Economic Conditions and Health:
Local Effects, National Effect and Local Area Heterogeneity

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Abstract

We study the relationship between health and changing economic conditions in local areas using a GVAR model that allows for dynamic and interdependent responses to local and national economic conditions. We examine quarterly British data for 2002-2016 for 131 local areas, which displays considerable heterogeneity in economic conditions. We find robust evidence that health improves as the local economy (employment) expands, but that it takes over 2 years to realise the full effect. This relationship holds for musculoskeletal, cardiovascular, respiratory, and mental health conditions. We find considerable response heterogeneity at the local area level with the strongest relationship between changes in economic conditions and health found for areas with more traditional industrial structures.

Keywords: Macroeconomic conditions, Local Areas, Health, Dynamics, Heterogeneity

JEL: I10, J21, C33, E32

1. Introduction

The global economic downturn caused by the COVID-19 pandemic has given renewed prominence to the long-standing question of whether macroeconomic conditions affect population health. Understanding the relationship is important for developing appropriate policy responses to economic shocks, including forecasting future healthcare demand (Banks et al., 2020). However, despite a substantial literature, there remains some uncertainty about whether recessions are good for population health (i.e. poor health is pro-cyclical) or whether health worsens in bad economic times (i.e. poor health is counter-cyclical) (see Bellés-Obrero and Vall Castello, 2018, for a review).

Much of the literature has examined mortality as a measure of population health (Ruhm, 2000, is the seminal paper), with many studies finding that deaths increase in good economic times. In contrast, fewer studies have investigated the relationship between economic conditions and morbidity. However, the loss of functional health caused by chronic conditions such as heart disease, diabetes, respiratory illness, back and neck pain, and mental health conditions is replacing premature mortality as the main contributor to disability-adjusted life years, for example as estimated by the Global Burden of Disease Study for developed countries (Murray et al., 2020). This shift has substantial implications for health care budgets. In the US, for example, individuals with at least one chronic health condition account for 90 percent of total health care spending, costing $1.1 trillion each year or around 6 percent of GDP (Buttorf et al., 2017; Waters and Graf, 2018). Similarly, in England, the treatment and care of people with chronic disease accounts for an estimated 70 percent of total health and social care expenditure, including about 50 percent of all GP visits, 64 percent of all outpatient appointments and over 70 percent of all inpatient bed days. There are also growing concerns about the increasing numbers of people with multiple long-term conditions (Department of Health, 2010, 2012). Importantly, chronic health problems typically start to increase sharply from middle working age when labour market conditions may have important effects. We therefore might expect different impacts (and different dynamics) for morbidity following changes in economic conditions than for mortality, for which around 86 percent of deaths in Britain occur after the age of 60 (ONS, 2016).

When modelling the relationship between economic conditions and population health it is important to allow for the fact that many types of health conditions evolve over time. Thus, identifying the profile of dynamic responses is informative. It is also important to allow for changes in economic conditions to affect health outcomes at both large and small spatial scales and for spillovers between areas. For example, an economic shock in one area may affect health in another if there are cross-area employment flows and both local and national changes in employment may result in changes in health. Local areas also differ considerably in their demographic and industrial composition, which might lead to different health responses to economic changes of similar sizes by area. These issues of short- versus long-run dynamics, potential spillovers between areas, and area-level heterogeneity have been shown to be important in studies of labour market outcomes (e.g. Lee and Pesaran, 1993; Manning and Petrongolo, 2017), well-being (e.g. Luttmer, 2005) and a variety of macroeconomic, financial and regional applications (e.g. Di Mauro and Pesaran, 2013).

To allow for these issues in the context of population health we adopt heterogenous panel methods within a Global Vector Autoregressive (GVARX) modelling framework (see Pesaran and Smith, 1995; Di Mauro and Pesaran, 2013; and Sarafides and Wansbeek, 2021).[1] This modelling approach enables us to provide insights into the dynamic and interdependent responses of health in different local areas to changes in exogenous economic circumstances at local and national levels, to examine how any impacts on population health develop over time, and to establish the extent of local area heterogeneity in responses to changes in economic conditions and the characteristics of areas most and least impacted.[2]

We apply this modelling approach to Britain, using data for the period 2002 to 2016. We focus on the relationship between the change in employment (i.e. growth) and reported chronic health conditions of working age individuals (aged 25-64). We expect that changes in employment opportunities are most directly salient for the health of this age group, as increased job insecurity has been shown to be one potential key pathway linking economic conditions to health outcomes (e.g. Johnston et al., 2020; Avdic et al., 2021). There is considerable local area variation in Britain both in the prevalence of chronic health conditions and economic conditions, and our sample period includes the large exogenous shock to the economy from the Global Financial Crisis (GFC). Thus, our data provide considerable time-series and spatial variation. The nature of our data leads to the question of what is the most relevant spatial area to best capture the impact of changes in local and national economic factors. Rather than impose the level of spatial aggregation *a priori* we choose it based on a sequence of formal statistical tests, premised on the assumption that a more disaggregated

[1] See Elhorst et al. (2021) for a useful discussion of the intersection of spatial econometrics and GVAR modelling to allow for cross-sectional dependence and spillovers across space and time.
[2] This is of interest not only to researchers but also to policy-makers. A recent example is the UK Government's COVID-19 Recovery Strategy presented to Parliament by the Prime Minister in May 2020, which points to estimates of the health effects of recessions (HM Government, 2020).

model is preferable unless the data suggest that aggregation is more appropriate (Lee et al., 1990; van Garderen et al., 2003). This approach provides one way to more formally address concerns raised by Lindo (2015), Ruhm (2016) and Peng et al. (2022) that estimates of the impact of economic shocks on health can differ over levels of spatial aggregation in the US. In particular, Lindo (2015) finds that using more disaggregated local units (counties) leads to smaller estimates than using larger units (States), and that there are likely to be significant spillover effects on health outcomes across small areas. Ruhm (2016) notes that further research is needed to better understand the differences between the effects of national versus more localised economic conditions.

We find robust evidence that reported chronic illness responds counter-cyclically to the business cycle; that is, the prevalence of chronic conditions decreases as local economic activity (employment) increases.[3] We also find spillovers across areas from national levels of health and dynamic responses of health in a local area to economic changes and lagged health conditions. Our approach allows us to derive three long run elasticities that saliently summarise the local area responses to economic changes. If we shut off potential spillovers from national health conditions and national economic conditions on local area responses, our estimates show that a one percentage point increase in local area employment growth results in an average long-run 1.2 percent fall in the prevalence of chronic health conditions. Allowing the aggregate national level of health to affect local area health amplifies the response to economic conditions and increases the long-run elasticity by around 50 percent. Finally, if we additionally allow for the effects of national changes in employment growth, the effect of a nationwide one percentage point increase in employment growth results in an average 2.6 percent fall in chronic health conditions in a local area in the long run. In terms of dynamic adjustment, these long-run effects are reached only after about two years.

Our estimates also show considerable heterogeneity across local areas in the response of health to changing economic conditions. While there is a counter-cyclical relationship in most 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. We find the best choice of local area disaggregation to be to a relatively low level of an area that

[3] Given that our main economic variable is based on employment rates and our health measure reflects illness, based on chronic health conditions, we define a counter-cyclical relationship when employment increases (+) and illness declines (-), and a pro-cyclical relationship to exist when employment increases (+) and illness increases (+).

contains on average around 600,000 individuals.

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 Section 5 the results. Section 6 concludes.

2. Related Literature

Ruhm's (2000) seminal paper, 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, working age adults, the elderly), across indicators of socioeconomic status and has been extended to some morbidities and health-related behaviours.[4] While a number of recent studies reproduce Ruhm's (2000) finding of a pro-cyclical relationship for overall mortality – which may have weakened in recent years (for example, Haaland and Telle, 2015; Granados and Ionides, 2017; 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). Atalay et al. (2021), for example, find no overall relationship between unemployment and mortality, apart from a reduction in transport accidents in economic downturns for young males. However, 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).[5] There is less

[4] 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; Avdic et al., 2021; Black et al., 2022; and for children, Dehejia and Lleras-Muney, 2004; Golberstein et al., 2019; Page et al., 2019; and Peng et al., 2022. 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).

[5] Some of the discussion of why the findings from the literature are mixed is due to alternative potential explanations of the relationship between economic conditions and health. These explanations reflect that mortality may reasonably behave differently to morbidity, and different forms of morbidity, as well as health-related behaviours, may respond differently to changing 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 (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 (e.g. Ruhm, 2016).

evidence for morbidity, as distinct from mortality (e.g. Haaland and Telle, 2015; Colombo et al., 2018; Wang et al., 2018; Wang and Tapia Granados, 2019). And within studies of morbidity there has been relatively little focus on chronic illness (e.g. Ruhm, 2003, 2007; Antonova et al., 2017; Colombo et al., 2018; Jofre-Bonet et al., 2018) despite its rising importance. Finally, while there is a large volume of studies, recent reviews (for example, Ruhm, 2016; van den Berg et al. 2017; and Bellés-Obrero and Vall Castello, 2018) conclude that the literature on whether and how economic conditions impact on health continues to find mixed results. Bellés-Obrero and Vall Castello (2018) suggest that the only well-established finding is that mental health deteriorates during economic slowdowns.

In terms of the modelling approach, after early time series studies (Brenner 1971, 1979), the most commonly used approach is a panel data model in which the unit of observation is a geographical location at a time period. This model explains the health of an area at a given time as a function of local area economic conditions, an area-fixed effect, an area-specific time trend, and national time controls (dummies). Identification comes from co-movements in economic conditions measured at the local area 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. This model uses the cross-section variation in the data, focusing on the deviation from group means to identify the effect of economic conditions in an area relative to national conditions on health outcomes. The effects of national economic conditions cannot be estimated separately from the effects of local conditions and the approach estimates a single elasticity, implicitly assuming that there is no coefficient heterogeneity across areas or that any coefficient heterogeneity can be subsumed into the error term. In this paper, the modelling approach we take allows estimation of the impact of changes in both national and local economic conditions and explicitly incorporates heterogeneity across areas. We also use a statistical approach to define the optimal level of local area aggregation for our analysis rather than impose it ex-ante.

3. A GVARX Model of Chronic Health Conditions

3.1 Our modelling approach

We model reported chronic health conditions through a set of reduced form equations that relate the prevalence of chronic health conditions in an area to the economic conditions in that area and nationally as they evolve over time. These dynamic reduced form equations accommodate feedback across areas, allowing us to capture both the direct effects of local economic changes on chronic conditions and those exerted indirectly through interdependent (national) economic changes. This approach to accommodating feedbacks draws on the GVAR modelling framework, as described in Mauro and Pesaran (2013) for example, adapted to accommodate the exogenous drivers of local and national economic conditions.

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

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

for $i = 1, \dots, N$ and $t = 1, \dots, T$. $c_{i,t}$ 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 in the same area at time *t*. The variables $\bar{c}_t = \frac{1}{N}\sum_{i=1}^{N} c_{i,t}$ 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 respectively, and f_t represents any other national non-economic variable(s) that may influence health.[6] Our data are at quarterly level, so *t* = quarter and we set *s* = 0,1 to allow economic changes and other non-economic influences to directly impact on health outcomes contemporaneously and for up to one quarter. The inclusion of $\bar{c}_t$ allows for a contemporaneous effect of the national level of chronic health conditions on local area health. Furthermore, as we explain in detail in Section 3.2, the presence of lagged $c_{i,t}$ and contemporaneous $\overline{c}_t$ can, indirectly, generate persistent longer run dynamic effects from the economic changes and other non-economic influences.[7] The area-specific intercepts μ_i represent unobserved time-invariant influences and the parameters, 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 across areas.[8]

Before we present the details of model estimation, we discuss the advantages of this model framework for the study of economic conditions on morbidity. First, it allows the responsiveness of health conditions to economic conditions to vary across local areas, as the

[6] Our focus is on responses of health to changing economic conditions. However, we include in our estimation the national change in consumer confidence index to capture consumer sentiment to allow us to isolate economic conditions from sentiment.
[7] We are therefore not simply estimating the short-run effects of any included lags.
[8] Note that the inclusion of an intercept in each local area equation captures the effects of area-specific (and time-invariant) factors on health, including any long-standing disparities in economic conditions across regions reflected in differences in the growth in area employment considered over the whole sample.

α_{is} and β_{is} are allowed to differ for $i = 1, \ldots, N$. This 'heterogenous panel' approach follows Pesaran and Smith (1995) in that elasticities are allowed to vary across units, with the 'typical responsiveness' being measured using aggregate statistics derived from the individual elasticities.[9] Second, it captures the influence of common national economic and non-economic effects - through the inclusion of $\overline{x}_t$ and f_t - that allows us to distinguish local area economic effects from common national effects. Specifically, note that:

$$\sum_{s=0}^{1} \alpha_{is}\, x_{i,t-s} + \sum_{s=0}^{1} \beta_{is}\, \overline{x}_{t-s} \quad = \quad \sum_{s=0}^{1} \alpha_{is}\left(x_{i,t-s} - \overline{x}_{t-s}\right) + \sum_{s=0}^{1} (\alpha_{is} + \beta_{is})\, \overline{x}_{t-s}$$

Thus, the α_{is} terms show the effect on area *i* health of local conditions (meaning the effect of x_{it} relative to $\overline{x}_t$ or, equivalently, the effect of x_{it} when $\overline{x}_t$ is unchanged) while the $(\alpha_{is} + \beta_{is})$ terms show the effect on area *i* health when x_{it} and $\overline{x}_t$ move together (i.e. when x_{it} increases by the same amount in all areas, in which case the relative terms $x_{it} - \bar{x}_t$ are zero).

Third, the GVAR methodology allows us to capture any interdependencies of health outcomes between areas through the national level of chronic conditions (the $\overline{c}_t$ term in equation (1)). There are two alternative reasons why $\bar{c}_t$ might be significant in the individual local area regressions. One reason would be spillovers between areas. The most obvious example would be a communicable disease. In that case, c_{it} in area *i* is likely to depend positively on economic conditions in area *i,* but will also be higher when the prevalence of the disease is higher in surrounding areas. There is then a common factor that spills over across areas, which would be captured by $\bar{c}_t$ in our modeling. An alternative reason would be common factors driving morbidity in different areas that are exogenous but affect the national level of health. For example, a National Health Service (NHS) advertising campaign might decrease heart disease in every area at the same time. This effect would be picked up by the $\bar{c}_t$ in our regressions but it is not a spillover effect.

For the non-communicable diseases that are the focus of our study, there are several channels which could generate a spillover effect. First, there may be contagion and imitation across areas because doctors and patients become more responsive and/or more sensitive to particular types of health conditions as they become more frequently observed elsewhere. An

[9] Our model is not a random coefficient model. A random coefficient model allows for parameter heterogeneity across areas but estimates the average parameter value assuming the heterogeneity is captured by some distribution. Our 'heterogenous panel' approach estimates separate parameters across the areas, and we examine their average value to give a sense of the results, but it does not impose or assume any structure on the parameter heterogeneity.

example would be heart attacks amongst women, which in the past have been misdiagnosed because they were less common in women than in men. As the incidence of these has increased, doctors have become more aware and more likely to diagnose these. Second, there may be dispersion effects that arise because increasing ill health in one area leads to more resources being spent in that area, which may decrease resources available in surrounding local areas. As a result, fewer resources for services designed to prevent or alleviate chronic health conditions such as physiotherapy or health-related education programs would be available in surrounding local areas, leading to increases in chronic health conditions in surrounding local areas. Third, bad economic times may generate general malaise in the population, i.e. a deterioration in mental well-being that spills across the country. Because of the correlation between mental health and long-term physical health conditions (e.g. Gruber et al., 2021), the deterioration in mental health might, for example, spillover into a rise in physical conditions (co-morbidities).

Our modelling approach unpacks the interactions between local areas to allow for economic conditions in area j to affect the prevalence of chronic disease in area i through a spillover effect. However, we do not know the balance between spillover effects and exogenous effects. If $\bar{c}_t$ picks up a common exogenous national factor, linking area *i* morbidity to economic conditions in area *j* is less appropriate. Our econometric modelling allows us to be agnostic as to whether spillover effects are present because we use our model estimates to calculate long-run elasticities with and without spillover effects. Details regarding these elasticities are provided in Section 3.2.

The GVARX framework also accommodates the presence of the exogenously-determined variables x_{it} (hence the 'X' in GVARX) and the inclusion of $\bar{c}_t$ along with $\bar{x}_t$, meaning that the model nests within it a fixed effects panel model with time dummies (see Appendix A). However, in our model the explanatory variables do not have the same deviation-from-group-mean interpretation as the fixed-effects panel model and that is why we are able to estimate both local and national effects. Nevertheless, any longstanding differences between areas such as a high prevalence of chronic conditions in areas with persistently poor economic conditions would not affect our estimates as the area-specific intercept, μ_i, will capture this effect.

Fourth, our 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. Since we estimate separate equations for each local area and have large *T* (57 quarters), we avoid the well-known issue that the fixed effects estimator is inconsistent for linear dynamic models, with the (Nickell) bias being potentially large for samples with small *T*. [10]

In common with nearly all the studies discussed in Section 2, however, we assume that changing macroeconomic conditions are exogeneous.[11] However, our sample period includes the GFC, which represents a large shock to economic conditions, with its impact on local area employment rates being clearly visible in Figure 1(a). Therefore, it less likely that changes in employment growth are driven by changes in chronic health conditions.

3.2 Measures of the local and the national effects of economic conditions on health

Equation (1) is estimated for each local area and involves complex interactions between areas. To obtain summary measures of the effects of economic conditions on chronic health conditions, 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 (2):

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

$\tilde{\boldsymbol{\mu}}$ is the $N \times 1$ vector containing the area-specific intercept $\tilde{\mu}_i$, the $\boldsymbol{x_t}$ contain the stacked $x_{i,t}$

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[10] In a dynamic panel model, most often a single ‘average’ coefficient is estimated on the lagged dependent variable, with any parameter heterogeneity across areas subsumed into the error. As a result, the constructed error is certain to be correlated with the lagged dependent variable and to generate inconsistencies in parameter estimates.

[11] That is, our model does not allow for economic conditions to be affected dynamically by changes in morbidity. A recent exception is Avdic et al. (2021) who use a shift-share instrumental variable approach in which exposure to macroeconomic fluctuations is estimated for 16 regions using variations in historical sector composition. This approach is not feasible in our modelling context with up to 131 separate area-specific equations, but we explore below (sub-section 5.3) whether the extent of the estimated relationship between changes in economic conditions and health differs by the (pre-sample) level of employment and the industrial structure of the local area.

and the $\widetilde{\boldsymbol{\delta}}$, $\widetilde{\boldsymbol{\alpha}}$, $\widetilde{\boldsymbol{\beta}}$ and $\widetilde{\boldsymbol{\gamma}}$ contain the parameters. $\widetilde{\boldsymbol{\alpha}}$ and $\boldsymbol{\delta}$ are diagonal NxN matrices and $\widetilde{\boldsymbol{\beta}}$ and $\widetilde{\boldsymbol{\gamma}}$ are Nx1 vectors. The individual relationships in (2) relate chronic health conditions in area *i* at time *t* to chronic health conditions in all areas through the variable $\overline{c}_t$ 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 averaging. Appendix C elaborates on the matrix representation in this section.

The system in (3) 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 $\mathbf{M} = (\mathbf{I} - \widetilde{\boldsymbol{\delta}}\mathbf{A})^{-\mathbf{1}}$, $\boldsymbol{\Phi_0} = \mathbf{M}\widetilde{\boldsymbol{\mu}}$, $\boldsymbol{\Phi_1} = \mathbf{M}\widetilde{\boldsymbol{\alpha}}$, $\boldsymbol{\Phi_2} = \mathbf{M}\widetilde{\boldsymbol{\beta}}$ and $\boldsymbol{\Phi_3} = \mathbf{M}\tilde{\boldsymbol{\gamma}}$, 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. To aid exposition, in Appendix D we provide a stripped-down version of our model (without matrix notation) that illustrates the interplay between areas captured through the matrix algebra of equation (4) and the nature of its system wide properties.

Since the system of health equations (4) summarises the relationship between chronic health conditions and economic conditions across all areas, it can be used to motivate three average measures of the effects of changes in economic conditions experienced through different channels. Specifically, the relationships in (4) can be used first to measure the effects of changes in the area's economic conditions, abstracting from feedbacks propagated through changes in aggregate health measures. These 'direct local' effects for each individual area are captured by the responses to a change in local economic conditions, the $\tilde{\alpha}_i$. These can be summarised across areas by:

$$Local\ (Direct) \qquad \epsilon^{LD} = \frac{1}{N}\sum_{\boldsymbol{i=1}}^{\boldsymbol{N}}\tilde{\alpha}_i \ = \frac{1}{N}\mathbf{w}'\tilde{\alpha} \qquad (5)$$

where $\mathbf{w}$ is a $N \times 1$ vector of ones used to sum up the $\tilde{\alpha}_i$ (which have been arranged along the diagonal of the *N*x*N* matix $\tilde{\alpha}$).[12] The measure ϵ^{LD} therefore describes the average responsiveness of the prevalence of chronic health conditions in an area to a change in local economic conditions relative to national conditions (or assuming national economic conditions are unchanged), before allowing for any spillovers across areas arising from a change in local

[12] This is simply an average of the $\tilde{\alpha}_i$ (see Appendix C).

economic conditions on changes in health in other areas.[13]

We can define the 'accumulated local' effects by scaling up the effects of the local changes to take into account the impact of national health spillovers on local health (from the responses to of $\overline{c}_t$) across areas. These accumulated local effects can be summarised by:

$$Local\ (Accumulated) \qquad \epsilon^{LA} = \frac{1}{N}\mathbf{w}'\boldsymbol{\Phi}_\mathbf{1}\mathbf{w} \qquad (6)$$

Here, $\mathbf{w}'\boldsymbol{\Phi}_\mathbf{1}$ is the $1 \times N$ vector showing the effect 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 $\tilde{\alpha}_i$ $'s$) and also allowing for the impact of the changes on health in other areas on the local area, the latter effect shown by the response to $\overline{c}_t$ in each local area estimate. The measure ϵ^{LA} then describes the average of these accumulated local effects, showing the effect of a 1 unit increase in $x_{i,t}$ if it was experienced across all areas at the same time but abstracting from the impact of changes in the national average level of economic conditions. These accumulated local effects collapse to be equal to the direct local effects if there are no spillovers in health outcomes across areas.

Finally, we can define the ‘national’ elasticity to measure the total effect on health in a typical area of a one unit increase in economic conditions across all areas at the same time, including the effect of the one unit increase in $\overline{x}_t$ that this increase across all areas implies:

$$National \qquad \epsilon^{N} = \frac{1}{N}\mathbf{w}'(\boldsymbol{\Phi}_\mathbf{1}\mathbf{w} + \boldsymbol{\Phi}_\mathbf{2}) \qquad (7)$$

In our empirical analyses we evaluate all three elasticities for a 1 percentage point increase in $x_{i,t}$ in all 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 at which estimation is undertaken is essential. But the most disaggregated area level may not be the optimal choice. While a well-specified disaggregated

[13] These elasticities are averages. We examine the heterogeneity in these elasticities at the local area level in Section 5.

model will generally outperform an aggregate model, this will not be the case if the disaggregate model is mis-specified. Grunfeld and Griliches (1960) indicate 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 if small sample sizes are used in the 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 smaller disaggregated local areas (detailed in Section 4.1).

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. Thus, s is the preferred level of spatial aggregation, which can be (as we will find) a combination of areas defined at different levels of spatial aggregation (see the discussion in Section 5.1).

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:

$$s_d^2 = \sum_{i,j=1}^{n} \hat{\sigma}_{ij}^2 \quad and \quad s_a^2 = \frac{\varepsilon_{at}\varepsilon_{at}'}{T-k_a}, \tag{8}$$

where $\hat{\sigma}_{ij}^2 = \frac{\varepsilon_{it}\varepsilon_{jt}'}{(T-k_i-k_j-tr(\mathbf{A}_i\mathbf{A}_j))}$ 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 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 mis-specification 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 percent of this distribution provides the critical value for the test of the statistical significance of the test statistic.

4. Data

Our data series for the different levels of spatial aggregation are derived from the unit records from the UK's Quarterly Labour Force Survey (QLFS), which is the largest (continuous) survey in the UK. The data cover England, Scotland and Wales (Britain), and are nationally representative. The QLFS is used by the Office for National Statistics (ONS) to produce official national and area labour market information (e.g. employment and unemployment rates), as well as statistics on long-term health conditions. We are unaware of any other UK data on health conditions that can be consistently constructed at the local area level over so many years.[14] We use these data to derive both health and economic condition series at

[14] With the exception of the National Census that is collected only at 10-year intervals, the QLFS is the largest

different local area levels for 57 quarters from 2002q2 to 2016q2 (with data from 2002q1 being used to create lags).

4.1 Measures of chronic health conditions

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 state-pension age in effect during most of our sample period, because we want to focus on the impacts of economic conditions for those likely to be most directly affected by changes in the labour market. This focus means we do not examine spillovers from economic changes affecting the working age population to older groups as such spillovers may induce complex indirect health responses to economic expansions and our focus is on the direct impact of such changes on chronic health. For example, an upturn in the economy could lead to a shortage of labour, with potentially negative effects on the quality of care in residential homes, resulting in worse health outcomes for the elderly (Stevens et al., 2015).

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. The 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 measure of chronic health conditions, which is the proportion of respondents in a local area at a point in time (quarter) answering in the affirmative.[15]

One potential limitation of using self-reported measures of chronic health conditions is that the reporting threshold might change with changing economic pressures. If, for example, 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. In particular, papers have studied whether people without a job might be more likely to report a disability

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continuing UK survey that asks respondents about health conditions. For the US, a future application (as suggested by an anonymous referee) could be to use the Selected Metropolitan/Micropolitan Area Risk Trends of the Behavioral Risk Factor Surveillance System (SMART BRFSS) which provides monthly data with county identifiers.

[15] There was a change in the health conditions question in the QLFS starting in 2013q2, so this applies to the last 13 quarters (out of 57 quarters) of our series. Starting in 2013q2 respondents were asked, "Do you have any physical or mental health conditions or illnesses lasting or expecting to last 12 months or more?". Analysis by the ONS suggests that this change caused an overall drop in the prevalence rate of people aged 16-54 of 0.9 per cent. To control for this change in question we include a shift dummy control in our models, taking value of 1 for the period 2013q1 onwards. We note that the QLFS does not ask respondents about episodes of acute illness, which might also be related to economic conditions. Examples include common colds, broken bones, workplace or road accidents, or acute hospital admissions for overdoses or poisonings.

(or poor health) to 'justify' their economic activity (e.g. Kapteyn et al., 2007; Lindeboom and Kerkhofs, 2009; Black et al., 2017). Naturally, this could be more salient if the health information is to be used to gain access to disability or other benefits. As Black et al. (2017) note, "The inflation of self-reported disability may be motivated by a fear that their survey responses could be used by officials to re-assess their welfare eligibility". Conversely, however, any bias could be lower in areas of high unemployment if individuals feel less social pressure to justify their economic inactivity (Black et al., 2017). Therefore, the direction of any potential bias is not clear.

In support of our measure of chronic health, the question asked to the QLFS respondents does not mention work limitations, is confidential in nature and it is not used for any assessment of benefits. In particular, the QLFS documentation states, "In advance of a first interview a letter is sent to every address in the selected sample explaining that the address has been selected and that an interviewer will be calling. Additionally, in the advance letter, respondents are assured that the information they give will be treated in the strictest confidence and will not be made available to analysts in any form in which individuals, or their households, can be identified." This is in contrast to data recorded by medical professionals in the UK, who issue sickness and other disability statements for their patients to allow them to access benefits.[16] Moreover, unlike the US, access to health care through work-related health insurance is not prevalent in Britain; with individuals being covered by the NHS and the take-up of private health insurance being low. In the QLFS data there is no strong economic reason for individuals to be more likely to state they had a condition in an economic downturn that is not a good reflection of health status.

More generally, there are several advantages from using data series that are constructed from self-reported measures of health. One advantage of survey-based measures is that they can capture subjective health problems that might not be collected in administrative medical records (Avdic et al., 2021). An individual may suffer from a health condition (e.g. poor mental health or a common musculoskeletal condition such as a bad neck or back) but as a result of stigma or choice decide not to see a medical practitioner. In the event that they did, it may not

[16] Questions about work limitation in the QLFS occur after the data we use here. Information on long-term illness is also collected in the national Census undertaken every 10 years, and has been used to examine the relationship between education and health in the UK (Clark and Royer, 2013). A similar chronic health question is examined in Ruhm (2003) for the US with 36% of his sample reporting a chronic ailment. He finds a strong pro-cyclical relationship, suggesting that any justification bias was not strong in that context.

be possible from medical records to identify any condition as chronic (as distinct from acute). Additionally, the use of biomarkers collected in some surveys are very specific, and it is often not easy to link them to any particular health condition or to identify that a condition is chronic. Moreover, biomarker data are not available at the local level over time as required for our analysis. Clearly there is an advantage from using mortality data, but it does not map clearly into many of the common chronic conditions that individuals experience in our working age sample.

We aggregate the individual responses in the QLFS to three different local area levels. These areas are defined by the Nomenclature of Territorial Units for Statistics (NUTS) used by the UK Office for National Statistics (ONS).[17] NUTS3 are defined as "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 around 400,000. NUTS2 are defined as "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 around 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 using 2010 definitions (see Appendix Figure B1).

To generate our measures of $c_{i,t}$, the prevalence of chronic health conditions in area i at time t, we map the respondent's local authority of residence onto the 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 chronic conditions 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.[18] 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).

[17] See https://ec.europa.eu/eurostat/web/nuts/background.

[18] 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.

4.2 Measuring local area economic conditions

We require a measure of economic conditions that reflects the economic buoyancy (or lack of) in the macroeconomic environment and (1) can be reliably derived at the local area level at which we estimate our model (e.g. NUTS3), (2) is economically salient for population health, and (3) is stationary.[19] Our measure of $x_{i,t}$ that meets these requirements is the growth (change) in the employment rate in local area i in quarter t. Employment rate growth satisfies requirement (1) because the QLFS provides a large enough sample for us to derive reliable quarterly local area employment rate series. It also fulfills requirement (2) that changing economic conditions need to be observable to the (local) population for them to impact population health through, for example, shifting perceptions of economic (and job) security (e.g. Avdic et al., 2021) or changing time constraints (Ruhm, 2000). We assume that an increase in the number of people in employment within an area signals greater labour market (and general economic) vibrancy to the population. An example would be when a major company moves into an area, or a large number of small businesses open, thus increasing employment, which would be directly observable as well as being reported in local media.

Our quarterly employment rate growth series for the NUTS1 areas, i.e. the 11 regions of Britain, is statistically significantly positively correlated with a measure of regional GDP, specifically model-based estimates of quarterly regional gross value added (GVA) output in real terms. The employment rate in levels, on the other hand, is uncorrelated with GVA, suggesting the change in the employment rate is better at capturing the buoyancy of the macroeconomic environment than the employment rate.[20] Furthermore, our employment rate growth series at annual level is statistically significantly positively correlated with annual series of gross disposable household income (GDHI) per head as well as annual growth in GDHI at NUTS1, NUTS2 and NUTS3 level.[21] GDHI growth is a good measure of the change

[19] The ONS does not produce quarterly labour market statistics at the NUTS3 level. If they did, they would need to be derived using the QLFS. We know of no other data sources that could be used to derive reliable time series of labour market or other economic indicators at the NUTS3 level over our sample period.

[20] The data source is "Model-based estimates of GVA: Experimental model-based estimates of quarterly regional gross value added for the nine English regions, Wales, Scotland and Northern Ireland", Office for National Statistics, June 2022. The correlation coefficients are 0.074 for employment rate growth, 0.094 for seasonally-adjusted employment rate growth, 0.006 for the employment rate and 0.007 for the seasonally adjusted employment rate. These correlation coefficients are based on 627 observations (11 NUTS1 areas * 57 quarters).

[21] The data source is "Regional gross disposable household income (GDHI): all ITL regions", Office for National Statistics, October 2022. The correlation coefficients are for GDHI per head at current basic prices 0.16 at NUTS1, 0.10 at NUTS2 and 0.04 at NUTS3 level; for annual growth in GDHI 0.22 at NUTS1, 0.15 at NUTS2 and 0.10 at NUTS3 level; for annual growth in GDHI per head 0.23 at NUTS1, 0.15 at NUTS2 and 0.11 at NUTS3 level. 154

in income that households have at their disposal, which in turn is likely to affect people's wellbeing and therefore potentially their health.

Employment rate growth also satisfies requirement (3) of being stationary. The chronic health conditions prevalence rates are stationary, i.e. they always return to their normal level. The employment rate series (for our sample period) – as opposed to the change in employment rate – are non-stationary. Thus, in the long-run, there cannot be a long-run relationship between chronic health conditions prevalence and employment levels. Employment rate growth is stationary which matches the stationarity of the health measure and so is an appropriate measure from a statistical perspective.[22]

Our use of the growth in the employment rate, as opposed to the rate itself, means that in our model 'poorer economic conditions' are defined by a falling employment rate and not by a low employment rate. This means that a once-and-for-all step reduction in the employment rate would not cause health to change permanently in our model; rather health would improve (pro-cyclical) or deteriorate (counter-cyclical) on impact in reaction to a fall in the employment rate, and this effect would be propagated over time. However, health would return to its 'steady-state' level as individuals come to terms with the economic circumstances and/or as the worsened health conditions are treated.

Instead of the change in the employment rate we could have used the change in the unemployment rate, which we can also derive using the QLFS. While the unemployment rate has been found to be important in previous studies, we prefer to use the employment rate in our context for two reasons. Firstly, it is not clear if, and how much, individuals in a local area, observe changes in the unemployment rate. In contrast to the national level, the unemployment rate is not routinely calculated in official statistics at NUTS3 level – the smallest local areas – so changes in the number of people unemployed in a local area may not be easily 'visible' to the population as might be the case for changes in the national unemployment rate. Secondly, on practical grounds, when we derive (see Section 4.3) the quarterly unemployment rate series at NUTS3 level, we have found that compared to employment rates the series are noisy – as expected given the underlying samples of unemployed captured in the QLFS. The samples of unemployed will be particularly small for local areas with smaller working-age populations

observations at NUTS1 level (11 NUTS1 areas * 14 years), 504 observations at NUTS2 level (36 areas * 14 years) and 1,834 observations at NUTS3 level (131 areas * 14 years).

[22] Over all areas we carried out the panel IPS test (Im et al., 1995). For the prevalence and the employment growth variable respectively, the results are -18.50 and -21.35. This means that the null of non-stationarity is strongly rejected.

and/or low unemployment rates, meaning that changes in the unemployment rate can be driven by only a few observations.

4.3 Variable construction

To derive the quarterly employment rates for the local areas, we sum over all respondents aged 16 to 64 who meet the ILO definition of employment in each quarter-area cell and divide this sum by the total number of respondents aged 16 to 64 in the quarter-area cell.[23] The samples used to construct the economic measures at NUTS1, NUTS2 and NUTS3 level are similar in size to those used for the construction of the chronic health conditions measure. We use the log difference of the local employment rate to create our employment rate growth variable.

To construct our measure of $\overline{x}_t$, the national values of the economic conditions variable, we calculate a 'leave-out' estimate for each area, where we leave out area *i* from the calculation of the national employment rate for area *i*. We weight by population and use the log difference of the national employment rate for each area to create the national employment rate growth variable for each area. As a further means of capturing broad national influences on health, Equation (1) also includes f_t, the change in the national consumer confidence (CCI) index produced by the OECD (2020). This variable is intended to capture aspects of well-being that could influence health outcomes beyond the economic conditions captured by the employment growth series. All variables are seasonally adjusted using quarterly dummies.

Figure 1 shows our data at NUTS3 level as box plots for each quarter of our sample period, with the GFC period highlighted for context. Figure 1(a) shows the relatively large changes in the employment rate over the period as we purposefully include the Global Financial Crisis (GFC) period to provide exogenous variation.[24] 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. Figure 1(b) shows on average around 33 percent of the

[23] We use the ILO definition of employment which is based on individuals aged 16 to 64 as a standard measure of economic activity. This definition is pertinent to our sample age and outcome measure. Most papers in the literature (see Section 2) that examine mortality and economic conditions also use working-age unemployment or employment rates as their main economic measure, even though most deaths occur in older individuals who are no longer in the labour force.

[24] Our model does not allow us to examine whether there are differences in results if we omitted the GFC period (see, for example, Carpenter et al., 2017). We only have 57 periods and our time-dependent dynamic framework makes it difficult to exclude periods unless there are dummies attached to this period (which would mean we estimate a threshold-GVAR model). But in this case an important dynamic to identify the relationship between economic activity and health is being excluded. However, we undertook extensive diagnostic testing on the residuals from the aggregate equation and from Chow tests, multiple break tests, Chow forecast tests, with chosen breaks around the GFC period, and found no evidence to indicate that this period should be treated differently.

population report having a chronic condition over this 14-year period. A first look at the figure suggests that there might be a counter-cyclical relationship between chronic health conditions and the employment rate, with the former rising (from around 30 to 35 percent) and the latter falling in the years following the GFC. However, Figure 1(c) shows the median quarterly change in the employment rate moved relatively frequently from positive to negative. Importantly, Figure 1 shows considerable variability between areas in all three series, indicating that aggregate macroeconomic changes do not translate into equally sized changes at the local level.[25]

5. Results

5.1. Optimal level of spatial disaggregation

We first select an appropriate level of disaggregation for the analysis, which formally addresses issues of the level of appropriate disaggregation raised, for example, by Lindo (2015) and Ruhm (2016). We estimate equations of the form of Equation (1) for all areas at the NUTS3, NUTS2 and NUTS1 levels.[26] The adjusted prediction criteria of Pesaran et al. (1989) given in equation (8) 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. Working at the 5 percent level of significance, the test procedure suggests using 81 areas, consisting of 60 of the 131 NUTS3 areas included in our sample and 21 of the 36 NUTS2 areas. Thus, the detail contained at the most disaggregated level is important for modelling in nearly half of the most local (NUTS3) areas, but the specifications can be significantly improved by aggregating over 71 of the NUTS3 areas to work with 21 areas at the NUTS2 level. There is no support for the estimation of the model using data measured at the NUTS1 (regional) level.

5.2. Local and national long-run employment elasticities

We estimate Equation (1) for each of the 81 optimal areas. To improve the precision of the

[25] The spatial distribution of the levels of health and employment is clear in the maps in Figure B2. For each of the 131 NUTS3 areas, the maps show, respectively, the prevalence of chronic conditions and the employment rate, each averaged over the 57 quarters in our sample. Comparison across the maps shows areas with lower employment rates have higher prevalence of chronic conditions.

[26] As part of this initial analysis, we examine the optimal lag structure and specification using the national model. A second lag was found to be insignificant. Therefore, second lags were not estimated for more disaggregate models.

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. This *t*-statistic threshold follows Clements and Hendry (2005) who find that the inclusion of variables below this threshold damages the predictive ability of an AR model. The joint insignificance of excluded variables is tested using an LM test. This leads to around 45 percent of the total number of parameters in the regressions being set to zero and in this "restricted" specification the employment rate growth elasticities are set to zero for 22 of the 81 areas. We focus on results from this restricted model in which the 22 areas contribute zero to the average. The zero restrictions improve the precision of the estimates but potentially introduce bias if the restrictions are not valid. In Appendix Table B1 we present results from an unrestricted model, i.e. where no variables are excluded. The restricted and unrestricted results are qualitatively and quantitatively similar, providing reassurance of the robustness of the restricted estimates.[27]

The average of the coefficients in the 81 regressions in the restricted specification of the local area model is:

$$\begin{aligned} c_{i,t} = \underset{(0.04)}{-0.001} + \underset{(0.15)}{0.563}\, c_{i,t-1} + \underset{(0.35)}{0.431}\, \overline{c}_t - \underset{(0.04)}{0.004}\, x_{i,t} - \underset{(0.01)}{0.001}\, x_{i,t-1} - \underset{(0.02)}{0.001}\, \overline{x}_t \\ - \underset{(0.02)}{0.001}\, \overline{x}_{t-1} - \underset{(0.00)}{0.000}\, t - \underset{(0.01)}{0.005}\, f_t + \underset{(0.02)}{0.004}\, f_{t-1} - \underset{(0.06)}{0.004}\, d_t + \varepsilon_{\ i,t} \end{aligned} \tag{9}$$

The coefficients in Equation (9) are the unweighted means of the coefficient estimates for the 81 individual areas and the figures in parentheses are the standard deviations of these estimates.

The signs on $x_{i,t}$, $x_{i,t-1}$, $\overline{x}_t$ and $\overline{x}_{t-1}$ are negative, indicating an average aggregate counter-cyclical relationship between employment growth and chronic health conditions. The signs on the lagged dependent variable $c_{i,t-1}$ and the national health variable $\overline{c}_t$ are positive and large in magnitude, indicating that there are significant dynamics in local health and

[27] In practice, when estimating a relationship 81 times, there will be occasions when a variable does not show significantly in that relationship, (even if it is truly part of the data generating process.). The question is whether to allow that coefficient to contribute to the average, even though, taken individually, it looks like it might be zero. For our main analyses we chose to set these coefficients to be exactly zero. Setting them to zero is likely to push the average closer to zero (making it more difficult to find significance) but reduces the variability (making it easier to find significance). In the unrestricted model reported in Appendix B we follow the alternative approach of using the probably small and poorly determined coefficient as it is rather than setting it to be exactly zero.

spillovers from national health to local health. The consumer confidence indices f_t and f_{t-1}, included to capture national influences on health other than economic ones, are negative and positive respectively. While the average coefficient is relatively large, the estimates at local level are poorly estimated in most of the 81 equations. The shift dummy variable d_t, which takes the value zero prior to 2013q2 and one thereafter to capture the change in the health conditions question in the QLFS noted earlier, is well defined in most equations. The estimated average coefficient on this variable is -0.004, and taken with the 0.563 coefficient on $c_{i,t-1}$, is consistent with the drop in the reported prevalence rate due to the wording change estimated by the ONS.

Importantly, the standard deviations in Equation (9) indicate there is considerable heterogeneity across areas in all the estimated coefficients, including the employment growth and lagged dependent variable estimates, and therefore there will be heterogeneity in the employment growth elasticity estimates across areas. In addition, the size of the average coefficients on the lagged dependent variable and the lagged change in economic conditions show the presence of dynamics in the movement to a steady state relationship.

While the average form of Equation (1) provides an indication of the influences at play, the local and national elasticities in Equations (5) - (7) provide much more informative measures of the impact of economic conditions on the prevalence of chronic health conditions. Table 1 presents summary statistics of these three elasticity estimates. The elasticities show the response to a 1 percentage point increase in the change in the local employment rate. We calculate the standard errors for the elasticities using the 'delta method', which takes into account the variance-covariance matrix of the fitted models' estimated coefficients weighted according to their contribution to the aggregate elasticity. Importantly, since the aggregate elasticities are averages of the area elasticities, the variance is scaled by 1/N and therefore the elasticities are estimated relatively precisely. The elasticity estimates in Table 1 are population weighted. Results for equal weighted aggregate elasticities are very similar.

Table 1 shows results for the pooled male and female sample (labelled "All") and for separate male and female models. The first two panels report the estimates of the local elasticities, the third panel the corresponding national estimates. The table also shows the percentage of the individual area elasticities which are significant at the 10% level.

Notably, all the estimated aggregate elasticities provide strong statistically significant (at the 1% level) evidence of a counter-cyclical effect of economic conditions on health outcomes: when employment rate growth falls, the proportion of the working-age population reporting having a chronic health condition rises.[28] The elasticities are of a similar order of magnitude using the male and female data separately, although the number of optimally chosen areas differs (76 and 87 respectively). Given this substantive lack of difference by gender we focus on estimates for the pooled model in the rest of the paper.

The Local (Direct) elasticity of Equation (5) for the pooled sample indicates that a 1 percentage point increase in local quarterly employment rate growth will, on average, lead to a fall in the rate of chronic health conditions of 1.2 percent in that area.[29] The Local (Accumulated) elasticity estimates from Equation (6), which allow for spillovers between areas from the responses to the national level of chronic conditions $\overline{c}_t$, are around 40 percent larger than the Local (Direct) elasticity estimates at -1.7. Thus, the direct effect of an increase in local employment rate growth on health in an area is scaled up as these health effects spill over to health outcomes elsewhere. The national estimate, from equation (7), which allows for responses to national changes in employment rate growth as well as local changes, indicates that the rate of chronic morbidity would fall by 2.6 percent on average following a 1 percentage point increase in employment rate growth in every area.[30] This strong counter-cyclical effect captured by the national elasticities is based on the individual local area effects *and* the areas' responses to national circumstances. While Table 1 shows the national elasticities to be less precisely estimated than the local elasticities, with standard errors of less than 0.01 they are still statistically significant.[31]

On average therefore, direct local responses to local conditions (generating the direct local elasticity of -1.2) are supplemented by the responses to spillovers from national health

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[28] The aggregate elasticities involve averaging across the area-specific elasticities. Intuitively, the variance of an average (σ^2/N) is much smaller than the variance of the individual estimates (σ^2). However, the smaller variance would not help if poorly determined individual estimates cancelled each other out, i.e. summing to close to zero on average. Therefore, our aggregate elasticities are strongly statistically significant because the area-level relationships predominantly have the same (counter-cyclical) sign (see Figure 2) rather than because averaging reduces the variance.

[29] The link to the results in equation (9) is as follows. The estimate is (-0.004 - 0.001)/(1-0.563) (the coefficients on x_t, x_{t-1} and c_{t-1} in Equation 9 respectively) which is approximately -0.012. This is the first statistic in Table 1.

[30] Our aggregate counter-cyclical result is consistent with other studies that have found that mental health conditions increase in hard times (see Bellés-Obrero and Vall Castello, 2018; Jofre-Bonet al., 2018; Avdic et al., 2021), with many individual level studies showing that unemployment leads to worse health (and wellbeing) outcomes (e.g. Kassenboehmer and Haisken-DeNew, 2009; Sullivan and von Wachter, 2009; Browning and Heinesen, 2012), and with the strong positive relationship between job insecurity and poor health outcomes (e.g. Clark et al., 2010; Green, 2011; Johnston et al., 2020).

[31] The estimates from the unrestricted model in Appendix Table B1 are similar, with a 1 percent point increase in employment growth leading to a -0.013 (Local Direct), -0.019 (Local Accumulated), and -0.035 (National) percent fall in chronic morbidity. As expected, the estimates are less well defined than those of the restricted model. Employment growth elasticities are statistically significant at the 10 percent level for only 15 of the 81 areas while they remain statistically significant at the 5 percent level for only 10 areas.

conditions and this increases the measured elasticity by around 50%. Both of these effects are then scaled up by the spillovers from changes to national economic conditions for a further 50% increase.[32] The national elasticity is thus roughly twice the size of the elasticity based only on the direct local influences. These results suggest that not allowing for feedback from spillovers between areas in response to national health and employment changes would have resulted in a substantive under-estimation of the morbidity costs of poorer local economic conditions. We explore this further in Section 5.5.

5.3 Exploring the extent of local area heterogeneity

Our modelling approach incorporates the importance of differences in the responses of different areas to changes in economic conditions. Here we explore this local area heterogeneity. Figure 2 plots the local elasticity estimates for each of the optimally chosen areas with elasticity estimates that are not set to zero, i.e. 81 – 22 = 59 areas. The Local (Direct) elasticity is on the y-axis, the Local (Accumulated) elasticity on the x-axis. Both sets show considerable heterogeneity in the responses across areas, though the Local (Direct) elasticity has a smaller range (around -0.06 to +0.02) than the Local (Accumulated) elasticity (-0.15 to 0.06). The figure also shows a strong positive association between the two elasticities (correlation coefficient 0.92).

The vast majority of the elasticity estimates lie in the lower left quadrant, implying a counter-cyclical relationship between employment rate growth and chronic conditions for both the Local (Direct) and the Local (Accumulated) elasticity. The bulk of Local (Accumulated) estimates lie in the range [-0.08, 0], with the lower bound of -0.08 implying that a one percentage point increase in employment rate growth is associated with an 8 percent fall in the rate of chronic morbidity. There are only five estimates in the upper right quadrant (indicating a pro-cyclical relationship), and only one of these is statistically significant at the 10 percent level. Thus, in the main, the health spillovers incorporated in the Local (Accumulated) elasticity estimates amplify the direct effects rather than changing the ranking of the estimates and the overall picture is one of a strong counter-cyclical relationship between macroeconomic

[32] We have re-estimated the model using unemployment rate growth as our measure of local area economic conditions. These estimates are less well defined than our estimates using employment rate growth, but the elasticity estimates support a counter-cyclical relationship. The Local (Direct) elasticity has a *t*-ratio of 1.84, and the Local (Accumulated) elasticity has a *t*-ratio of 1.73, with around 25% of the individual local areas being statistically significant.

conditions and morbidity but with substantive heterogeneity across local areas.[33]

Figure 3 shows the spatial variation in the Local (Accumulated) elasticity across Britain. Dark green areas indicate the most counter-cyclical employment rate growth-health relationships and red areas the most pro-cyclical. We see considerable spatial heterogeneity with a tendency of stronger counter-cyclical relationships in Scotland, Wales and the north of England.

Given this substantive heterogeneity, we examine what factors are associated with differences in area estimates. As the Local (Direct) elasticity measures the responsiveness of health to area-specific economic conditions only, i.e. taking aggregate economic conditions as fixed, we focus on the Local (Accumulated) elasticity estimates to explore heterogeneity across areas. We examine two potential sets of factors. First, is the response associated with the long-run 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 response? We examine the age structure, the extent of chronic illness and the rurality of the area.[34] We use measures of these factors at local area level before the start of our analysis period (measured in the 2001 Census).

In Figure 4 we show binned scatter plots of the Local (Accumulated) elasticity estimates from the restricted model, and the associated weighted regression line, on characteristics for each area. Panel A presents the association of the elasticity estimates with local economic conditions. Panel A(a) shows only a weak gradient between the strength of the response and the overall level of employment.[35] However, Panel A(b) shows a clearer association between industrial composition and the extent to which chronic health conditions are counter-cyclical. Areas with more negative responses have higher concentrations of "blue-collar" industries (agriculture and construction and, to a lesser extent, manufacturing) and public service employment, and lower concentrations of financial, real estate and business activities. In areas with relatively low economic activity per head public sector employment (e.g. schools, hospitals, local government, welfare services) tends to be a larger share of total

[33] The unrestricted model estimates show a similar pattern (see Appendix Figure B3).

[34] Bruning and Thuilliez (2019) find heterogeneity of responses of mortality to macro conditions in a fixed effects framework by population, average educational level and share of migrants in France.

[35] The 2001 Census only provides employment rates for those aged 16-74, rather than for those aged 25-64. A low employment rate among the young might reflect higher participation in post-compulsory education, and a low rate among those aged over 65 might reflect a greater financial ability to retire younger. Such trends might dampen the gradient between the employment rate and the size of the counter-cyclical elasticities.

employment, as public service activity is driven by population numbers and primarily financed from central government. Therefore, a large public sector share of employment is likely to be an indication of a more deprived area. Aggregating industries into goods producing versus service producing, we see a positive correlation with the proportion of employment in goods producing industries and thus a negative correlation with its counterpart, employment in service producing industries.

Panel B presents the distribution of the Local (Accumulated) elasticities by measures of demographic composition. Panels B(c) and (d) show that the counter-cyclical responses are stronger in areas with populations that are older and in poorer health. However, Panel B(e) shows no differences between urban and rural areas. Regression coefficients for these association are provided in Appendix Table B2.[36]

5.4. Dynamic health adjustment to macroeconomic change

Our elasticity estimates are, as shown in Section 3, measures of the long-run health effects of changes in economic circumstances measured by employment rate growth. Our modelling approach allows us to examine the speed of adjustment towards this long-run effect. Figure 5 illustrates some of the underlying dynamic processes, tracing out the time paths of the Local (Direct), the Local (Accumulated) and the National effects of changes in local area employment rate growth. One standard error confidence intervals are shown (following the approach commonly used in the time series literature). The figure highlights the importance of the lagged dependent variables and lagged values of the explanatory variables in Equation (1) as they generate the dynamic responses. It shows that the long-run effects represent a build-up over eight quarters for the Local (Direct) elasticity, around 10 to 12 quarters for the Local (Accumulated) elasticity that incorporates spillovers across areas, and more than three years for the National elasticity.

The difference between the Local (Direct) and Local (Accumulated) elasticities again illustrates the importance of allowing for feedbacks across areas. The parameters of Equation (9) show the average value of the coefficient on the lagged dependent variable is 0.563. The standard deviation of 0.15, however, shows that there is considerable heterogeneity in the dynamics across local areas, with some coefficients being much closer to unity, reflecting a

[36] The table also shows the coefficients for the unrestricted model and again shows the similarity of results for the restricted and unrestricted models.

much more prolonged adjustment in these areas. The time path of the Local (Accumulated) elasticity, by accommodating the interactions across areas, reflects the slower adjustment in these areas. Allowing on top of this for responses to changes in economic conditions at the national level shows that it takes around three 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 to instantly observe the full response to changing economic conditions.[37]

One possible concern arises if individuals migrate to areas with better economic conditions and more healthy individuals are more likely to move. This would mean that our results were biased towards finding a pro-cyclical effect, whereas in fact we find counter-cyclical effects. However, we find the start of the health response within one quarter of an economic shock. It seems unlikely that a large enough number of individuals move between areas sufficiently quickly to affect the initial impact estimates, although migration could impact on longer-term estimates. However, we do find that the long-term counter-cyclical relationship remains when we model at the more spatially aggregated NUTS2 areas (with 1.5 million people on average). This allows for migration within (but not across) larger areas.[38]

5.5 Elasticities for separate chronic health conditions

Data from the QLFS also allow us to provide elasticities by broad types of chronic health condition. In particular, if respondents report in the affirmative to the question, "Do you have any health problems or disabilities that you expect will last for more than a year?", they are then given a list of 17 types of health problems from which they can select any number. In an extension, we estimate Equation 1 separately for four broad condition groups: (1) Musculoskeletal (e.g. problems with arms, hands, legs, feet, back or neck), (2) Cardiovascular (e.g. heart problems, blood pressure, circulatory problems), (3) Respiratory (e.g. chest or breathing problems, asthma, bronchitis), and (4) Mental Health (e.g. anxiety, depression, bad nerves, panics).[39] Details of the conditions included in each group are Appendix Table B3.[40]

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[37] The illustrated time path does not capture the compounding effects – if there are any – arising if the increase in chronic health conditions resulting from a reduction in employment leads to further subsequent reductions in employment.

[38] See Dustmann and Fasani (2016) for a similar argument in the context of the effect of local area crime on mental health in the UK.

[39] Equation (1) is estimated with c_{it} replaced by c_{it}^{h}, prevalence of health condition *h* in area *i* at time *t*, and with $\overline{c}_t$ replaced by $\overline{c}_t^{h}$, the prevalence of the health condition *h* at the national level.

[40] We have grouped all other conditions (which have very low prevalence) into a separate "Other" category. We do not provide elasticities estimates for this group as it comprises a very eclectic list of conditions.

Separating chronic illness into broad condition groups allows us to test whether the counter-cyclical relationship we found for overall chronic conditions holds for physical as well as mental health (Ruhm, 2015). Mental health has been the focus of many recent studies (e.g. Ruhm, 2000, 2003; Charles and DeCicca, 2008; Tefft, 2011; McInerney and Mellor, 2012; Golberstein et al., 2019, Ruhm, 2019; Case and Deaton, 2020; Avdic et al., 2021; Black et al., 2022). Additionally, examining prevalent chronic conditions including cardiovascular-related and respiratory morbidity is important (e.g. Birgisdóttir et al., 2018; Colombo et al., 2018), as is a focus on musculoskeletal conditions as they are the most frequently reported reason for workplace sickness absence (ONS, 2017).

In moving to the analysis of the separate health conditions, we run tests to ensure that the modelling approach of (1) remains appropriate on econometric grounds. Panel unit root tests (Im et al., 2003) of the time series properties of the individual chronic health measures showed that the series for the Musculoskeletal, Cardiovascular, and Respiratory conditions, can be considered stationary series, as is the case for overall health conditions. However, the mental health series has a unit root.[41] The implication is that, unlike the other conditions, an increase in the prevalence of mental health conditions persists, so an unexpected rise in these conditions leaves them permanently higher than they would have been in the absence of the shock. This is consistent with the recent finding using German panel data in Avdic et al. (2021) that, “the impact of the Great Recession reveals that adverse effects on mental health are persistent and remained even after the economy recovered”. Given this, the form of equation (1), estimated elasticities, etc., are unchanged in our estimation method but the analysis for mental health is conducted using the growth in the proportion of the population with the condition. In contrast to the other relationships estimated here, the results reflect a relationship between the prevalence of mental health conditions and the employment rate (rather than the change in the employment rate).

Table 2 presents the Local (Direct), Local (Accumulated) and National elasticity estimates for the four broad condition groups.[42] As expected given the existing literature, we find a strong counter-cyclical effect for mental health conditions, but importantly we also find a counter-cyclical effect for musculoskeletal, cardiovascular and respiratory conditions, which make up the bulk of chronic morbidity in Britain. The Local (Direct) estimates suggest that a

[41] The panel unit root tests provided test statistics – to be compared to standard normal distribution – valued at -21.6, -18.4, -18.2, and -16.6 for the null of non-stationarity for Musculoskeletal, Cardiovascular, Respiratory, and Overall chronic conditions respectively, while the statistic for Mental Health is -1.76.

[42] We also estimate an unrestricted version of the models for each of the conditions. As for overall conditions we find similar elasticity estimates to the restricted version, but these are less well defined.

1 percentage point fall in employment rate growth (or the employment rate for mental health) in the local area drives a 2.1 percent rise in chronic musculoskeletal conditions, with the corresponding estimates for cardiovascular, respiratory and mental health conditions being 1.7 percent, 1.3 percent and 1.4 percent, respectively. The spillover effects scale the direct elasticity most for mental health conditions, but very little for cardiovascular conditions. If we additionally take into account the national effect of employment changes, our estimates imply larger counter-cyclical responses for musculoskeletal (4.1 percent), cardiovascular (5.3 percent) and respiratory (4.4 percent) conditions, as we find for overall chronic morbidity.

6. Conclusions

This paper examines an important economic and public health question: how does population health respond to changing macroeconomic conditions? We provide new evidence for Britain by applying a GVARX model that captures dynamic responses and allows for interdependencies and heterogeneity between local areas. This modeling approach enables us to provide insights into (1) the speed of any response, (2) the extent of local area heterogeneity in the relationship between health and the economy, and (3) to identify the characteristics of local areas most and least impacted by economic change. We also incorporate a statistical approach to the optimal amount of spatial aggregation.

We use this approach to examine the link between the economy and the prevalence of chronic health conditions for those of working age in Britain. Examining chronic health conditions is important because they are the main cause of poor health and disability, accounting for a substantive component of health care expenditures. We have focused this study on individuals of working age (25-64) because they are most likely to be directly affected by changes in labour market conditions. In addition, the prevalence of chronic conditions starts to sharply increase in older working age groups. This focus complements the larger literature that has examined the relationship between economic conditions and mortality, where most deaths occur after retirement age and different dynamics and pathways might be evident (e.g. Stevens et al., 2015).

Our paper is not without limitations. First, we have mentioned potential issues with using self-reported chronic health conditions that could lead to either overestimation or underestimation of the link between the economy and health. However, we have also noted potential advantages, in that our measures can capture many health problems that might not be well measured in medical or administrative data (e.g. hospital records might not capture common chronic musculoskeletal conditions or mental health problems). We would also argue that providing some results for common chronic conditions given their high prevalence, which increase sharply within working ages (often indicating increased mortality risk), is an important complement to studies of mortality. Second, ideally, we would have liked the data series to have covered previous recessionary periods in Britain, but such data on chronic health conditions across local areas is not available. This means that our results might be specific to our data period (2002-16). Third, as with the vast majority of previous studies linking economic conditions to health outcomes, we have assumed that macroeconomic conditions are exogeneous in the model. However, our data series spans the GFC period, which provides a large economic shock and considerable exogeneous temporal and spatial variation across local areas to aid identification.

Our main results are the following. First, we find robust evidence that health improves as the economy (as measured by employment rate growth) expands and worsens as the economy contracts, thus indicating a counter-cyclical relationship for chronic health conditions. This is the case for the vast majority of the local areas we examine. In terms of magnitude, we find a 1 percentage point increase in local area employment growth leads to a 1.7 percent drop in chronic health conditions, abstracting from responses to nationwide economic conditions, and to a 2.6 percent drop when all national effects are taken into account. Similar effect sizes are obtained irrespective of gender. To provide context, the GFC period saw around a 5-percentage point fall in employment rates. Using this figure, our model would predict an increase in chronic health conditions of 8.5 percent following the GFC, abstracting from national effects and an increase of 13 percent allowing for all spillovers. Importantly, this strong counter-cyclical relationship is found for both physical and mental health conditions.

Second, accommodating feedback from changes in health across local areas leads to increases in the effects of macroeconomic circumstances by around 50 percent compared to the estimates without such feedback. We suggest that such spillovers reflect contagion, but we need to be cautious because they may also be capturing national exogenous changes in health. However, the modelling approach we use allows us to provide a range of salient elasticity estimates. Regardless, the counter-cyclical relationship we find is substantive.

Third, these effects occur with a lag: we find that it takes around 2 or 3 years for the health effects of a change in employment to fully work through. Fourth, we identify considerable heterogeneity across local areas in the health response to changed economic conditions, where the estimated effects are largest in areas with a more traditional industrial composition, older populations and populations with poorer long-term health. This mirrors the long-term association in levels of poorer areas and poorer health in Britain (and many other economies). Finally, using a statistical testing approach to identify the optimal local area shows this to be a relatively small one for Britain, containing on average around 600,000 individuals. Overall, we believe that these findings help to further the understanding of the health costs of economic downturns and where to target policies to combat these.

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Figure 1:
Employment and Chronic Health Conditions (2002-2016)

Figure 1(a) Employment Rate

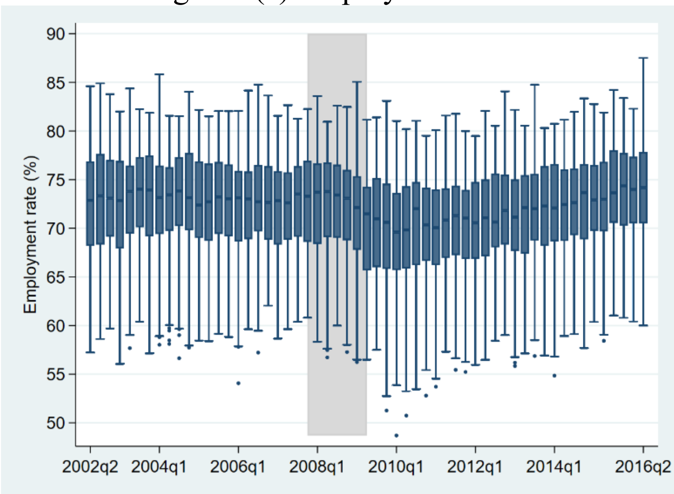


Figure 1(b) Chronic Health Conditions

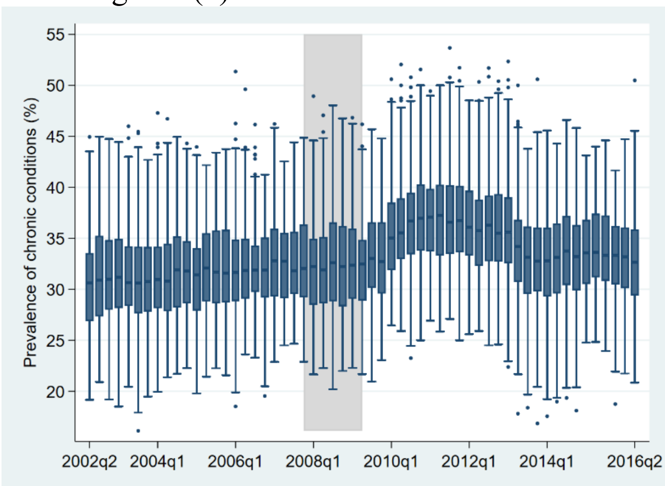
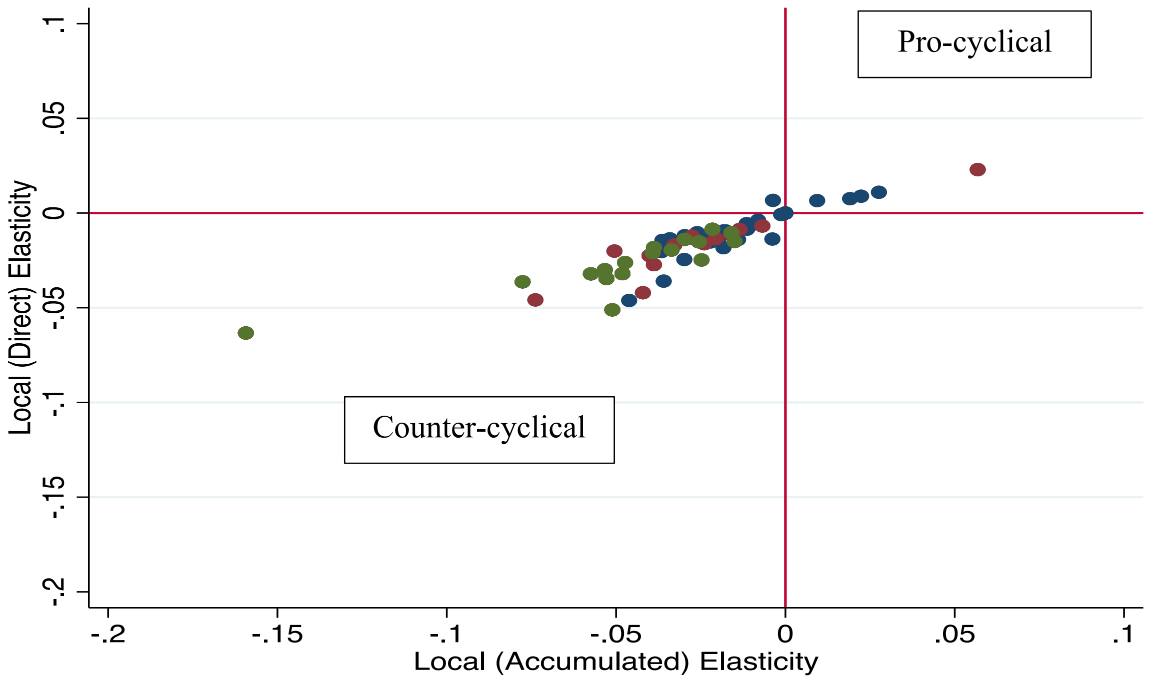


Figure 1(c): Employment Rate Growth

Notes: Data Source: QLFS 2002q1-2016q2. Figures show box plots of the small area (NUTS3) variation for each quarter. Shaded areas indicate the Global Financial Crisis period (2007q4 to 2009q2).

Figure 2:

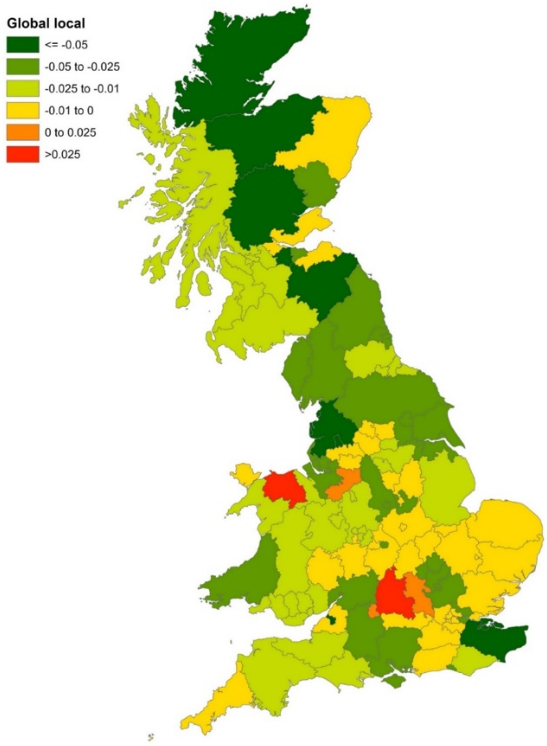
Local (Direct) and Local (Accumulated) Elasticities by Optimal Local Area



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 3:

Local (Accumulated) Elasticities by Optimal Local Area

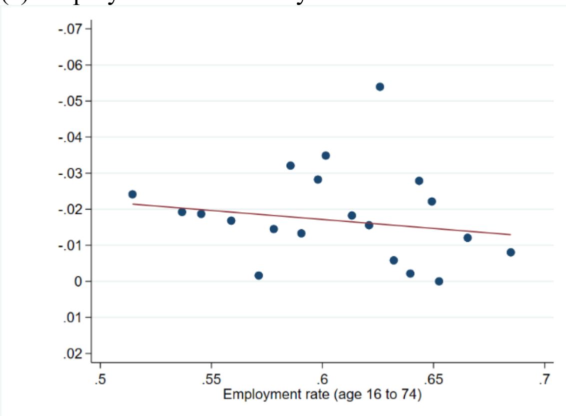


Notes: Estimates from Restricted Model. Restricted model is for the NUTS2/NUTS3 combinations of 81 optimal areas with 22 of them set to zero (included in the yellow areas).

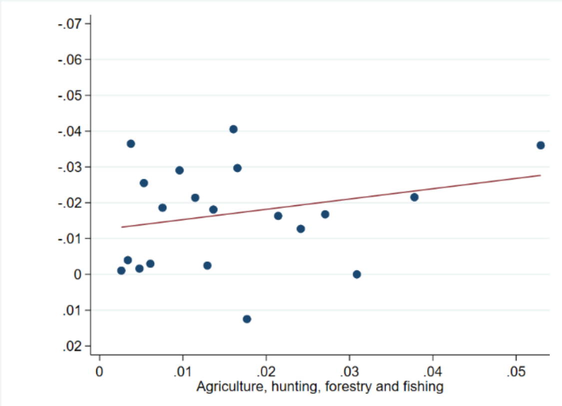
Figure 4:
Association of Local (Accumulated) elasticities with 2001 Census characteristics of the local area

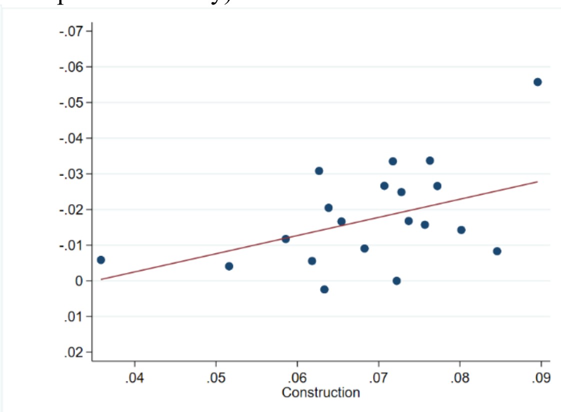
Panel A: Economic conditions

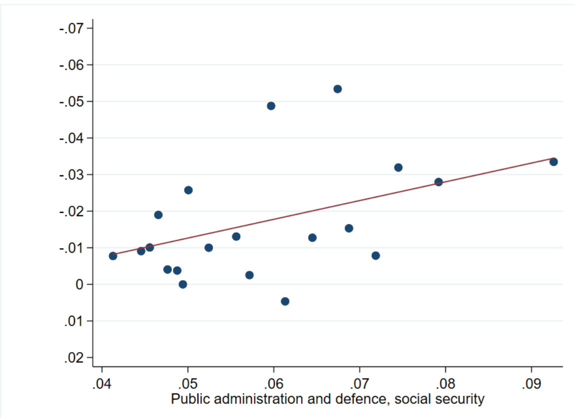
(a) Employment rate 16-74 year olds

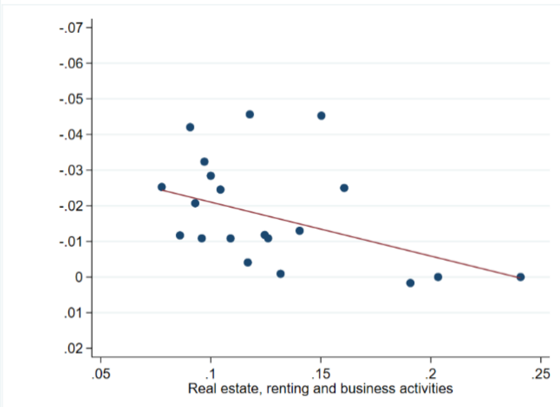


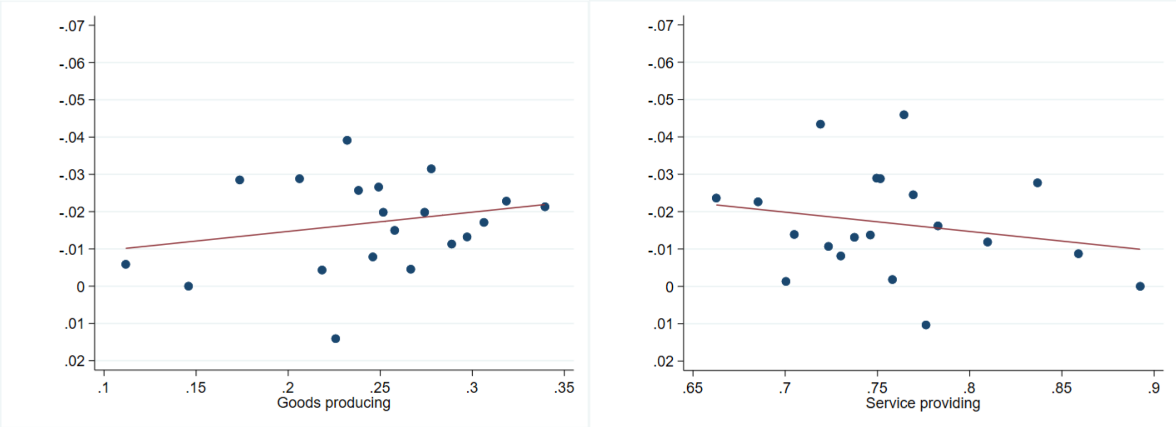
(b) Industrial composition (proportion of employment in specific industry)





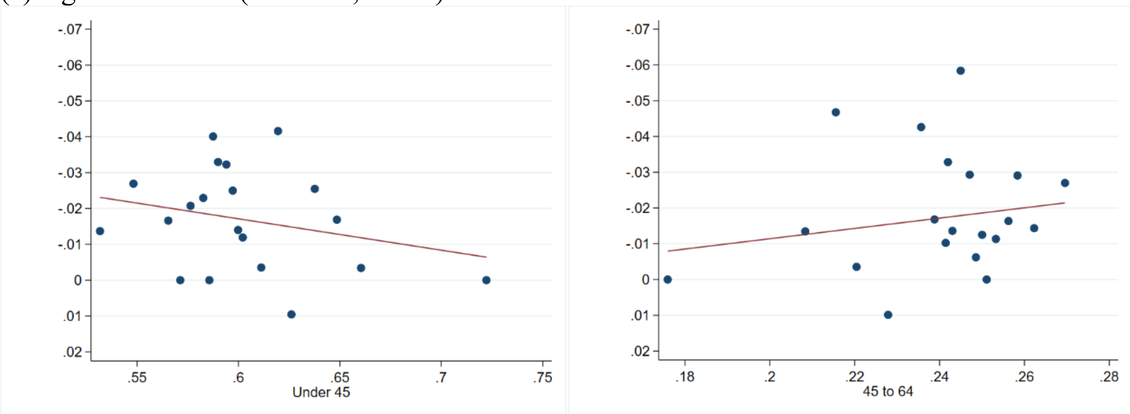




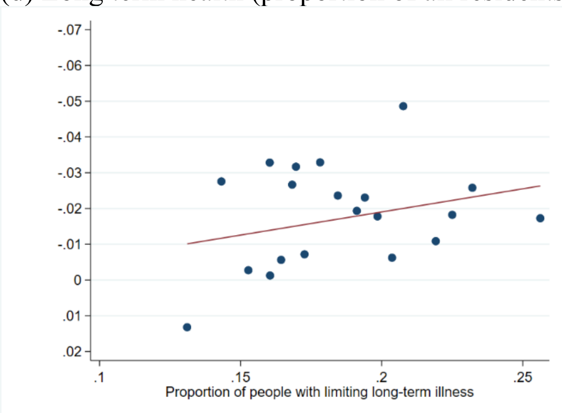

Goods producing
Service providing

Panel B: Demographic structure

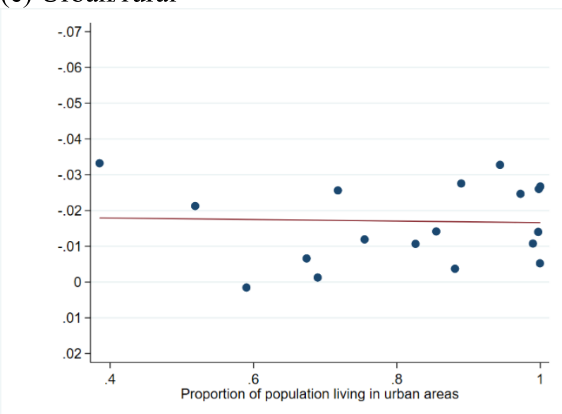
(c) Age distribution (under 45, 45-64)



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



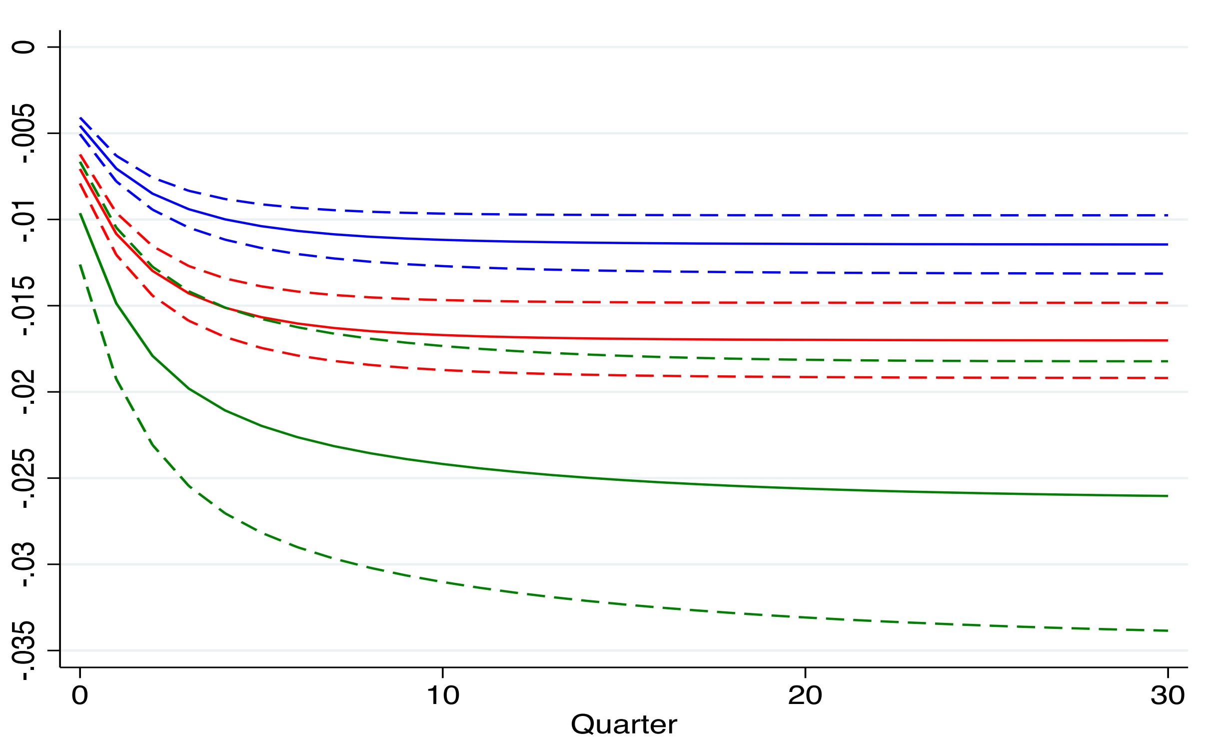
(e) Urban/rural



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 5:

Dynamics of Local (Direct), Local (Accumulated), and National Elasticities



Notes: Estimates from Restricted Model. Blue Line = Local Direct elasticity; Red Line = Local Accumulated elasticity; Green Line = National elasticity; one standard error confidence intervals in dashed lines.

Table 1:

Long-Run Employment Rate Growth Elasticities

	Restricted Model		
	All	**Male**	**Females**
Local (Direct)	-0.012***	-0.009***	-0.011***
	(0.002)	(0.001)	(0.002)
t-ratio	-6.74	-7.08	-6.19
% with |*t*|>1.64	36%	33%	26%
Local (Accumulated)	-0.017***	-0.015***	-0.017***
	(0.002)	(0.002)	(0.002)
t-ratio	-7.78	-6.82	-7.08
% with |*t*|>1.64	38%	34%	25%
National	-0.026***	-0.025***	-0.024***
	(0.008)	(0.009)	(0.009)
t-ratio	-3.28	-2.93	-2.81
% with |*t*|>1.64	42%	42%	31%
Optimal Number of Areas	81	76	87

Notes: * significant at 10%, ** significant at 5%, *** significant at 1%. Restricted model means variables with poorly determined coefficients are dropped, resulting in the elasticities for 22 of the 81 optimal areas for "All" being set to zero. Data source: QLFS 2002q1 to 2016q2.

Table 2:

Long-Run Employment Rate Growth Elasticities by Chronic Condition

	Musc	**Cardio**	**Resp**	**Mental**
Local (Direct)	-0.021***	-0.017***	-0.013***	-0.014***
	(0.004)	(0.003)	(0.003)	(0.001)
t-ratio	-5.46	-5.24	-4.30	-11.16
% with |*t*|>1.64	33%	26%	19%	57%
Local (Accumulated)	-0.028***	-0.018***	-0.018***	-0.034***
	(0.005)	(0.004)	(0.004)	(0.006)
t-ratio	-5.80	-4.93	-4.20	-5.81
% with |*t*|>1.64	32%	26%	17%	40%
National	-0.041***	-0.053***	-0.044***	-0.025**
	(0.013)	(0.015)	(0.018)	(0.014)
t-ratio	-3.20	-3.65	-2.42	-1.76
% with |*t*|>1.64	35%	31%	32%	27%
Optimal Number of Areas	81			

Notes: * significant at 10%, ** significant at 5%, *** significant at 1%. Restricted model means variables with poorly determined coefficients are dropped, resulting in the elasticities for 22 of the 81 optimal areas being set to zero. Data source: QLFS 2002q1 to 2016q2.

APPENDIX A

Comparison with the Fixed Effect Panel Model

The fixed effect panel model with time dummies often used in the literature effectively regresses $c_{i,t} - \bar{c}_t$ 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).

However, there will be a close correspondence between our Local (Direct) elasticity and the elasticity we would obtain using the fixed effects panel model. The reason is that the fixed effects model is nested within our modelling specification. To illustrate this, consider the equation obtained by summing the long-run equation (2) over all areas and dividing by *N*:

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

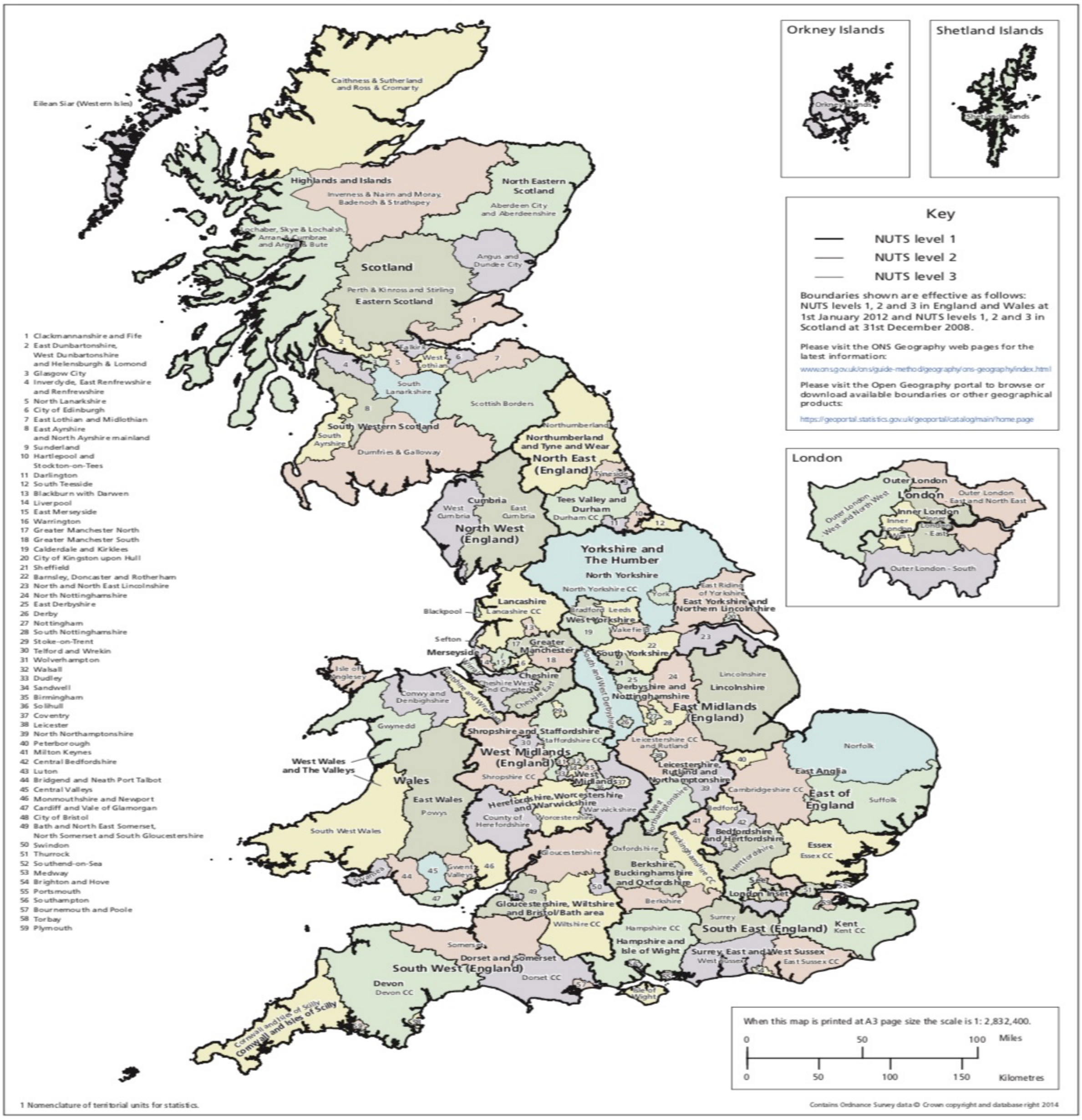
where the absence of a subscript i means the coefficients are themselves averaged across *I*. Comparison of (2) with (2') shows that, dropping the terms involving heterogeneity across area parameters into the error, a regression of $c_{i,t} - \overline{c}_t$ on $x_{i,t} - \overline{x}_t$ will provide an estimate of $\tilde{\alpha}$. This is precisely the estimate obtained by the fixed effects estimator with year-quarter dummies. However, such a model would not allow us to capture the influence of the changes in economic conditions propagated through the $\overline{c}_t$ or the national effects obtained through $\overline{x}_t$ in (2) and therefore would only capture part of the effect of a change in economic conditions. Our model is thus more general, and in addition provides estimates of the heterogenous response at local area level.

APPENDIX B

Figure B1:

Great Britain NUTS Level 1, 2 and 3 Local Areas (2012)

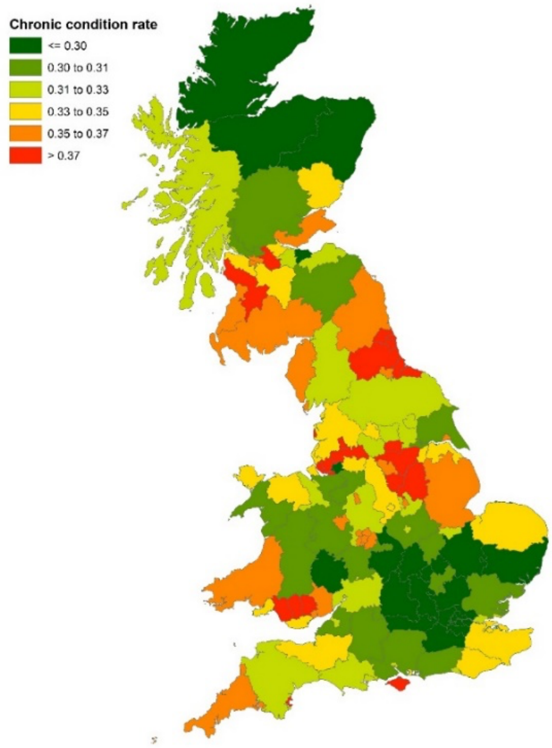
Great Britain: NUTS[1] Levels 1, 2 and 3, 2012

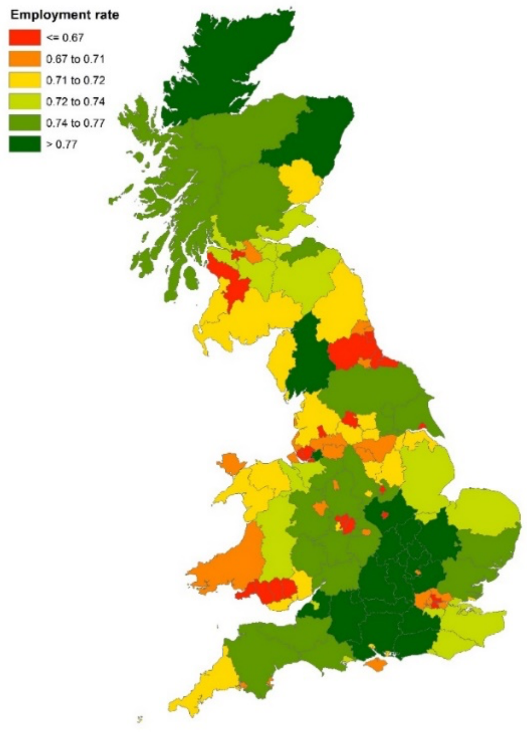


Source: Office for National Statistics (ONS).

Figure B2:

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



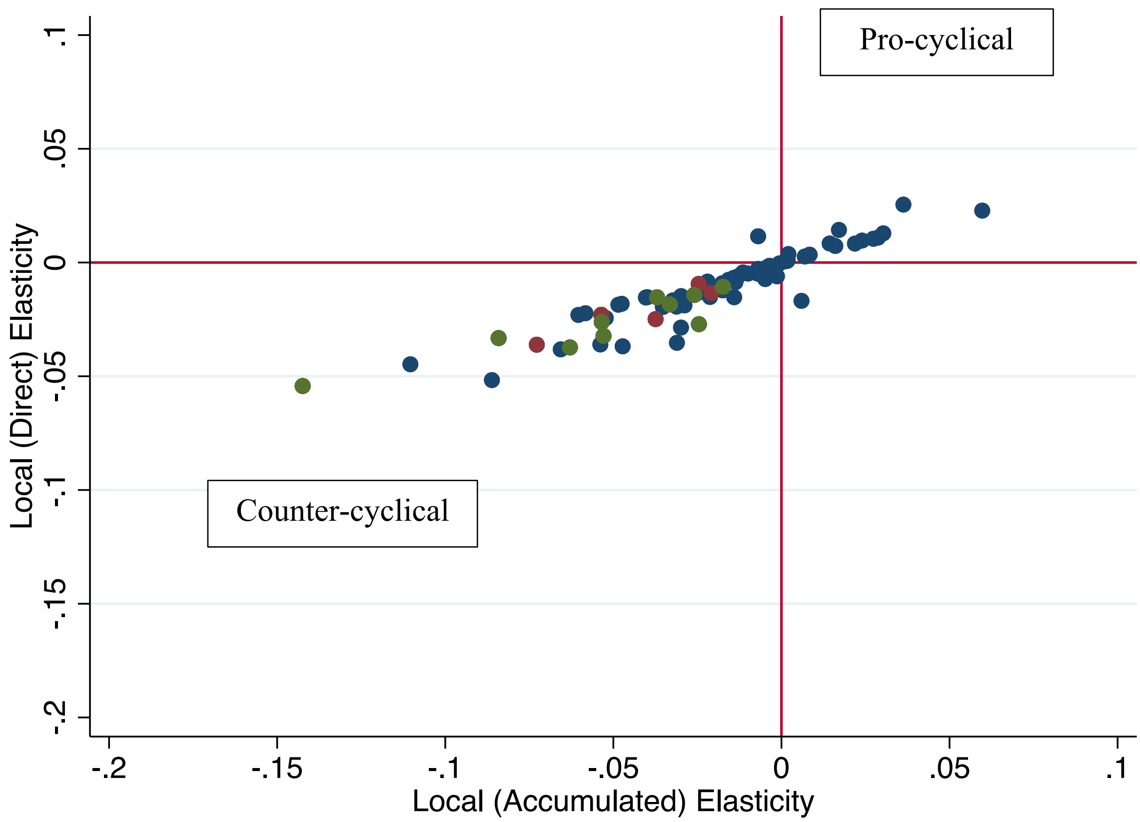


Notes: Data from QLFS 2002q2 to 2016q2.

Figure B3:

Local (Direct) and Local (Accumulated) Elasticities by Optimal Local Area

(Unrestricted model)



Notes: Estimates from 81 areas in the Unrestricted Model. Blue Dot = |t|=<1.64; Red Dot = |t|-stat>=1.64; Green Dot = |t|-stat>=1.96.

Table B1:

Long-Run Employment Elasticities (Unrestricted Model)

	Unrestricted Model		
	All	**Male**	**Female**
Local (Direct)	-0.013***	-0.010***	-0.012***
	(0.003)	(0.003)	(0.003)
t-ratio	-4.46	-3.53	-4.28
% with |*t*|>1.64	27%	17%	22%
Local (Accumulated)	-0.019***	-0.017***	-0.019***
	(0.004)	(0.005)	(0.005)
t-ratio	-4.37	-3.38	-3.87
% with |*t*|>1.64	19%	14%	15%
National	-0.035*	-0.0307	-0.029
	(0.021)	(0.020)	(0.022)
t-ratio	-1.68	-1.53	-1.30
% with |*t*|>1.64	11%	8%	9%
Optimal Number of Areas	81	76	87

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

Table B2:

Correlations between Characteristics of Local Areas and Local (Accumulated) Elasticity Estimates

Local area characteristics	**Restricted Model Coeff. [p-val.]**	**Unrestricted Model Coeff. [p-val.]**
Economic activity level		
Employment rate in 16-74 population	0.050 [0.359]	0.040 [0.559]
Industrial structure (proportion of population employed in):		
Agriculture	-0.289 [0.134]	-0.503 [0.037]
Construction	-0.509 [0.012]	-0.755 [0.003]
Manufacturing	-0.024 [0.647]	-0.095 [0.153]
Financial intermediation	0.096 [0.408]	0.160 [0.273]
Real estate and business activities	0.151 [0.008]	0.227 [0.002]
Public sector	-0.512 [0.002]	-0.518 [0.016]
Age composition		
Under 45	0.088 [0.133]	0.132 [0.072]
45-64	-0.144 [0.202]	-0.243 [0.087]
65 plus	-0.166 [0.121]	-0.226 [0.094]
Health		
Proportion population with limiting long term health condition	-0.129 [0.101]	-0.144 [0.148]
Urbanisation		
Proportion of population urban	0.002 [0.870]	0.016 [0.333]

Notes: Each coefficient is from a separate regression of the Local (Accumulated) elasticity from the restricted and unrestricted models on the relevant local area characteristic. 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.

Table B3:
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

APPENDIX C

Measures of the local and national effects of economic conditions on health

(i) Local (Direct) elasticity

Equation (1) can be written:

$c_{i,t} = \mu_i + \lambda_i c_{i,t-1} + \delta_i \bar{c}_t + \alpha_{i0} x_{i,t} + \alpha_{i1} x_{i,t-1} + \beta_{i0} \bar{x}_t + \beta_{i1} \bar{x}_{t-1} + \gamma_{i0} f_t + \gamma_{i1} f_{t-1} + \varepsilon_{i,t}$ (A1)

To derive the 'long-run' version of the equation, i.e. where we assume we are in a steady state, write $c_{i,t} = c_{i,t-1}$, $x_{i,t} = x_{i,t-1}$, $\bar{x}_t = \bar{x}_{t-1}$ and $f_t = f_{t-1}$. Then Equation (A1) gives:

$(1-\lambda_i) c_{i,t} = \mu_i + \delta_i \bar{c}_t + (\alpha_{i0} + a_{i1}) x_{i,t} + (\beta_{i0} + \beta_{i1}) \bar{x}_t + (\gamma_{i0} + \gamma_{i1}) f_t + \varepsilon_{i,t}$ (A2)

and:

$c_{i,t} = \frac{\mu_i}{1-\lambda_i} + \frac{\delta_i}{1-\lambda_i} \bar{c}_t + \frac{\alpha_{i0}+\alpha_{i1}}{1-\lambda_i} x_{i,t} + \frac{\beta_{i0}+\beta_{i1}}{1-\lambda_i} \bar{x}_t + \frac{\gamma_{i0}+\gamma_{i1}}{1-\lambda_i} f_t + \frac{\varepsilon_{i,t}}{1-\lambda_i}$

$= \tilde{\mu}_i + \tilde{\delta}_i \ \bar{c}_t + \tilde{\alpha}_i \ x_{i,t} + \tilde{\beta}_i \ \bar{x}_t + \tilde{\gamma}_i \ f_t + \varepsilon_{i,t}$

The Local (Direct) effect for area *i* is $\frac{\alpha_{i0}+\alpha_{i1}}{1-\lambda_i}$. Equation (5) defines ϵ^{LD}, which is the average of the direct local effects:

Local (Direct)

$$\epsilon^{LD} = \frac{1}{N} \sum_{i=1}^{N} \tilde{\alpha}_i = \frac{1}{N} \sum_{i=1}^{N} \frac{\alpha_{i0} + \alpha_{i1}}{1 - \lambda_i}$$

(ii) Local (Accumulated) elasticity

The accumulated local effect takes account of any spillovers across areas through $\bar{c}_t = \frac{1}{N} \sum_{i=1}^{N} c_{i,t}$. Equation (6) defines ϵ^{LA}, the average of the accumulated local effects:

Local (Accumulated)

$$\epsilon^{LA} = \frac{1}{N} \mathbf{w}' \mathbf{\Phi_1} \mathbf{w} = \frac{1}{N} \mathbf{w}' \left(\mathbf{I} - \tilde{\boldsymbol{\delta}} \boldsymbol{A} \right)^{-1} \tilde{\boldsymbol{\alpha}} \mathbf{w}$$

$$= \frac{1}{N} [1 \quad 1 \quad \cdots] \begin{pmatrix} 1 - \frac{\tilde{\delta}_1}{N} & -\frac{\tilde{\delta}_1}{N} & \cdots - \frac{\tilde{\delta}_1}{N} \\ -\frac{\tilde{\delta}_2}{N} & 1 - \frac{\tilde{\delta}_2}{N} & \cdots - \frac{\tilde{\delta}_2}{N} \\ -\frac{\tilde{\delta}_3}{N} & -\frac{\tilde{\delta}_3}{N} & \ddots \end{pmatrix}^{-1} \begin{pmatrix} \tilde{\alpha}_1 & 0 & \cdots & 0 \\ 0 & \tilde{\alpha}_2 & \cdots & 0 \\ 0 & 0 & \ddots & \end{pmatrix} \begin{bmatrix} 1 \\ 1 \\ \vdots \end{bmatrix}$$

$$= \frac{1}{N}\sum_{j=1}^{N}\sum_{i=1}^{N} wt_{i,j}\tilde{\alpha}_j$$

where the $wt_{i,j}$ are weights, showing the elements in $\left(\mathbf{I} - \tilde{\boldsymbol{\delta}}\boldsymbol{A}\right)^{-1}$ and based on all the $\frac{\delta_i}{1-\lambda_i}$'s, that reflect the impact of changes in x_{it} on c_{jt} directly and allowing for feedback across areas through $\bar{c}_t$. In the background, a change in $x_{i,t}$ in one area causes a direct change in $c_{i,t}$ in that area, which in turn causes a change in $\bar{c}_t$. Depending on the values of the $\frac{\delta_j}{1-\lambda_j}'$s, this results in a rise or a fall in $c_{j,t}$; i.e. in all the other areas. These changes in turn affect $\bar{c}_t$, resulting in a further change in $c_{i,t}$ and a second round of effects across all areas. The same argument also motivates a third and many subsequent rounds of effects. These spillovers happen contemporaneously but are all captured by the $wt_{i,j}$. The Local (Accumulated) elasticity shows the average of this accumulated effect of a change in x_{it} on c_{it} across all area i's.

(iii) National elasticity

The national measure in (7) summarises the responses of health conditions to changes in the conditions in the local and aggregate economy, again accumulating the effects to take account of spillovers captured by the $\bar{c}_t$. So, we can write:

National

$$\epsilon^N = \frac{1}{N}\mathbf{w}'(\mathbf{\Phi_1}\mathbf{w} + \mathbf{\Phi_2}) = \frac{1}{N}\mathbf{w}'\left\{\left(\mathbf{I} - \tilde{\boldsymbol{\delta}}\boldsymbol{A}\right)^{-1}\tilde{\boldsymbol{\alpha}}\mathbf{w} + \left(\mathbf{I} - \tilde{\boldsymbol{\delta}}\boldsymbol{A}\right)^{-1}\tilde{\boldsymbol{\beta}}\right\}$$

$$= \frac{1}{N}[1 \quad 1 \quad \cdots]\left\{\begin{pmatrix} 1-\frac{\tilde{\delta}_1}{N} & -\frac{\tilde{\delta}_1}{N} & \cdots -\frac{\tilde{\delta}_1}{N} \\ -\frac{\tilde{\delta}_2}{N} & 1-\frac{\tilde{\delta}_2}{N} & \cdots -\frac{\tilde{\delta}_2}{N} \\ -\frac{\tilde{\delta}_3}{N} & -\frac{\tilde{\delta}_3}{N} & \ddots \end{pmatrix}^{-1}\left(\begin{pmatrix} \tilde{\alpha}_1 & 0 & \cdots & 0 \\ 0 & \tilde{\alpha}_2 & \cdots & 0 \\ 0 & 0 & \ddots & \end{pmatrix}\begin{bmatrix} 1 \\ 1 \\ \vdots \end{bmatrix} + \begin{bmatrix} \tilde{\beta}_1 \\ \tilde{\beta}_2 \\ \vdots \end{bmatrix}\right)\right\}$$

$$= \frac{1}{N}\sum_{j=1}^{N}\sum_{i=1}^{N} wt_{i,j}\ \{\tilde{\alpha}_j + \tilde{\beta}_j\ \}$$

The weights continue to reflect the impact of changes in economic conditions in area *j* on health in area i, but the changes in economic conditions now include both local and national effects. Hence, for example, consider the case where there is a one percent increase in $x_{j,t}$ across all areas, resulting in a one percent increase in $\bar{x}_t$ also. The direct local and national effect on area *j* health is $\{\tilde{\alpha}_j + \tilde{\beta}_j\ \}$ while the effect on area *i* health is $wt_{i,j}\ \{\tilde{\alpha}_j + \tilde{\beta}_j\ \}$, taking account of the spillovers, including the second and subsequent round effects. The sum of all these effects shows the total effect of the increase in economic conditions in area *j* on all areas. The National elasticity measures the average size of this effect.

APPENDIX D

Example to illustrate the system wide properties of a GVARX model

The description of the GVARX model in Sections 3.1 and 3.2 provides a succinct statement of the modelling approach and the relevant elasticities. But the matrix algebra obscures some of the interesting system-wide properties of the GVARX model and this Appendix considers a simple stripped-down version of the model to illustrate these properties.

Consider an economy with three areas of equal size (1,2,3) with economic conditions in an area directly affecting health in the area, and with the effects of illness in each area spilling over equally to the other two. For simplicity, assume parameter homogeneity across the areas and that δ captures the extent of the spillover effects and α captures the effect of economic conditions in all three areas:[43]

$$c_{1t} = \delta(c_{2t} + c_{3t}) + \alpha x_{1t} \tag{A1}$$

$$c_{2t} = \delta(c_{1t} + c_{3t}) + \alpha x_{2t} \tag{A2}$$

$$c_{3t} = \delta(c_{1t} + c_{2t}) + \alpha x_{3t} \tag{A3}$$

To understand the underlying drivers of health in each area, we solve (A1)-(A3) simultaneously; this is achieved through the matrix transformation at (4) in the text. So, taking (A1) and (A3) together, and then (A2) and (A3) together, to eliminate c_{3t}, we find:

$$(1-\delta^2)\, c_{1t} = (\delta + \delta^2) c_{2t} + \alpha x_{1t} + \alpha\delta x_{3t} \tag{A4}$$

$$(1-\delta^2)\, c_{2t} = (\delta + \delta^2) c_{1t} + \alpha x_{2t} + \alpha\delta x_{3t} \tag{A5}$$

and, using (A4) and (A5) to eliminate c_{2t}, we have:

$$(1-\delta-2\delta^2)\, c_{1t} = \alpha\, [(1-\delta)x_{1t} + \delta x_{2t} + \delta x_{3t}\,]\,. \tag{A6}$$

Equation (A6) makes explicit that economic conditions in areas 2 and 3 affect health in area 1 through the spillover effects, and that these effects, and the direct effect from area 1 economic conditions, are 'scaled up' through successive feedbacks across the sectors.

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[43] In terms of equation (3) in the text, here we have $\widetilde{\boldsymbol{\delta A}} = \begin{bmatrix} 0 & \delta & \delta \\ \delta & 0 & \delta \\ \delta & \delta & 0 \end{bmatrix}$ and $\tilde{\boldsymbol{\alpha}} = \begin{bmatrix} \alpha \\ \alpha \\ \alpha \end{bmatrix}$.

For example, with δ = 0.4 and α = 0.2, we have:

$$0.28\, c_{1t} = 0.2\ [0.6x_{1t} + 0.4\, x_{2t} + 0.4\, x_{3t}\ ] .$$

and a 1% increase in x_{1t}, x_{2t} and x_{3t} in turn raises c_{1t} by (0.2*[0.6/0.28]) = (0.2*2.14) = 0.43%, by (0.2*[0.4/0.28]) = (0.2*1.43) = 0.29% and by (0.2*[0.4/0.28]) = (0.2*1.43) = 0.29% respectively. The 'impact effect' of a change in area 1's economic conditions on area 1 health is 0.2 here; the effect of a system wide change, measured assuming economic conditions change in the same way in all areas, on area 1's heath is 0.43+0.29+0.29=1.01. In this example, where the relationships are the same in all three areas, the 'impact effect' of a change in economic conditions is the same across areas and the average across areas – our **Local (Direct) elasticity** – is also 0.2. Similarly, the effect of a system wide change is the same across areas and the average – our **Local (Accumulated) elasticity** – is 1.01 too. Of course, this would not be the case if the parameters differed across area.[44]

The dynamic properties of a system with spillovers can be very complex. For example, consider the above 3-area model in which the effects of changes in each are propagated over time with a single lagged dependent variable:

$$c_{1t} = \lambda\, c_{1t-1} + \delta(\, c_{2t} + c_{3t}\,) + \alpha x_{1t} \qquad \text{(A1')}$$

and similarly for areas 2 and 3. Denoting the lag operator by L, so that $c_{1t-1} = Lc_{1t}$, we can define $\widetilde{c_{1t}} = (1 - \lambda L)c_{1t}$ and $\tilde{\delta} = \frac{\delta}{(1-\lambda L)}$ and write (A1') as:

$$\widetilde{c_{1t}} = \tilde{\delta}\ (\,\widetilde{c_{2t}} + \widetilde{c_{3t}}\,) + \alpha x_{1t}$$

and similarly for areas 2 and 3. The solution for the system is now in the same form as that for (A1)-(A3) so that:

$$\left(1 - \tilde{\delta} - 2\tilde{\delta}^2\right)\widetilde{c_{1t}} = \alpha\ \left[\left(1 - \tilde{\delta}\right)x_{1t} + \tilde{\delta} x_{2t} + \tilde{\delta} x_{3t}\ \right] . \qquad \text{(A6')}$$

Expressed explicitly in terms of lags, this gives

$$\left(1 - \delta - 2\delta^2\right)c_{1t} = (3 - 4\delta)\lambda\, c_{1t-1} - (3 - \delta)\lambda^2\, c_{1t-2} + \lambda^3\, c_{1t-3}$$

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[44] If we also included $\overline{x}_t$ in this simple model, i.e. included $\beta(x_2 + x_3)$ in (A1) and analogously in (A2) and (A3), then there would be an additional route through which x affects c. For example, if $\beta = 0.1$ then the effect of a 1 percent increase in each of x_1, x_2 and x_3 would be to 1.01 calculated above plus 0.1/0.28 = 1.01 + 0.35 = 1.36.

$$+\quad \alpha \left[\begin{array}{r} (1-\delta)x_{1t} + (2-\delta)\lambda\, x_{1t-1} + \lambda^2\, x_{1t-2} \\ + \delta x_{2t} + \delta\lambda\, x_{2t-1} \\ + \delta x_{3t} + \delta\lambda\, x_{3t-1} \end{array} \right].$$

A relatively simple area-specific dynamic, with one lagged dependent variable and only contemporaneous effects from economic conditions, implies a complicated dynamic response when considered as a system, with each area explained by three lagged dependent variables and contemporaneous and lagged values of economic conditions across all areas.[45]

To illustrate this, assume $\lambda = 0.5$, $\delta=0.2$ and $\alpha=0.1$ (so that the long run effects are the same as the earlier illustration), then (A6') gives:

$$\begin{aligned} 0.72\, c_{1t} = {} & 1.1\, c_{1t-1} - 0.55\, c_{1t-2} + 0.125 c_{1t-3} \\ & +0.16 x_{1t} + 0.18 x_{1t-1} + 0.05 x_{1t-2} + 0.04\, x_{2t} + 0.02\, x_{2t-1} + \\ & 0.04\, x_{3t} + 0.02\, x_{3t-1} \end{aligned}$$

which illustrates how economic conditions in all areas can continue to exert complex dynamic health effects in each area over some time.

[45] The complexity grows as the size of the system grows so that, in a system with *n* areas, each area's model would include *n* lagged dependent variables and up to *n-1* lags in economic conditions.