reliability of economic and health measures in small areas. His empirical analysis focuses on the extent to which effects from outside the area may affect health within an area and thus the appropriate level of geographical aggregation for the unit of observation. He replicates and updates earlier US state-level estimates of the relationship between economic conditions and mortality (and also of the relationship between economic conditions at the time of conception and infant health). He then examines how the estimated effects vary when the analysis is conducted at differing levels of geographic aggregation, chosen on a *a prioiri* basis rather than according to statistical criteria. His overall conclusion is that the level of geographical aggregation matters in US data. Results from lower level units (counties) are found to be generally smaller in magnitude than those from larger areas (states) and there are also significant spillover effects on health outcomes across small areas (counties).

While not an explicit study of different levels of aggregation, Ruhm (2016) investigates for mortality whether recessions may have a different effect compared to normal cycles. He extends the standard panel model to include not only area level unemployment rates but also the effect of recession periods. He also tests for different effects at three different spatial levels (state, country and large county) by estimating separate panel fixed effects models at these three different levels. He finds (as in Ruhm, 2000, 2003, and 2015) that in the US downturns are good for health (mortality falls) and recessions increase the protective effect on total mortality (including for suicides which are generally counter-cyclical). In terms of difference across different levels of aggregation, he finds effect sizes to be around 25% larger at the county than state level. In particular, at the state level a 1 percentage point increase in unemployment decreases mortality by 0.3%, with the corresponding effect at country level of around 0.4%. He also notes further research is needed to better understand the differences between the effects of national versus more localised economic conditions.

These findings motivate our use of a different modelling approach, which allows for dynamics, statistical selection of appropriate area level, heterogeneous responses by area, and spillovers between areas. The relative paucity of work in this literature focussing on chronic illness, and the importance of chronic health conditions for individuals, society and the economy motivates our choice of chronic health conditions as an outcome.

3. A Dynamic Panel Model of Chronic Health Conditions

3.1 Our modelling approach

We model reported chronic health conditions through a set of reduced form equations relating the prevalence of chronic conditions in an area to the economic conditions in that area as they evolve over time. The approach is described below with reference to a single summary measure of the prevalence of chronic conditions in the area, but it is readily extended to consider specific conditions separately later in the paper. The dynamic reduced form equations accommodate feedback across areas, allowing us to capture both the direct effects of economic changes on chronic conditions and those exerted indirectly through interdependent economic and social experiences.

The dynamic reduced form model incorporating these influences in a panel setting is given as follows:

$$c_{i,t} = \mu_i + \lambda_i \, c_{i,t-1} + \delta_i \, \overline{c}_t + \sum_{s=0}^{1} \alpha_{is} \, x_{i,t-s} + \sum_{s=0}^{1} \beta_{is} \, \overline{x}_{t-s} + \sum_{s=0}^{1} \gamma_{is} \, f_{t-s} + \varepsilon_{i,t} \qquad (1)$$

for $i = 1, \ldots, N$ and $t = 1, \ldots, T$. $c_{i,t}$ is the (logarithm of the) prevalence of chronic health conditions in area *i* at time *t* and $x_{i,t}$ is the economic variable of interest (e.g. the employment rate) in the same area at time *t*. The measure of the prevalence of all chronic health conditions reports (the logarithm of) the number of respondents reporting a health condition relative to the total number of respondents. The variables $\overline{c}_t = \frac{1}{N}\sum_{i=1}^{N} c_{i,t}$ and $\overline{x}_t = \frac{1}{N}\sum_{i=1}^{N} x_{i,t}$ are the national values for chronic conditions prevalence and the economic variable of interest, and f_t

represents any other national variable(s) that influence health.[4] The parameters μ_i represent unobserved area-specific fixed effects and λ_i , δ_i , α_{is}, β_{is} and γ_{is} $(s = 0,1)$, capture the responsiveness of $c_{i,t}$ to the various influences, with the responsiveness allowed to differ from area to area.

Equation (1) can accommodate complicated dynamic and interdependent responses of poor health in different areas to changes in economic circumstances. One, inclusion of the lagged dependent variable and the lagged economic variable allows for potentially complex dynamic responses of health to changes in economic circumstances. Two, inclusion of the national measure of chronic conditions, $\overline{c}_t$, and the national measures of economic and other conditions, $\overline{x}_t$ and f_t, accommodates common time-variation in chronic conditions and the influence of economic factors experienced at the national level. Specifically, the 'reference' health effect $\overline{c}_t$ captures effects generated through contagion and imitation (e.g. doctors and patients becoming more responsive and/or more sensitive to particular types of health conditions as they become more frequently observed) and through any dispersions (e.g. if the health effects of a recession in one area result in a national deterioration in the effectiveness of the workforce and to a further round of increases in national levels of chronic health).

Our model of the prevalence of chronic health conditions differs in a number of important respects from the fixed effects panel model commonly used in the literature. First, the model explicitly allows the responsiveness of health conditions to economic conditions to vary across areas, with the α_{is} and β_{is} differing for $i = 1, \ldots, N$. This 'heterogenous panel' approach follows Pesaran and Smith (1995) in that elasticities are allowed to vary across units, with 'typical responsiveness' being measured using aggregate statistics derived from the individual elasticities. Second, the model captures explicitly the influence of common national economic and other effects - through the inclusion of $\overline{x}_t$ and f_t - while standard fixed effects models abstract from common effects by using time dummies. Our approach allows us to distinguish local area economic effects on health outcomes from common national effects. Third, the model captures the interdependencies of health outcomes between areas, through $\overline{c}_t$. Its inclusion, along with the inclusion of $\overline{x}_t$, means the model nests within it the traditional

[4] We use the quarterly change in the national consumer confidence (CCI) index (OECD, 2020) as our measure of f_t.

fixed effects model with time dummies.[5] Fourth, the model accommodates the possibility of slow or partial adjustment to changes in economic conditions through the inclusion of the lagged dependent and independent variables. In the absence of these dynamic effects there is a risk that the model is mis specified and that the estimates are biased. Finally, as in studies that apply the fixed effects panel model in this literature we assume that changing macroeconomic conditions are exogeneous in the model. That is, our model does not allow for employment growth itself to be affected dynamically by changes in morbidity. [6]

3.2 Measures of the direct and the global effects of economic conditions on health

Equation (1) involves complex interactions between areas.[7] To obtain measures of the overall effects of economic conditions on ill-health, we start by writing the 'long-run' version of (1) as:

$$c_{i,t} = \tilde{\mu}_i + \tilde{\delta}_i \ \overline{c}_t + \tilde{\alpha}_i \ x_{i,t} + \tilde{\beta}_i \ \overline{x}_t + \tilde{\gamma}_i \ f_t + \varepsilon_{i,t} \qquad (2)$$

where $\tilde{\mu}_i = \frac{\mu_i}{1-\lambda_i}$, $\tilde{\alpha}_i = \frac{\alpha_{i0}+\alpha_{i1}}{1-\lambda_i}$ etc..., which shows the steady-state relationship between the variables. Stacking the $c_{i,t}$ in the $N \times 1$ vector $\boldsymbol{c_t}$ provides a compact representation of the individual equations in (1):

$$\mathbf{c_t} = \tilde{\boldsymbol{\mu}} + \tilde{\boldsymbol{\delta}}\boldsymbol{A}\boldsymbol{c_t} + \tilde{\boldsymbol{\alpha}}\boldsymbol{x_t} + \tilde{\boldsymbol{\beta}}\overline{x}_t + \tilde{\gamma}_i \ f_t + \boldsymbol{\varepsilon_t} \qquad (3)$$

Here $\tilde{\boldsymbol{\mu}}$ is the $N \times 1$ vector containing the unobserved fixed effects $\tilde{\mu}_i$; the $\boldsymbol{x_t}$ contain the stacked $x_{i,t}$; and the $\tilde{\boldsymbol{\delta}}, \tilde{\boldsymbol{\alpha}}, \tilde{\boldsymbol{\beta}}$ and $\tilde{\boldsymbol{\gamma}}$ contain the parameters. The individual relationships in (1) relate chronic health conditions in area *i* at time *t* to conditions in all areas through the variable

[5] The traditional model with time dummies effectively regresses $c_{i,t} - \overline{c}_t$ on $x_{i,t} - \overline{x}_t$ imposing a specific and restrictive structure on the interactions between areas and the aggregate. If the restriction is not valid, this will introduce cross-section dependence in the residuals and biases in estimation (see, for example, Sarafides et al. (2009)). We estimate the fixed effects model most frequently used in this literature in Section 5.

[6] With a much longer time series than is available in most data on morbidity, it might be possible to incorporate such a feedback mechanism.

[7] The approach to accommodating feedbacks draws on the analysis of wage-wage interactions of Lee and Pesaran (1993) and the cross-country interactions captured by the 'Global VAR' modelling approach described in Mauro and Pesaran (2013), for example.

$\overline{c}_t$ but the latter variable is itself just an average of the individual $c_{i,t}$ in $\boldsymbol{c_t}$ and the $\mathbf{A}$ matrix captures this simple averaging.

The system in (2) can then be written as:

$$\boldsymbol{c_t} = \boldsymbol{\Phi_0} + \boldsymbol{\Phi_1} \boldsymbol{x_t} + \boldsymbol{\Phi_2} \overline{x}_t + \boldsymbol{\Phi_3} f_t + \tilde{\boldsymbol{\varepsilon}}_t \qquad (4)$$

where, if $\mathbf{M} = (\mathbf{I} - \widetilde{\boldsymbol{\delta}}\mathbf{A})^{-\mathbf{1}}$, $\boldsymbol{\Phi_0} = \mathbf{M}\widetilde{\boldsymbol{\mu}}$, $\boldsymbol{\Phi_1} = \mathbf{M}\widetilde{\boldsymbol{\alpha}}$, $\boldsymbol{\Phi_2} = \mathbf{M}\widetilde{\boldsymbol{\beta}}$ and $\boldsymbol{\Phi_3} = \mathbf{M}\tilde{\boldsymbol{\gamma}}_{\boldsymbol{i}}$ so that the $\mathbf{M}$ captures the way in which the effects of changes in health conditions in one area are dissipated across all areas. Since the system of health equations (4) summarizes the relationship between chronic health conditions and economic conditions across all areas, it can be used to motivate measures of the effects of changes in economic conditions experienced through different channels. Specifically, the relationships in (3) can be used first to measure the '*direct*' effects of changes in the area's economic conditions, abstracting from the feedbacks propagated through aggregative health measures. The direct effects for individual areas are captured by the $\tilde{\alpha}_i$ and summarised across areas by:

$$direct \qquad \epsilon^D = \frac{1}{N}\mathbf{w}'\tilde{\alpha}\mathbf{w} \qquad (5)$$

where $\mathbf{w}$ is a $N \times 1$ vector of ones used to sum up the $\tilde{\alpha}_i$. The measure ϵ^D therefore describes the average responsiveness of the prevalence of chronic health conditions in an area to changes in local economic conditions, before allowing for any feedbacks across areas. We can define the '*global*' effects by scaling up the effects of the local changes to fully take into account any feedbacks. The global effects can be summarized by:

$$global \qquad \epsilon^G = \frac{1}{N}\mathbf{w}'\boldsymbol{\Phi_1}\mathbf{w} \qquad (6)$$

Here, $\mathbf{w}'\boldsymbol{\Phi_1}$ is the $1 \times N$ vector showing the total impact on all areas' health of a change in the value of $x_{i,t}$ $(i = 1,..,N)$, experienced through the local channel (i.e. captured by the $\tilde{\alpha}_i$ $'s$) but taking account of the interactions between areas. Thus, the measure ϵ^G describes the average of these local effects, showing the effect of a 1% increase in $x_{i,t}$ if it was experienced across all areas at the same time. Note that the global effects collapse to be equal to the direct effects if there are no interdependencies in health outcomes across areas.

3.3 Choice of the level of spatial disaggregation

A study using data aggregated at the national level would clearly be unable to distinguish local influences from common national influences. Therefore, some level of area disaggregation by sub-national geographical units is essential. But the most disaggregated data available might not be the optimal choice. While a well-specified disaggregated model will generally outperform an aggregate model, the result could be reversed if the disaggregate model is misspecified. Grunfeld and Griliches (1960) note that an aggregate model would outperform a more disaggregated model in at least two special cases: first, if macro influences that are included in the aggregate model are incorrectly excluded from the disaggregate model and second, if measurement errors found in the disaggregate model cancel out in the aggregate. While the first of these problems is unlikely in our approach as we explicitly acknowledge the potential interdependencies between area health outcomes, the second might be relevant given the small sample sizes often used in this literature to derive economic and health series for disaggregated areas.

Our approach to choosing the preferred level of spatial aggregation is based upon a sequence of tests which use the assumption that a more disaggregated model is preferable unless the data suggest that aggregation is appropriate. The practical building blocks for this test are three official definitions of areas, which range from broad regions to small disaggregated local areas. Assume that data is available at M levels of disaggregation, with level 1 being the national level, say, and level M representing the most disaggregated level providing data on N_M different (spatially contiguous) areas. Our initial null is that level M is the preferred level of aggregation but, for each of the areas described at level M-1, we test whether there is a case for aggregating over the subsets of the n_M areas that make up the more aggregated regions. Having grouped the areas where the test rejects the more disaggregated specification, we then move onto test the chosen level M-1 areas against their level M-2 counterparts, and so on, so that the preferred level of spatial aggregation could ultimately consist of areas defined at various different levels of aggregation.

The tests are based on the 'adjusted' prediction criteria of Pesaran et al. (1989) and the testing procedure in van Garderen et al. (2003). The prediction criteria for a disaggregated model and the corresponding aggregate model are, respectively:

$$s_d^2 = \sum_{i,j=1}^{N} \hat{\sigma}_{ij}^2 \quad and \quad s_a^2 = \frac{\varepsilon_{at}\varepsilon_{at}'}{T-k_a}, \qquad (7)$$

where $\hat{\sigma}_{ij}^2 = \frac{\varepsilon_{it}\varepsilon_{jt}'}{(n-k_i-k_j-tr(\mathbf{A}_i\mathbf{A}_j))}$ with ε_{it} being the vector of residuals from the disaggregate model i and k_i the number of explanatory variables in the i^{th} model. $\mathbf{A}_i = \mathbf{X}_i(\mathbf{X}_i'\mathbf{X}_i)^{-1}\mathbf{X}_i'$

denotes the explanatory variables in (1) by $\mathbf{X}_i$ and ε_{at} is the vector of residuals from the aggregate model. The criteria are intuitively sensible, being based on the sum of squared errors from the competing models' explanations of the aggregate chronic health conditions series. The degrees-of-freedom adjustments in the formulae ensure that the disaggregated model's criterion will on average be smaller than that of the aggregate model if the disaggregated model is true.

In comparing level M and level *M-1* area groupings, our null is that the more disaggregated model is true, so that we would expect the statistic $s_a^2 - s_d^2$ to be greater than zero. If $s_a^2 - s_d^2$ is significantly less than zero, we would reject the null on the grounds that there is misspecification in the disaggregated model and choose to work with the more aggregated series. The significance of the test statistic $s_a^2 - s_d^2$ is judged through a simulation exercise in which the disaggregated model is assumed true and its estimated version is used to generate 1000 artificial series for each of the N_M areas comprising the level M area (taking the estimated parameters of the models - including the estimated variance-covariance of the errors for use in generating random errors - as the true data generating process). These 1000 artificial series are then used to estimate new versions of the disaggregated and aggregated models and to derive 1000 observations of the test statistic. In this way, we generate a distribution for the statistic under the (true-by-construction) assumption that the disaggregate model is true. Comparison of the statistic that was actually observed with the threshold defined by the bottom 5% of this distribution provides the critical value for the test of the statistical significance of the test statistic.

4. Data

Our data are an aggregated series drawn from the UK's Quarterly Labour Force Survey (QLFS), the largest household survey in the UK. The data cover England, Scotland and Wales (Britain), and are nationally representative as they are used to provide official national and local area labour market statistics. The QLFS asked all respondents about their chronic health conditions. We use data for the 57 quarters from 2002q2 to 2016q2 (with data from 2002q1 being used to create lags), which contains the GFC period.

We derive the prevalence series for chronic health conditions for respondents aged 25 to 64 years. The lower age limit is to ensure we use respondents who have (mostly) finished education and are part of the potential labour force. The upper age limit is based on the statepension age in effect during most of our sample period.[8] Using respondents aged 25 to 64 with a valid response to the question as to whether they have a chronic health condition gives a sample of 3.2 million observations, which are used to create the prevalence series at the local area levels.

Our primary health measure is derived from the question asked to all respondents, “Do you have any health problems or disabilities that you expect will last for more than a year?” From this we derive our main measure: the proportion of respondents in a local area at a point in time answering in the affirmative. In an extension to our main model, we examine the link between macroeconomic conditions and five broad categories of chronic health conditions. If a respondent states they have a chronic condition, they are given a list of 17 types of health problems from which they can select any number. We group these 17 health problems into five broad categories: (1) Musculoskeletal conditions, (2) Cardiovascular conditions, (3) Respiratory conditions, (4) Mental health conditions, and (5) Other conditions. Details of the conditions included in each group are shown in Appendix Table A1.

Although we are using series aggregated to local areas, our measures are based on individual self-reports of their health. One limitation when using any self-reported measure of health or health-behaviors is that reporting thresholds could change in response to economic pressures. If, for example, it is the case that individuals on average report more accurately in an upturn, but over-report ill health in a downturn, then our results may over-estimate the impact of the economic cycle. However, the QLFS data, which is collected in a confidential way from individuals, is not used to prove eligibility for state benefits (unlike data recorded by medical professionals). Therefore, there is no economic reason for individuals to be more likely to state they had a condition in an economic downturn.[9]

We aggregate the individual responses to three different area levels. These areas are defined by the Nomenclature of Territorial Units for Statistics (NUTS) used by the UK Office

[8] This choice means we cannot examine spillovers from economic shocks affecting the working age population to older groups. Such spillovers may induce complex health responses to positive shocks. For example, health could be pro-cyclical, but an upturn in the economy could lead to a shortage of labour, with potentially negative effects on the quality of care in residential homes for the elderly, resulting in worse health outcomes. We restrict our focus to the working age population to avoid such interactions.

[9] In a similar way, changes in health care utilization data may capture increased diagnosis rather than a change in underlying health. Therefore, comparing our series with health care utilisation data does not provide any information about any potential reporting bias. Nor does looking at trends in mortality over the period, since we are focusing on the working age population, and the link and timing between earlier life morbidity and mortality is unclear. For suicides, which often occur in the working age population, Vandoros et al. (2019) finds that suicides, which are not subject to reporting error, increased over the GFC period in Britain.

for National Statistics (ONS).[10] NUTS3 are "small regions for specific diagnoses". In the UK, they correspond to either one local authority (the local unit of government) or several contiguous local authorities. They range in population from 30,000 to 1.7 million, with an average of 400,000. NUTS2 are "basic regions for the application of regional policies". They consist of two to eight contiguous NUTS3 areas, although there are a few NUTS2 areas that are coterminous with a single large NUTS3 area. The average population is 1.5 million. NUTS1 are the largest areas, defined as "major socioeconomic regions". There are 11 NUTS1, 36 NUTS2, and 134 NUTS3 areas in Britain (see Appendix Figure A1).

To generate our measures of $c_{i,t}$, the prevalence of chronic health conditions in area *i* at time t (and in the extended model, $c_{i,t}^{h}$, with h denoting the category of chronic health condition), we map the respondent's local authority of residence onto the 2010 NUTS1, NUTS2 and NUTS3 areas. We drop three very low population NUTS3 areas, so we use 131 areas at this level of disaggregation. Our time variable *t* is a calendar quarter.

We calculate the prevalence of any chronic condition for each quarter-area cell by dividing the number of respondents (aged 25 to 64) who report having a chronic condition by the total number of respondents (aged 25 to 64) in a cell and we use the logarithm of this variable in the model estimation. At the most disaggregated NUTS3 level our chronic health prevalence series is based on an average sample of 429 observations per data point, and 1,560 at the more aggregated NUTS2 level.[11] Our estimation uses 7,467 data points at NUTS3 level (57 quarters*131 NUTS3 areas), 2,052 data points at NUTS2 level (57 quarters * 36 NUTS2 areas) and 627 data points at NUTS1 level (57 quarters * 11 NUTS1 areas).

Our measure of the buoyancy of the macroeconomic environment, $x_{i,t}$, is the growth in the local employment rate in area *i* in quarter *t*. The use of the growth in the employment rate, as opposed to the rate itself, means we abstract from the effects of long-standing differences in economic circumstances across regions – assumed captured by the area fixed effects – and focus on the effects of changing economic circumstances. We choose employment growth rather than unemployment growth as it is less likely to suffer from measurement error at the small area (NUTS3) level.[12] To derive the employment rate, we sum

[10] Developed by Eurostat for each country in the European Union. See: https://ec.europa.eu/eurostat/web/nuts/background.

[11] For estimation of models split by gender, the corresponding samples are 203 and 225, and 741 and 819, for males and females at NUTS3 and NUTS2 level, respectively.

[12] The growth in employment series also has the reassuring property of being unambiguously stationary. We get

over all respondents aged 16 to 64 who meet the ILO definition of employment and divide this sum by the total of residents in the area aged 16 to 64. We use the log difference of the employment rate in the model. The samples used to construct the economic measures at the NUTS3 and NUTS2 levels are similar in size to those used for the construction of the chronic health conditions measures. We also construct the national employment rate $\bar{x}_t$ which is population weighted and again use the log difference of this variable in the model estimation.[13] All variables are seasonally adjusted using quarterly dummies.

Figure 1 shows the time-series dimensions of the data at the national level for 2002q2-2016q2. The grey bars show the employment rate (left axis) and the lines (right axis) represent (1) the prevalence of all chronic conditions (bright blue line) and (2) separate trends for each of the five types of condition. The figure shows relatively large changes in the employment rate over the period as it (purposefully) includes the Global Financial Crisis (GFC) period. The employment rate was around 73 percent for the period 2001 to 2008, followed by a reduction during the GFC, and increasing from around 2012 onwards. In terms of ill-health, on average around 33 percent of the population report having a chronic condition over this 16-year period. The figure shows a strong counter-cyclical co-movement of health with economic conditions, the proportion of the population reporting having a chronic condition increasing substantially (from around 30 to 35 percent) during the GFC period, then returning to trend by around 2013. For the five groups of chronic health conditions, we see a similar trend for all conditions with the exception of the set of mental health conditions. For mental health conditions there was an increased rate of growth from around 2008 which has not fallen back but has continued until 2016.

Figure 2 illustrates the cross-sectional spatial dimension of our data. For each NUTS3 area (131), the maps show, respectively, the prevalence of any chronic conditions, and the employment rate, each averaged over the 57 quarters. As expected, given the well-known socioeconomic gradient in health, comparison across the maps shows areas with lower employment rates have higher prevalence of chronic conditions.

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the same counter-cyclical results as reported below using unemployment growth but the estimates are poorly defined.

[13] As noted above, to more fully capture national changes in economic conditions, equation (1) includes f_t, the quarterly change in the national consumer confidence (CCI) index produced by the (OECD, 2020). Our results are robust to inclusion or exclusion of this measure. The main direct and global estimates we present in Table 1 are virtually unchanged and remain significant at the 1% level when we exclude the index from the model.

5. Results

5.1. Optimal level of spatial disaggregation

We first select an appropriate level of disaggregation for the analysis. We estimate equations of the form of Equation (1) for all areas at the NUTS3, NUTS2 and NUTS1 levels. The adjusted prediction criteria of Pesaran et al. (1989) given in equation (7) are used to assess the relative performance of the models estimated at the various levels of disaggregation, starting from the most disaggregated (NUTS3) level. The results indicate that the analysis of the economic effects on health should be conducted at a relatively high degree of disaggregation. The test procedure suggests using 91 areas, consisting of 74 of the 131 NUTS3 areas included in our sample and 17 of the 36 NUTS2 areas.[14] Thus the detail contained at the smallest (NUTS3) level is important for modelling in most cases, although the specifications can be significantly improved by aggregating to the NUTS2 level in a relatively small number (17) of cases. There is no support for the use of data measured at the NUTS1 level.

5.2. Direct and Global long-run employment elasticities

We estimate Equation (1) for each of the 91 optimal areas.[15] To improve the precision of the parameter estimates, we conduct a specification search in each local area regression to eliminate any poorly determined coefficients, dropping variables for which the (absolute) value of the *t*-statistic is less than unity.[16] The joint insignificance of excluded variables is tested using an LM test. This leads to around 45% of the total number of parameters in the regressions being set to zero and in this restricted specification the employment growth elasticities are set to zero for 23 of the 91 areas. We focus on results using the restricted model.[17]

The 'average' form of the 91 regressions in the restricted specification of the local area

[14] Results suggest a similar – if slightly greater - degree of aggregation when estimating separate models for men and women. For men, the procedure suggests using 73 areas (consisting of 52 NUTS3 and 21 NUTS2 areas), and for women the corresponding figure is 87 areas (68 NUTS3 and 19 NUTS2 areas).

[15] In Section 6 below, we examine specific health conditions separately. Given that respondents typically report having more than one health condition at any point in time, the sum of respondents reporting a particular health condition, over all conditions, will be greater than the total number reporting a health condition (which is used to construct the dependent variable in equation (8)).

[16] The *t*-statistic threshold follows Clements and Hendry (2005) who find that the inclusion of variables below the threshold damages the predictive ability of an AR model.

[17] While the restricted specification produces a greater number of local areas for which a statistically significant employment elasticity is found than the unrestricted version in which no parameters are dropped, our substantive findings hold across both specifications. Estimates for the main models using the unrestricted specification are in the Appendix.

model is:

$$c_{i,t} = \underset{(0.03)}{0.005} + \underset{(0.14)}{0.571}\, c_{i,t-1} + \underset{(0.28)}{0.450}\, \overline{c}_t - \underset{(0.04)}{0.004}\, x_{i,t-1} - \underset{(0.01)}{0.001}\, x_{i,t-2}$$
$$- \underset{(0.02)}{0.015}\, \overline{x}_{t-1} - \underset{(0.01)}{0.001}\, \overline{x}_{t-2} - \underset{(0.01)}{0.001}\, t - \underset{(0.02)}{0.005}\, f_{t-1} + \underset{(0.02)}{0.006}\, f_{t-2} + \varepsilon_{i,t} \qquad (8)$$

The coefficients in Equation (8) are the (unweighted) means of the coefficient estimates for the individual areas and the figures in parentheses are the standard deviations of these estimates. The signs on $x_{i,t-1}$ and $x_{i,t-2}$ are negative, indicating an average aggregate counter-cyclical relationship between employment growth and chronic health. The lagged dependent variable $c_{i,t-1}$ and the national health variable $\overline{c}_t$ are positive, indicating significant dynamics and interdependencies. There is considerable heterogeneity across areas in the employment growth and lagged dependent variable estimates, which will generate heterogeneity in the global employment elasticity estimates across areas.

While the average form of Equation (1) provides an indication of the influences at play, the direct elasticities and the global elasticities in Equations (5) and (6) provide more accurate measures of the impact of macroeconomic conditions on the prevalence of chronic health conditions. Table 1 presents summary statistics of the elasticity estimates presented in Equation (8) for the pooled male and female sample (labelled "All") and for the separate male and female models. The top panel reports the estimates of the direct elasticities, the lower panel the corresponding global estimates (i.e. after allowing for feedback between areas). The comparable unrestricted estimates are in Appendix Table A2.

All the estimates provide strong statistically significant (at the 1% level) evidence of a counter-cyclical effect of economic performance on health outcomes: in bad economic times health worsens (the proportion of the population reporting having a chronic health conditions increases).[18] The direct elasticity for men and women together indicates that a 1 percentage point increase in the local quarterly employment growth rate will, on average, lead to the rate of chronic conditions falling by 1.0 percent in that area. The global elasticity estimates are on average around 70 percent larger than the direct elasticity estimates, so the direct effect of an increase in local employment growth on health in an area is scaled up as these health effects

[18] In the separate 91 area level equations (not reported here) there is a statistically significant (at the 10%) global employment elasticity for 42% (38) of the 91 areas, while 27% (25) are significant at the 5% level.

impact on health elsewhere. Our global estimate for the pooled sample shows that, ultimately, the rate of chronic morbidity would fall by 1.7 percent on average following a 1 percentage point increase in employment growth in each area. These results suggest that not allowing for feedback from interdependencies across areas, as in the standard fixed effects panel model, could lead to a substantive underestimation of the morbidity costs of bad economic times. We return to this point in Section 5.5.

The estimated elasticities for the unrestricted model are slightly higher than those for the restricted model, with a 1 percent point increase in employment growth leading to a 2.3 percent fall in chronic morbidity. However, the estimates are less well defined, with the employment growth elasticities statistically significant (at the 10%) for 26 of the 91 areas, with 16 areas remaining statistically significant at the 5% level. The direct and the global elasticities are of a very similar order of magnitude for estimates using the male and female data separately (estimated over their corresponding optimally-chosen areas of 73 and 87 respectively). Given this lack of difference by gender, for brevity we only provide estimates and discussion for the pooled model in the rest of the paper.

The direct and the global employment elasticities differ in magnitude but are highly correlated (with a correlation coefficient of 0.94) across areas. Figure 3 plots the two sets of estimates for the restricted model. The estimated direct elasticity is on the y-axis, the global on the x-axis. The vast majority of estimates lie in the lower left quadrant, showing the estimated counter-cyclical relationship between employment growth and chronic conditions. There are only seven estimates in the upper right quadrant (which indicates a pro-cyclical relationship). Statistical significance (of the global elasticity) is highlighted by the colours of the dots: 'Green' indicating a |t|-stat>=1.96 (25 areas), 'Red' indicating a |t|-stat>=1.64 (13 areas), and 'Blue" indicating a |t|-stat<1.64 (53 areas; including 23 set to zero). The relationship is positive, confirming the close correspondence in the ranking of the direct and global estimates by area. This shows that, in the main, the feedback incorporated in the global estimates simply amplifies the direct effects rather than changing the ranking of the estimates. The overall picture is one of a strong counter-cyclical relationship between macroeconomics conditions and morbidity with substantive heterogeneity across local areas.[19]

[19] The unrestricted model estimates in Appendix Figure A2 show that these results are robust to inclusion of areas with estimated coefficients which do not meet our significance criteria.

5.3 Exploring the extent of local area heterogeneity

Our modelling approach allows us to directly explore potential causes of this local area heterogeneity in the response to changes in economic conditions. Figure 4 shows the spatial heterogeneity in the estimated global employment elasticities across Britain. Dark green areas indicate the most counter-cyclical employment-health relationship and red areas the most pro-cyclical. The bulk of estimates lie in the range [-0.08, 0], with the lower bound of -0.08 implying that a one percent point increase in employment growth is associated with an 8% fall in the rate of chronic morbidity. For only a few areas do we find a pro-cyclical estimate, and only one of these is statistically significant.[20]

This observed heterogeneity in the response of chronic health conditions to changes in the economic environment raises the question of what factors are associated with the different strength of responses across local areas. We examine two potential explanations. First, is the response associated with the economic conditions of the area? We define these in terms of the level of economic activity and the composition of economic activity. Second, is the demographic composition of the areas associated with the size of the employment response? We examine the age structure, the extent of chronic illness and the rurality of the area.[21] We use measures of these factors at local area level before the start of our analysis period (measures from the 2001 Census). We use these as they measure long term aspects of the area employment and population structure.

In Figure 5 we show binned scatter plots of the global employment elasticity estimates and the associated weighted regression line on characteristics for each area. Figure 5, Panel A presents the association of the estimates with local economic conditions. Panel A(a) shows relatively little association between the strength of the response and the overall level of economic activity. But Panel A(b) shows a clear association between industrial composition and the extent to which chronic health conditions are counter-cyclical. Areas with more negative responses have higher concentration of "blue-collar" industries (agriculture and construction and, to a lesser extent, manufacturing) and public services, and lower

[20] A similar geographical dispersion of estimates is found for the unrestricted model as shown in Appendix Figure A3, with the bulk of estimates again suggesting a counter-cyclical relationship.

[21] Bruning and Thuilliez (2019) find heterogeneity of responses of mortality to macro shocks in a fixed effects framework by population, average educational level and share of migrants. This has not to our knowledge, been systematically examined for chronic ill-health.

concentration of financial, real estate and business activities. Panel B presents the distribution of estimates by measures of demographic composition. Panels B(c) and (d) show a clear association between larger (counter-cyclical) responses in areas with populations that are older and in poorer health. Panel B(e) shows that areas which are more rural have larger responses. The regression coefficients for these association are presented in Table A3. All of these are significant except for the association with overall level of activity and the share of employment in manufacturing.

5.4. Dynamic health adjustment to macroeconomic change

The estimates discussed above relate to the *long-run* outcome of changes in economic circumstances as captured by employment growth. Our modelling approach also allows us to examine the speed of adjustment towards the long-run outcome. Figure 6 provides a summary of the underlying dynamic processes, tracing out the time paths of the global (and, for comparison, the direct) effects of changes in the area employment rates with 90% confidence intervals. The figure highlights the importance of the lagged dependent variables and lagged values of the explanatory variables in Equation (1), showing that the long-run outcomes represent an accumulation of effects over five or six quarters for the direct elasticity and around ten quarters for the global elasticity.

The difference between the global and the direct elasticities again illustrates the importance of allowing for feedbacks across areas. The parameters of Equation (8) showed the average value of the coefficient on the lagged dependent is 0.571, but with a standard deviation of 0.14 there is considerable heterogeneity in the dynamics across areas, with some coefficients much closer to unity, reflecting a much more prolonged adjustment in these areas. The time path of the global elasticity, by accommodating the interactions across all areas, reflects the slow adjustment in these areas. It shows that it will take over two years before the effects of a macroeconomic upturn or downturn are fully reflected in chronic morbidity. This accumulation of effect is plausible, as the nature of chronic health problems is such that we would not expect an instant change in response to worsening economic conditions.

5.5. A comparison to standard fixed-effect panel model estimates

Our modelling framework incorporates a number of features that are absent from the fixed effects panel model typically employed in this literature. Specifically, the simple fixed effects model incorporates year-quarter dummies to accommodate the effects of common time-varying influences on health and, while lagged values are sometimes included in a dynamic panel, the model is also often estimated as a static relationship. The simplest model also assumes parameter homogeneity across areas or, less restrictedly, that the effects of any parameter heterogeneity can be subsumed into the error. If the included explanatory variables are correlated with the subsumed heterogenous terms or with any omitted dynamics, then the estimated coefficients will be biased.[22] It is thus useful to compare the results of Table 1 with those obtained from a fixed effects panel model.

Table 2 reports the elasticities obtained from a set of fixed effects panel models, each including employment growth in the area alongside year-quarter time dummies, local area fixed effects, and a local area-specific linear time trend to control for national time confounders, area-level time-invariant characteristics and potentially confounding linear area-specific time trends. The table reports results based both on all 131 areas and on our optimally chosen 91 areas to check on the effect of the aggregation in this context. It reports, in the top panel of each part of the table, the static regressions that are often estimated in the literature, and in the bottom panel, the dynamic regressions which correspond more closely to our own model.

The responsiveness of health to local area employment growth rate is the main parameter of interest. The elasticity estimates in Table 2 are similar for the pooled male and female samples and for the separate male and female samples, and they are all the same sign (negative) and have the same level of significance (at the 1% level). The estimated elasticity of health conditions to employment growth for the static fixed effects panel model, based on the pooled male and female data, is -0.003 while the corresponding (long-run) elasticity obtained from the dynamic model is -0.012 (-0.004/(1-0.641)). Both estimates are well-defined but the substantial difference between them - with the dynamic specification providing an elasticity that is four times larger than the static specification - shows the importance of explicitly taking into account the dynamics of health movements even in the context of the fixed effects panel estimator. The fixed effect dynamic estimates indicate a 1 percentage point increase in the local quarterly employment growth rate in a local area will reduce the rate of chronic conditions by 1.2 percent. This is very close to the direct elasticities using our GVAR specification in Table 1.

[22] This would be the case, for example, if the responsiveness of health outcomes to economic circumstances in an area is related to the area's economic circumstances.

The close correspondence between these two sets of estimates is not unexpected as the fixed effects model is nested within our modelling specification. To illustrate this, consider the equation obtained by summing the area equation (2) over all areas and dividing by *N*:

$$\bar{c}_t = \tilde{\mu} + \tilde{\delta}\ \bar{c}_t + \tilde{\alpha}\ \bar{x}_t + \tilde{\beta}\ \bar{x}_t + \tilde{\gamma}\ f_t + \varepsilon_t \qquad (2')$$

where the absence of a subscript *i* means the coefficients are themselves averaged across *I*. Comparison of (2) with (2') shows that, dropping the terms involving heterogeneity across area parameters into the error, a regression of $c_{i,t} - \bar{c}_t$ on $x_{i,t} - \bar{x}_t$ will provide an estimate of $\tilde{\alpha}$. This is precisely the estimate obtained by the fixed effects estimator with year-quarter dummies. Of course, this simply highlights the fact that the fixed effects model cannot capture the influence of the changes in economic conditions propagated through the $\bar{c}_t$ in (2) and therefore only captures the 'direct' economic effects. As we have shown in Table 1, omitting this feedback results in a substantial understatement (of nearly 50%) of the full effects of economic changes on health.

6. Does the relationship differ across types of chronic condition?

We can extend our dynamic model to examine the effects of economic circumstances on a set of reported health conditions, which allows for feedback across areas *and* across different types of chronic conditions. The equivalent equation to (1) is:

$$c_{i,t}^{h} = \mu_i^h + \lambda_i^h c_{i,t-1}^h + \gamma_i^h c_{i,t}^{all} + \delta_i^h \bar{c}_t^{all} + \sum_{s=0}^{1} \alpha_{is}^h x_{i,t-s} + \sum_{s=0}^{1} \beta_{is}^h \bar{x}_{t-s} + \varepsilon_{i,t}^h \qquad (1')$$

for $h = 1,\ldots,H$. $c_{i,t}^h$ is the prevalence of chronic health condition *h* in area *i* at time *t*. The weighted average of the $c_{i,t}^h$, which shows the general level of chronic health conditions in the area at the time, denoted $c_{i,t}$ up to this point in the paper, is now denoted $c_{i,t}^{all} = \sum_{h=1}^{H} \omega_i^h c_{i,t}$, and the previously denoted economy-wide variable $\bar{c}_t$ is now denoted $\bar{c}_t^{all}$. In (1'), the parameters μ_i^h represent unobserved area- and condition-specific fixed effects and $\lambda_i^h, \gamma_i^h, \delta_i^h$, and α_{is}^h and $\beta_{is}^h (s = 0,1)$, capture the responsiveness of $c_{i,t}^h$ to the various influences, differing from area to area and from health condition to condition. This condition-specific model in equation (1') captures the contagion, imitation and dispersion effects across areas embedded within equation (1). It thus allows for inter-correlated effects (i.e. co-morbidity movements) across the health condition types. It also allows for different degrees of responsiveness and different dynamic processes for the separate health conditions.

Arranging the $c_{i,t}^h$ in the $N \times 1$ vector $\boldsymbol{c}_t^h$ and then stacking these in turn in the $(NH) \times$

1 vector $\boldsymbol{c_t} = (\boldsymbol{c}_t^{1\prime}, .., \boldsymbol{c}_t^{\boldsymbol{H}\prime})'$ enables us to obtain a compact representation of the individual equations of exactly the same form as (3). The corresponding $\boldsymbol{A}$ matrix captures both the cross-condition effects as well as the cross-area interactions: the matrix therefore reflects the ω_i^h weightings showing the relative prevalence of the conditions in the areas as the national averages are 'unpacked' and written in terms of their constituent elements. Having grouped the equations in this way, the system can also be written as in (4), with the complexities of the feedbacks across conditions and across areas captured by the $\boldsymbol{\Phi}'$s, and the responsiveness of the conditions to economic circumstances can again be summarised by the direct and global elasticities of (5) and (6).

We examine the five broad condition types defined above: (1) Musculoskeletal, (2) Cardiovascular, (3) Respiratory, (4) Mental Health, and (5) Other conditions. Table 3 shows the average direct and global elasticities for the five set of conditions. The number of local areas with significant ($|t|$>1.64) global elasticities is highest for Cardiovascular (40%) and Musculoskeletal (35%) conditions and lowest for respiratory conditions (24%). The table shows a strong and statistically significant counter-cyclical relationship with employment growth in the local area for all condition types. The magnitudes for four condition types other than mental health are all similar with global elasticities in the range [-0.027, -0.021]. The largest response is for mental health problems with a direct elasticity of -0.037 and a global elasticity of -0.042. The latter suggests that a 1 percent point increase in employment growth in the local area drives a 4.2 percent fall in chronic mental health. The difference between the direct and global elasticities is between 60% larger for cardiovascular conditions and 40% larger for musculoskeletal and Other conditions and is smallest (14%) for mental health conditions, indicating that that the importance of feedback mechanisms varies by condition. Overall, however, we again find that allowing for the feedbacks and dynamics in our model leads to substantially larger estimates than indicated by the direct effects.[23]

These aggregate elasticities again hide considerable local area heterogeneity. Figure 7 shows the elasticity estimates at the local level for the separate conditions. The vast majority of both the direct and global elasticity estimates are counter-cyclical, but lie in a relatively large range of -0.15 to 0. The proportion of pro-cyclical estimates to total estimates is small

[23] These consistent negative estimates across the five types of health conditions also suggest that any changes in reporting behavior with the cycle would have to occur strongly for all health condition to negate our results.

and relatively similar across the 5 condition types.[24]

Finally, we examine whether dynamic health adjustment to changes in economic conditions differs by type of health condition. Figure 8 provides the time paths for each condition for the direct and global responses. Our analysis of any condition in Figure 6 showed that it takes around 10 quarters for the full effect of economic changes to fully impact on health (i.e. to get to the long-run elasticity value). Figure 8 shows differences across the conditions in the time to full impact. While the dynamic path to full impact for cardiovascular and respiratory conditions takes around 10 and 6 quarters, respectively, to manifest, we find slower adjustments for musculoskeletal, mental health and other conditions. Broadly, the speed of adjustment is correlated within condition with the size of the effect. For those conditions with a larger long-run effect of a change in economic circumstances (mental health and musculoskeletal), the time taken to arrive at the long-run effect is greater. In particular, for mental health conditions, the economic effect is largest (Table 3) and it takes around 20 quarters for the full health adjustment to take place (Figure 8).

7. Conclusions

This paper examines an important economic and public health question: how does population health change in response to changing macroeconomic conditions? The fixed effects panel data model commonly used in the literature, although having the advantage of being straightforward to implement, is relatively uninformative about what level of spatial aggregation to use, does not easily allow identification of local area heterogeneity in the relationship, does not easily incorporate co-movements and feedback effects across local areas or health condition types, and does not identify the dynamics of how the effects filter through the economy. We take a different modelling approach and apply a dynamic GVAR panel data model to this question, which directly informs on these issues. It allows for feedback between local areas, for responses to changes in both national and local area economic circumstances, and provides a natural way of estimating heterogeneity in responses across areas. It also allows us to trace out the time path of responses. We also provide a statistical approach to the optimal amount of spatial aggregation, the latter being an important issue raised in recent studies

[24] For musculoskeletal conditions, of the 32 local areas that have a significant ($|t|>1.64$) global employment elasticity, 29 are counter-cyclical and only 3 pro-cyclical. The corresponding numbers for cardiovascular conditions are 19 counter-cyclical areas compared to 1 pro-cyclical areas; for respiratory conditions is 11 areas compared to 3 areas; for mental health conditions is 26 areas compared to 2 areas; and for other condition types is 23 areas compared to 2 areas. For the remaining local areas, we do not identify any significant relationship. Note that for 23 areas the parameters for the employment elasticities in the restricted specification are set to zero but the results are similar from the unrestricted model that sets no parameters to zero.

(Ruhm, 2015, Lindo, 2015), but one that has been addressed to date without recourse to formal statistical tests.

We apply this approach to examine the link between the economy and reported chronic health conditions in Britain for those of working age. Our main results are the following. First, we find robust evidence of a counter-cyclical relationship for chronic health conditions. In terms of magnitude, we find a 1 percentage point increase in local area employment growth leads to a 1.7% drop in chronic health conditions, with similar effect sizes by gender. For context, the GFC period saw around a 5-percentage point drop in employment rates. Using these estimates our model would predict an increase in chronic health conditions of 8.5 percent following the GFC. Second, ignoring dynamics and feedbacks in our model would have led to an underestimated the effects of macroeconomics circumstances by around 50%. Third, if we had applied the standard fixed effects panel data model used in the literature, we would have substantively under-estimated the extent of this counter-cyclical relationship. Fourth, we identify considerable heterogeneity across local areas in the health response to changed economic conditions, with a conservative range of -0.08 (i.e. a 1 point increase in the local area employment growth leads to an 8% fall in chronic conditions) to 0. The estimated effects are largest in areas with a more traditional industrial composition, older populations and populations with poorer long-term health, which fits with the long-term association of poorer areas and poorer health that exists in Britain (and many other economies). Fifth, these effects occur with a lag: we find that it takes around 10 quarters for the health effects of a change in employment to fully eventuate. Sixth, when we examine 5 broad types of chronic condition in a unified framework that embeds cross-condition and cross-area effects, we find that all conditions respond counter-cyclically, with strongest effects for mental health conditions, followed by musculoskeletal conditions, but still substantive effects for cardiovascular, respiratory and other types of conditions. Our estimates suggest that a 1 percent point increase in the employment growth rate leads to 4.2% drop in mental health conditions, a 2.7% fall in musculoskeletal conditions, and a fall for cardiovascular, respiratory and other conditions of around 2.4%. It takes longer for those conditions with the largest estimated effects (mental health conditions and musculoskeletal conditions) to fully work through the economy, with the quickest response being for respiratory conditions. Finally, our statistical testing approach identifies the optimal local area to be a relatively small one, containing on average around 600,000 individuals.

Overall, we conclude that a modelling approach that more fully captures dynamics and feedbacks in the relationship between economic conditions and health, and allows identification of local area heterogeneity in this relationship, provides new insights that are useful for understanding the health-related costs of downturns and where to target policies to combat these.

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Table 1:

Long-Run Employment Elasticities

	Restricted Model		
	All	**Male**	**Females**
Direct	-0.010***	-0.009***	-0.009***
	(0.001)	(0.001)	(0.001)
t-ratio	-7.90	-7.03	-6.39
% with |*t*|>1.64	38%	27%	25%
Global	-0.017***	-0.016***	-0.015***
	(0.002)	(0.002)	(0.002)
t-ratio	-8.83	-7.21	-6.86
% with |*t*|>1.64	42%	29%	26%
Optimal Number of Areas	91	73	87

Notes: * significant at 10%, ** significant at 5%, *** significant at 1%. Restricted model is for the NUTS2/NUTS3 combinations for 68 optimal areas with estimates for 23 areas set to zero.

Table 2:

Fixed Effects Panel Model Employment Elasticities

All Areas	**All**	**Males**	**Females**
Static model			
Local Area Employment Growth Rate	-0.003***	-0.003***	-0.002***
	(>0.001)	(>0.001)	(0.001)
Dynamic model			
Local Area Employment Growth Rate	-0.004***	-0.005***	-0.004***
	(>0.001)	(>0.001)	(0.001)
Lagged Rate of Chronic Conditions	0.641***	0.658***	0.640***
	(0.011)	(0.025)	(0.022)
Year-Quarter Controls	Y	Y	Y
Local Area Fixed Effects	Y	Y	Y
Area-Specific Linear Time Trends	Y	Y	Y
Number of Areas	131	131	131
Optimal Areas			
Static model			
Local Area Employment Growth Rate	-0.002***	-0.003***	-0.002***
	(>0.001)	(0.001)	(0.001)
Dynamic model			
Local Area Employment Growth Rate	-0.004***	-0.005***	-0.004***
	(>0.001)	(0.001)	(0.001)
Lagged Rate of Chronic Conditions	0.652***	0.606***	0.636***
	(0.015)	(0.018)	(0.022)
Year-Quarter Controls	Y	Y	Y
Local Area Fixed Effects	Y	Y	Y
Area-Specific Linear Time Trends	Y	Y	Y
Number of Areas	91	73	87

Notes: Robust standard errors in parentheses, clustered at area level. Coefficients are percentage changes in the outcome variable per unit change in the explanatory variable. Observations weighted by number of respondents to chronic health question in each area-year-quarter cell. For All model using 131 local areas there are 7,467 observations (131 * 57 quarters). For the All models using the optimal areas there are 5,187 observations (91 areas * 57 quarters); for the Male models using the optimal areas there are 4,161 observations (73 areas * 57 quarters); for the Female models using the optimal areas there are 4,959 observations (87 areas * 57 quarters).
* significant at 10%, ** significant at 5%, *** significant at 1%.

Table 3:

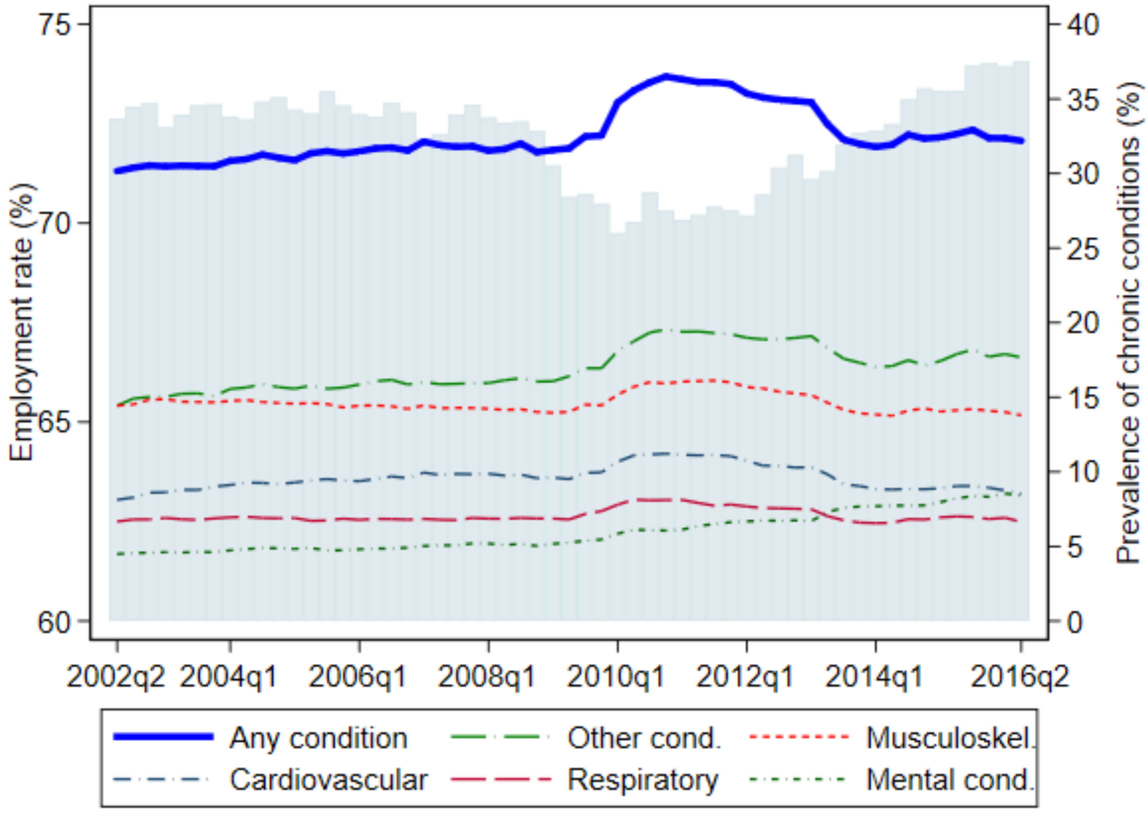
Direct and Global Long-Run Employment Elasticities by Chronic Condition Type

	Musc	**Cardio**	**Resp**	**Mental**	**Other**
Direct	-0.019***	-0.015***	-0.014***	-0.037***	-0.017***
	(0.004)	(0.003)	(0.003)	(0.005)	(0.005)
t-ratio	-5.28	-5.57	-4.22	-7.63	-3.53
% with |*t*|>1.64	35%	24%	18%	34%	25%
Global	-0.027***	-0.024***	-0.021***	-0.042***	-0.024**
	(0.005)	(0.004)	(0.004)	(0.006)	(0.005)
t-ratio	-5.07	-5.44	-4.88	-6.91	-4.62
% with |*t*|>1.64	35%	40%	24%	30%	29%
Optimal Number of Areas			91		

Notes: * significant at 10%, ** significant at 5%, *** significant at 1%. Restricted model. Pooled males and females. Restricted model is for the NUTS2/NUTS3 combinations for 68 optimal areas with estimates for 23 areas set to zero.

Figure 1:

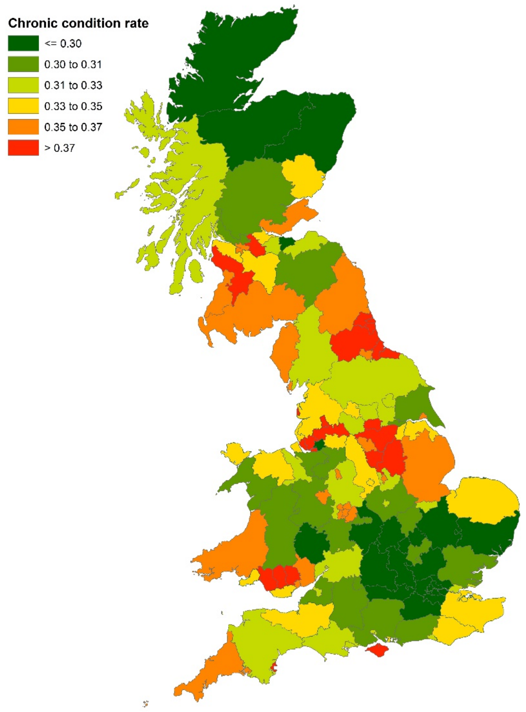
National Quarterly Employment Rates and Chronic Conditions Prevalence

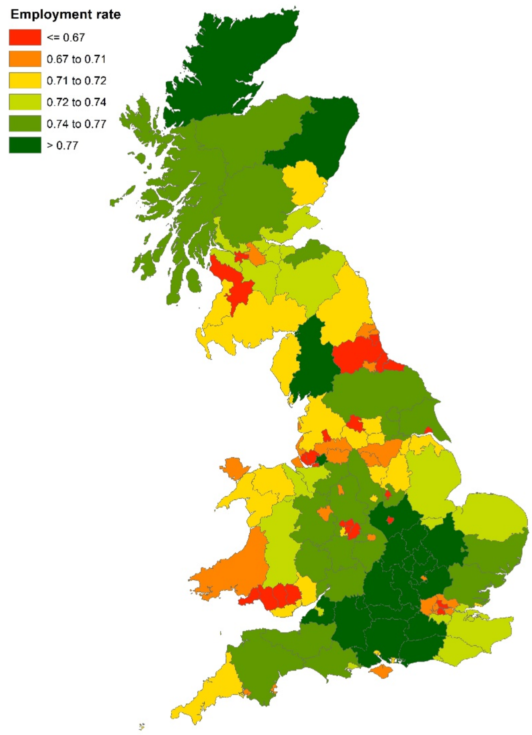


Note: Data from QLFS 2002q2 to 2016q2.

Figure 2:

Means of Chronic Condition Rate and Employment Rate for NUTS3 (131 Areas)

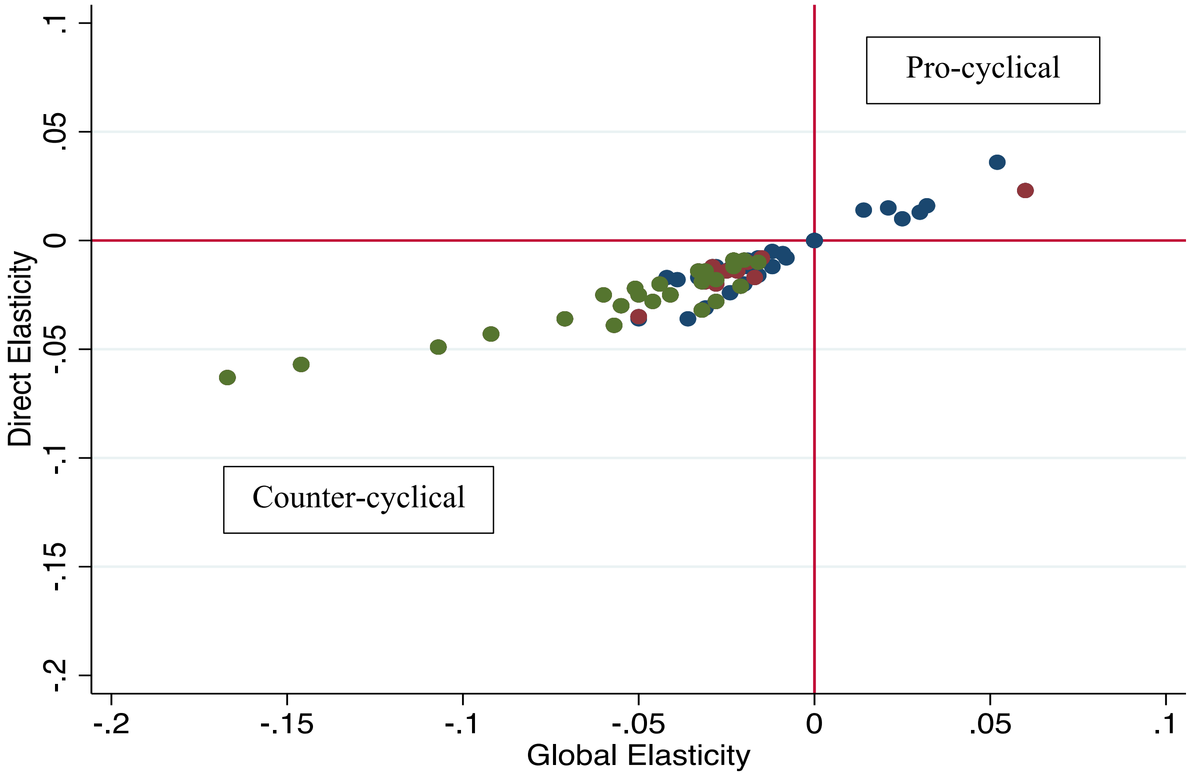




Note: Data from QLFS 2002q2 to 2016q2.

Figure 3:

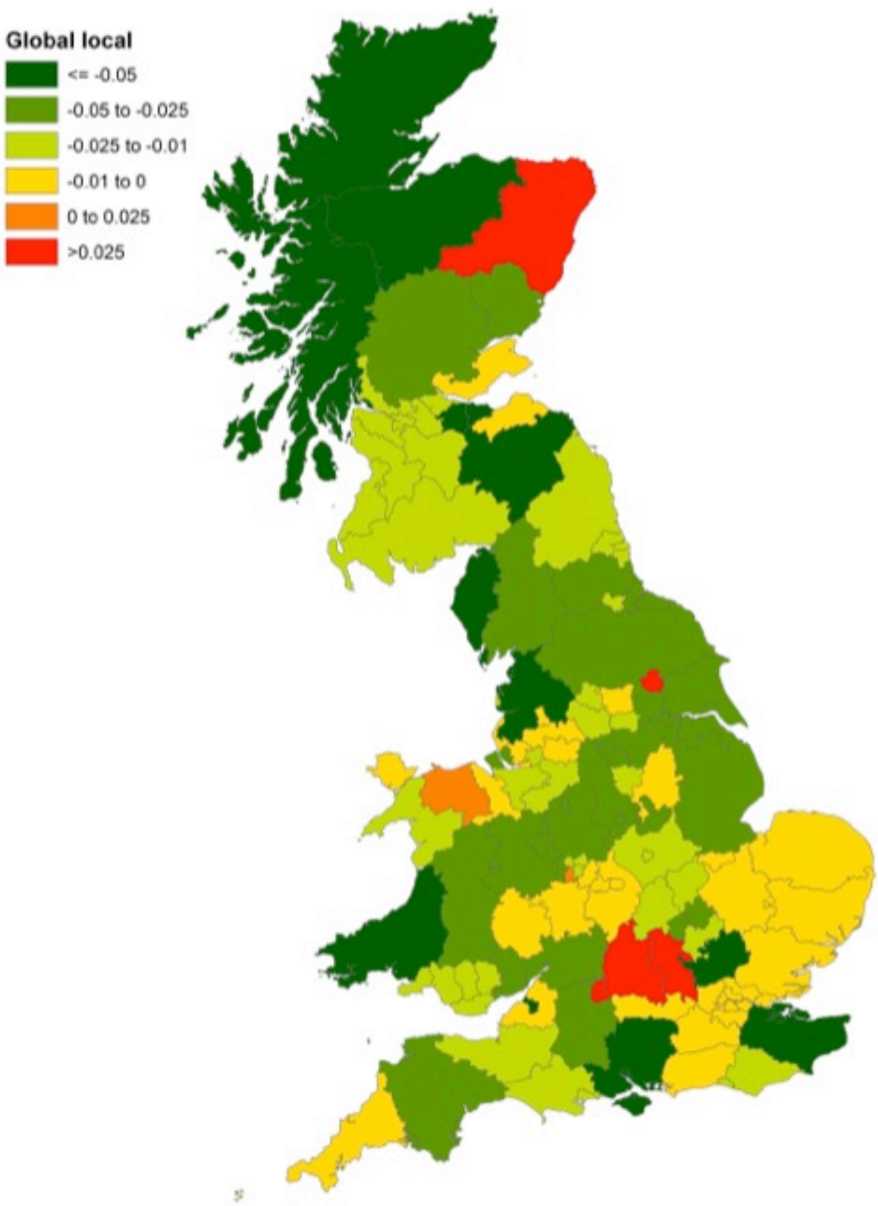
Direct and Global Elasticities by Optimal Local Area



Notes: Estimates from Restricted Model. Blue Dot = |t|=<1.64; Red Dot = |t|-stat>=1.64; Green Dot = |t|-stat>=1.96. Areas for which coefficients set to zero in estimation are excluded from the Figure.

Figure 4:

Global Employment Elasticities by Optimal Local Area



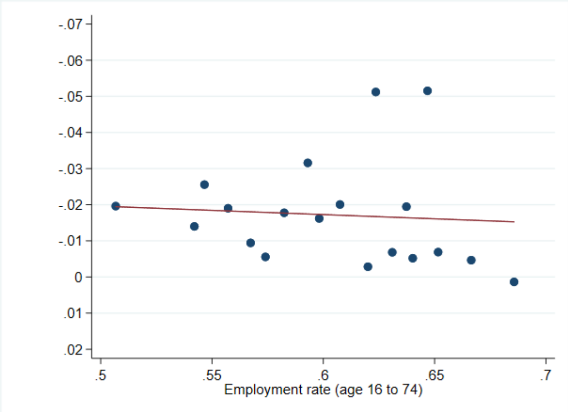
Notes: Estimates from Restricted Model. Restricted model is for the NUTS2/NUTS3 combinations for 68 optimal areas with 23 areas set to zero.

Figure 5:

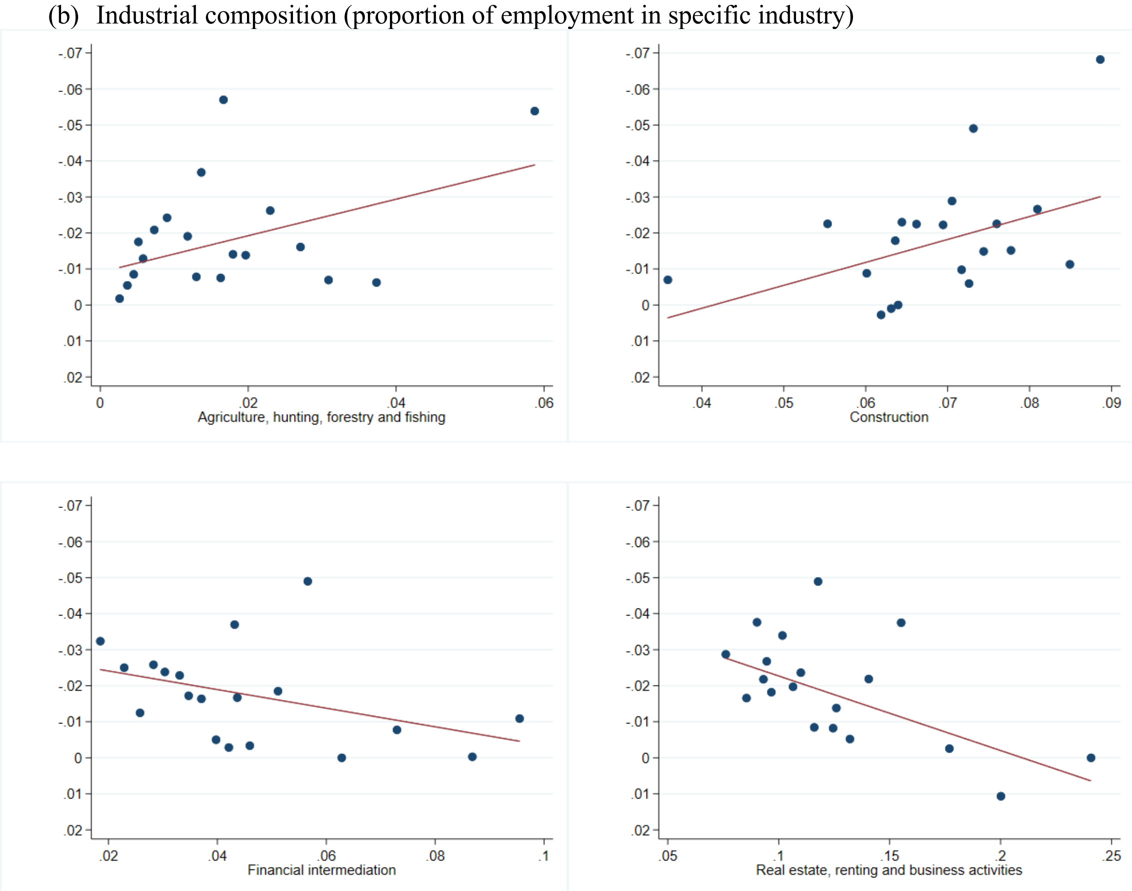
Association of economic change and chronic health by characteristics of the local area

Panel A: Economic conditions

(a) Economic activity amongst 16-74 year olds

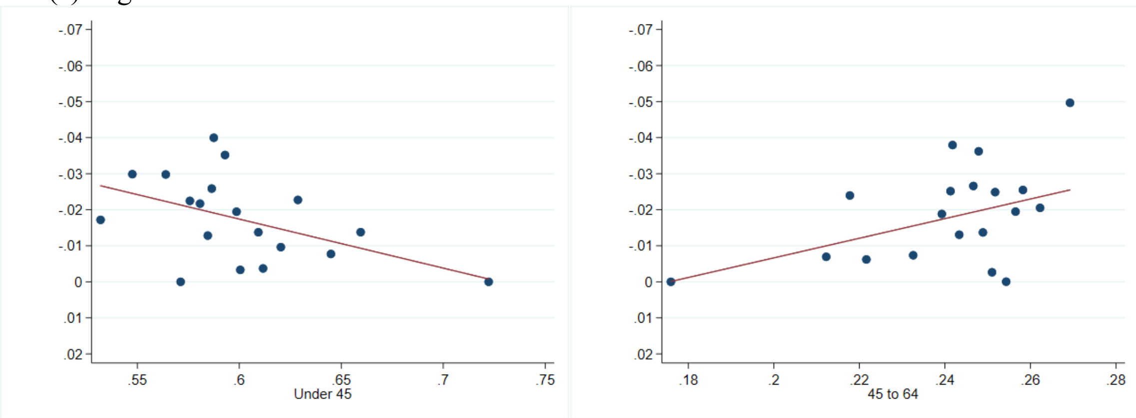


(b) Industrial composition (proportion of employment in specific industry)

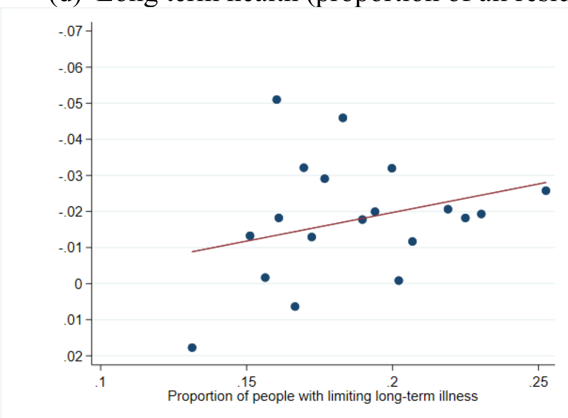


Panel B: Demographic structure

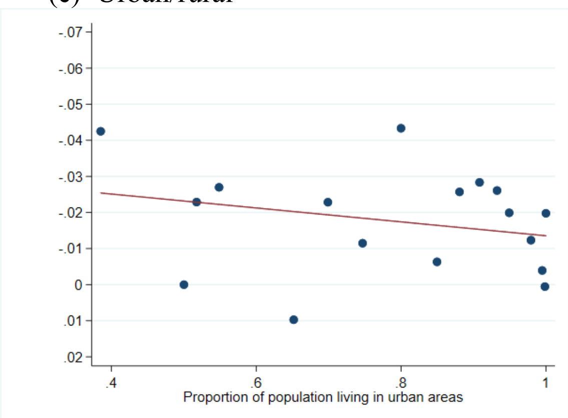
(c) Age distribution



(d) Long term health (proportion of all residents)

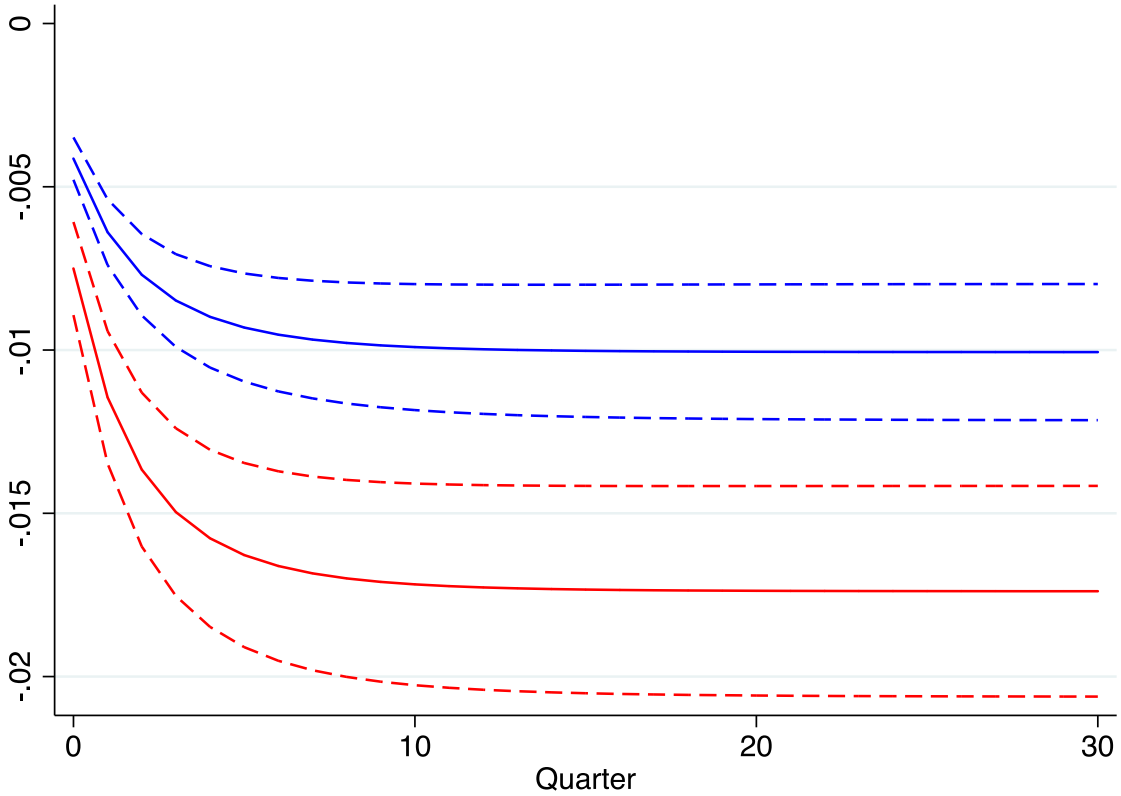


(e) Urban/rural



Notes: Bins, means and regression line weighted by population size. Characteristics from 2001 Census except for urban/rural which is from 2011 Census. Areas with over 10,000 resident population are defined as urban.

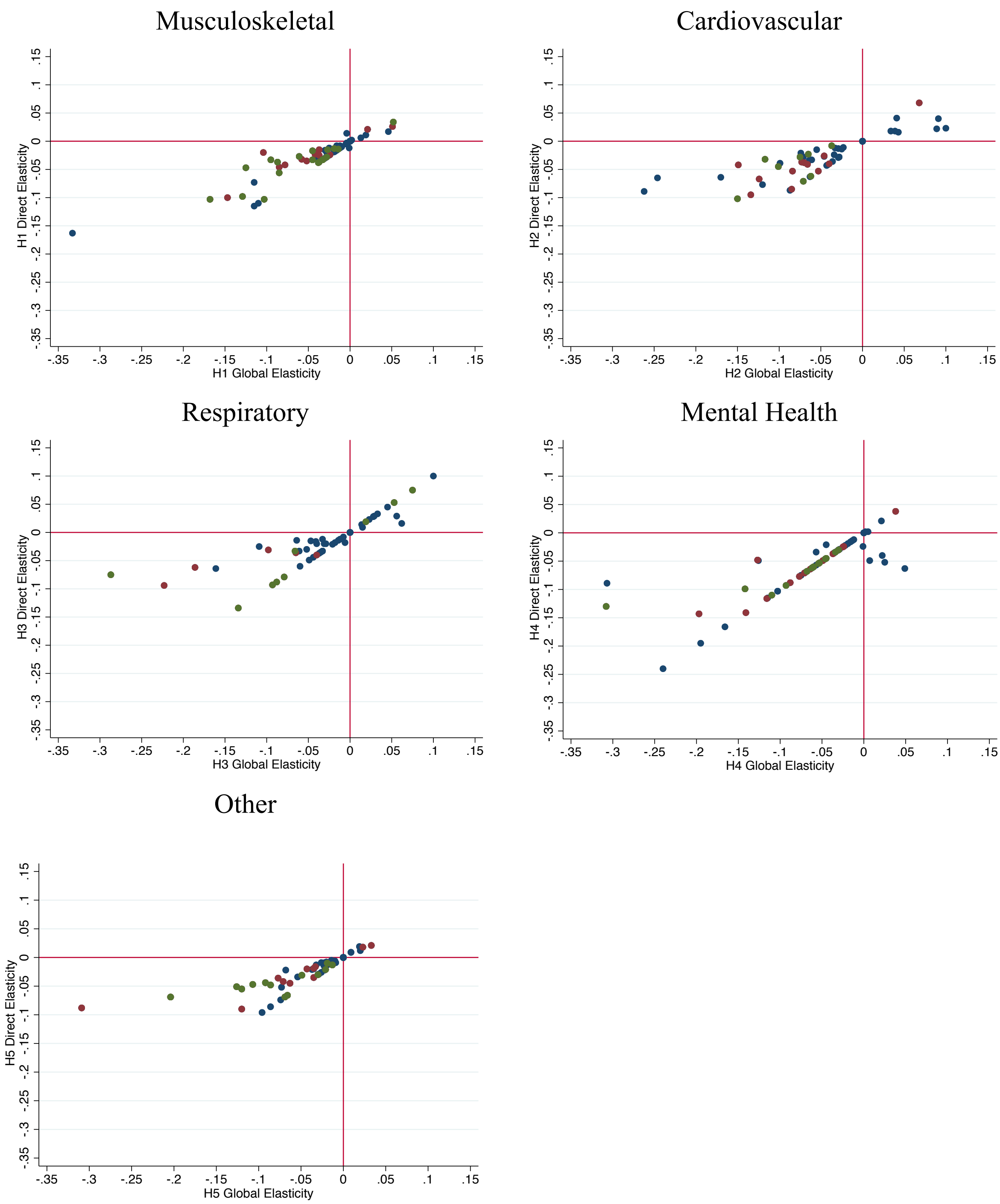
Figure 6: Dynamics of Direct and Global Elasticities



Notes: Estimates from Restricted Model. Blue Line = Direct elasticity; Red Line = Global elasticity; 90% confidence intervals in dashed lines.

Figure 7:

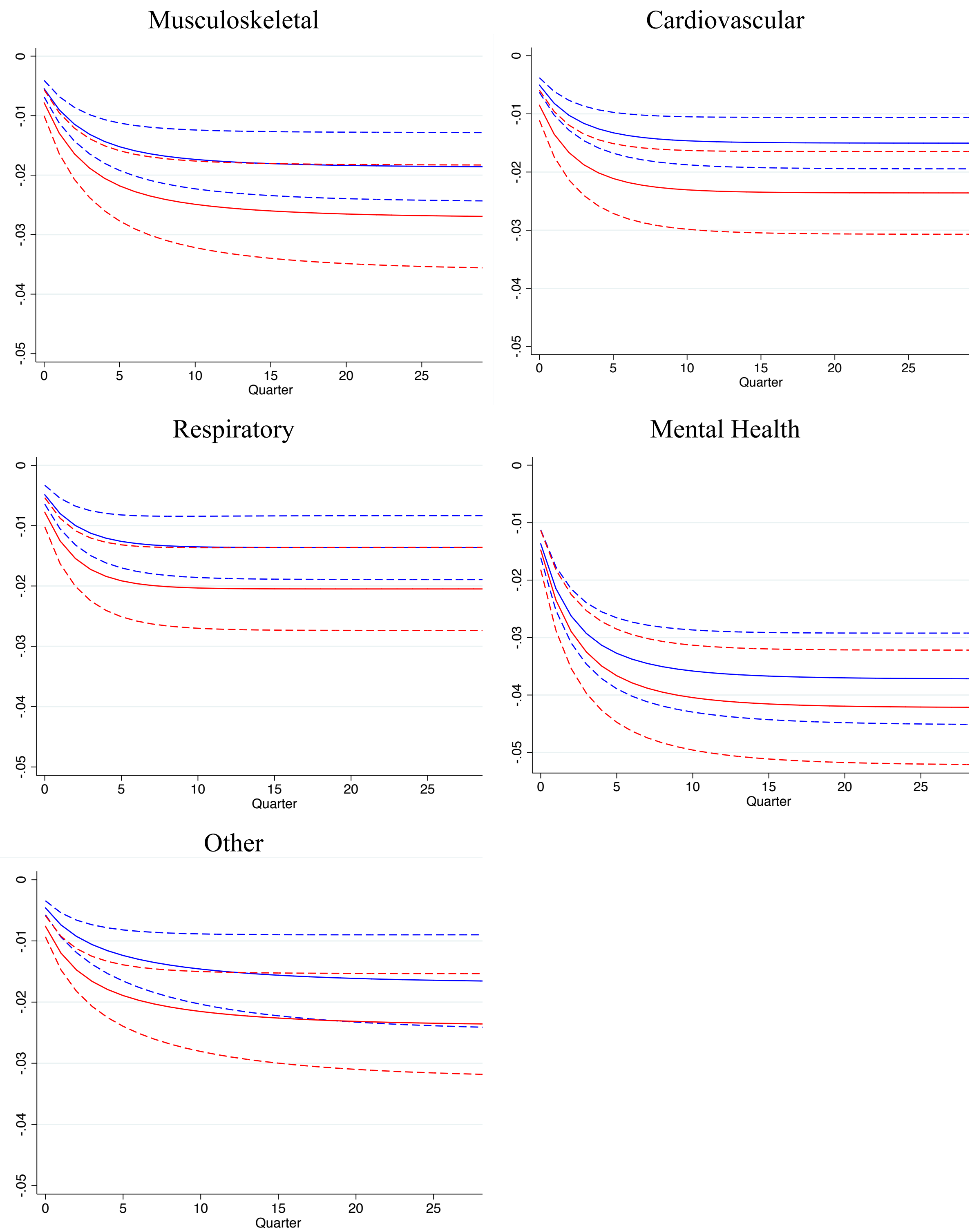
Direct and Global Elasticities by Optimal Local Area for Condition Types



Notes: Estimates from Restricted Model. Blue Dot = |t|=<1.64; Red Dot = |t|-stat>=1.64; Green Dot = |t|-stat>=1.96. For the mental health figure one large outlying positive elasticity (0.293) excluded to maintain consistent scaling across all conditions.

Figure 8:

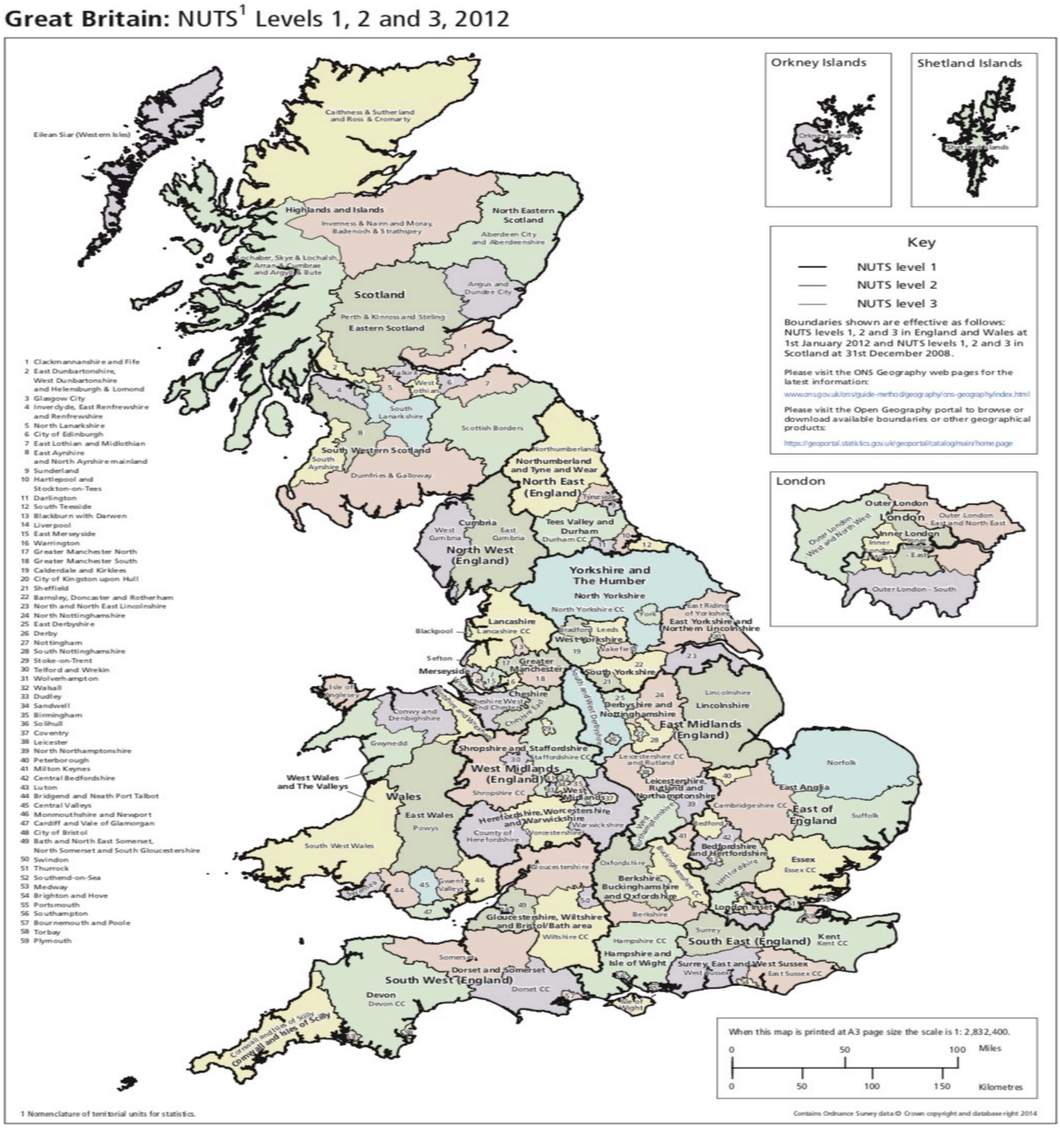
Dynamics of Direct and Global Elasticities by Condition Type



Notes: Estimates from Restricted Model. Blue Line = Direct elasticity; Red Line = Global elasticity; 90% confidence intervals by dashed lines.

APPENDIX

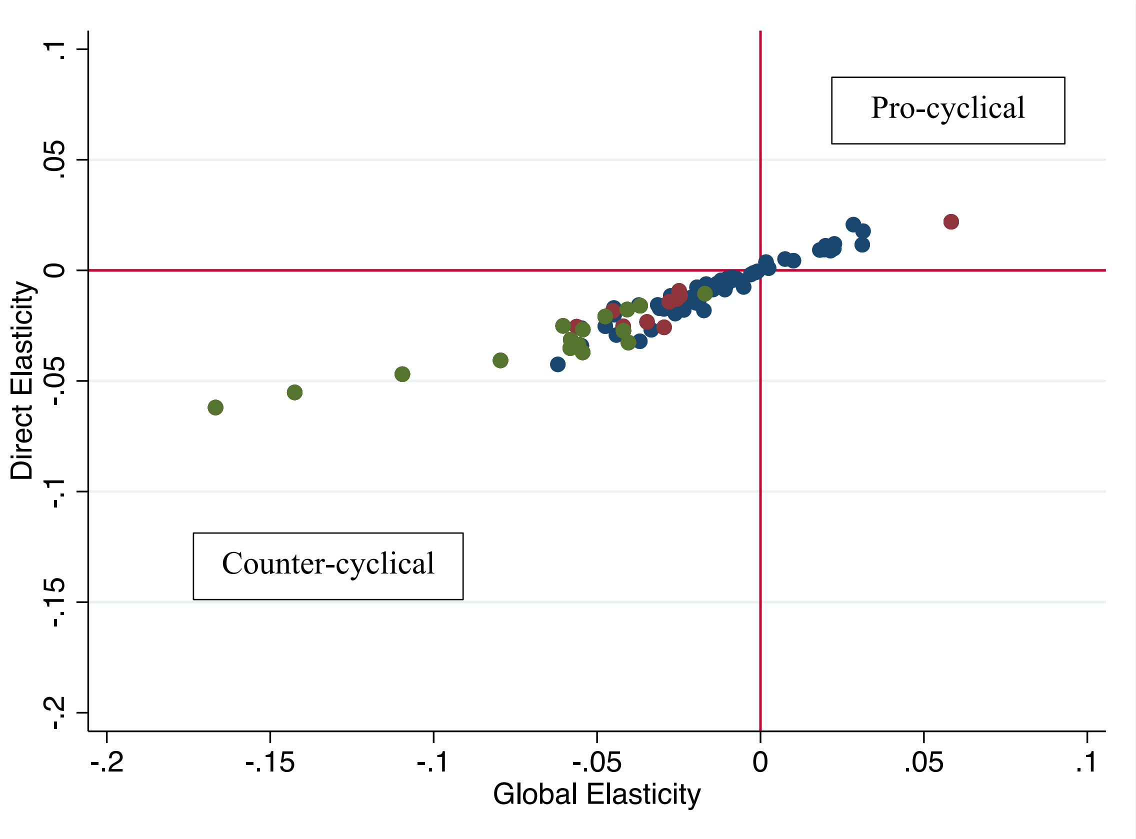
Figure A1:
Great Britain NUTS1, 2 and 3 Local Areas (2012)



Source: Office for National Statistics:
https://www.ons.gov.uk/methodology/geography/ukgeographies/eurostat

Figure A2:

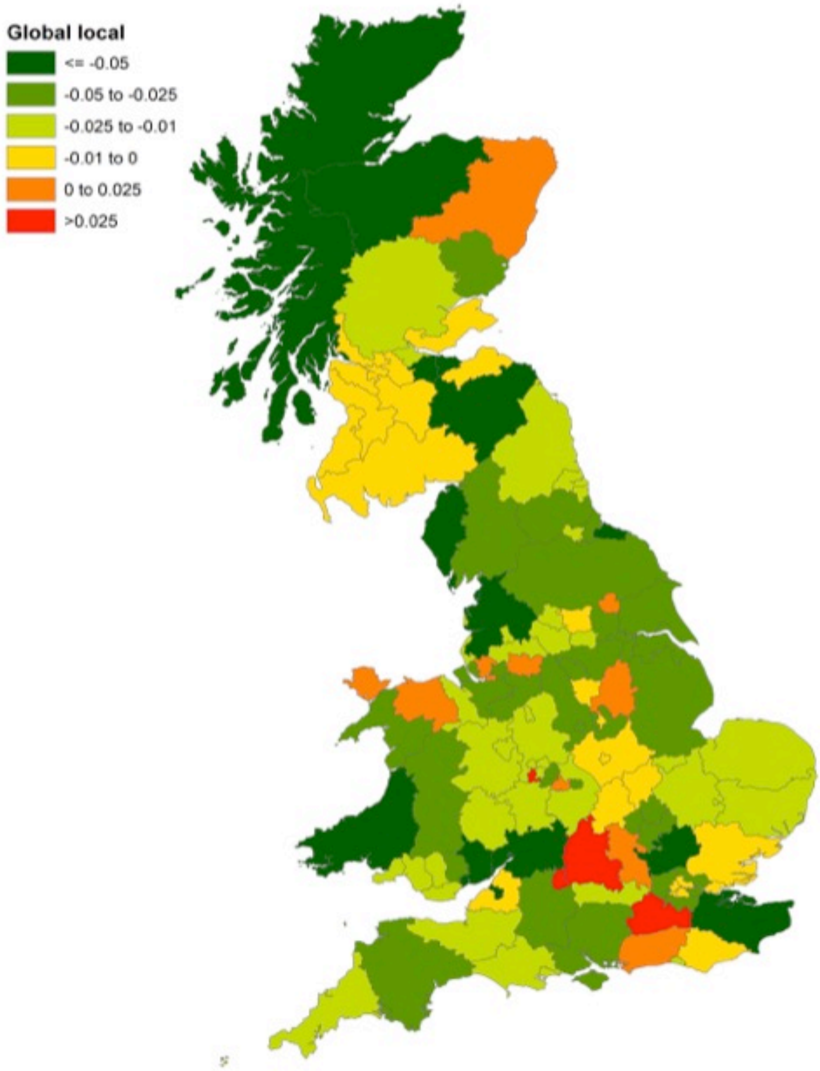
Matched Direct and Global Elasticities by Optimal Local Area



Notes: Estimates from Unrestricted Model. Blue Dot = |t|=<1.64; Red Dot = |t|-stat>=1.64; Green Dot = |t|-stat>=1.96.

Figure A3:

Global Employment Elasticities by Optimal Local Area Disaggregation



Note: Estimates from Unrestricted Model.

Table A1:
Specific Health Problems Constituting Chronic Condition Groups

Group of chronic conditions	Specific health problems included in group
(1) Musculoskeletal	Problems or disabilities (including arthritis or rheumatism) connected with … arms or hands; … legs or feet; … back or neck
(2) Cardiovascular	Heart, blood pressure or blood circulation problems
(3) Respiratory	Chest or breathing problems, asthma, bronchitis
(4) Mental health	Depression, bad nerves or anxiety; Mental illness, or suffer from phobia, panics or other nervous disorders
(5) Other conditions	Difficulty in seeing (while wearing spectacles or contact lenses); Difficulty in hearing; A speech impediment; Severe disfigurement, skin conditions, allergies; Stomach, liver, kidney or digestive problems; Diabetes; Epilepsy; Severe or specific learning difficulties (mental handicap); Progressive illness not included elsewhere (e.g. cancer, multiple sclerosis, symptomatic HIV, Parkinson's disease, muscular dystrophy); Other health problems or disabilities

Table A2:
Long-Run Employment Elasticities (Unrestricted Model)

	Unrestricted Model		
	All	**Male**	**Female**
Direct	-0.013***	-0.010***	-0.011***
	(0.003)	(0.003)	(0.003)
t-ratio	-4.53	-3.35	-3.86
% with $\|t\|>1.64$	30%	18%	21%
Global	-0.023***	-0.018***	-0.019***
	(0.005)	(0.005)	(0.005)
t-ratio	-4.90	-3.44	-3.97
% with $\|t\|>1.64$	29%	19%	17%
Optimal Number of Areas	91	73	87

Note: * significant at 10%, ** significant at 5%, *** significant at 1%.

Table A3:
Correlations between Characteristics of Local Areas and Chronic Health Responses to Economic Changes

Local area characteristics	**Coefficient**
Economic activity level	
Employment rate in 16-74 population	0.023***
	(0.06)
Industrial structure (proportion of population employed in):	
Agriculture	-0.51***
	(0.19)
Construction	-0.64***
	(0.23)
Manufacturing	-0.08
	(0.06)
Financial intermediation	0.26**
	(0.13)
Real estate and business activities	0.21***
	(0.06)
Age composition	
Under 44	0.14**
	(0.06)
45-64	-0.27**
	(0.12)
65 plus	-0.21*
	(0.12)
Health	
Proportion population with limiting long term health condition	-0.16*
	(0.09)
Urbanisation	
Proportion of population urban	0.019
	(0.013)

Notes: Each coefficient is from a separate regression of the global elasticities from the restricted model on the relevant local area characteristic. Standard errors in parentheses. All characteristics are from the 2001 Census, except for urban versus rural population, which is from the 2011 Census. All regressions weighted by population size. . *, ** and *** *p*-values less than 0.10, 0.05 and 0.01, respectively.