NiReMS: A REGIONAL MODEL AT HOUSEHOLD LEVEL COMBINING SPATIAL ECONOMETRICS WITH DYNAMIC MICROSIMULATION

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NiReMS: A Regional Model at Household Level Combining Spatial Econometrics with Dynamic Microsimulation

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Abstract

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Classification: D15, D31, D6, E65

Keywords: Microsimulation, Heterogenous Agents, Universal Credit, Spatial econometrics, Structural macroeconomic models

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1 Introduction

The onset of the Covid-19 pandemic brought about disruptive changes to the functioning of, and externalities within and between, almost all economies. This includes the United Kingdom (UK) and its constituent nations (England, Wales, Scotland and Northern Ireland) and the associated subnational regions. Limits to labour mobility severely affected production and its dynamics, and supply chain disruptions affected inter-regional and international trade. Mobility of factor inputs and trade are two of the most prominent channels through which regions and countries generate externalities upon each other and through which shocks are transmitted. While these standard interaction channels were severely restricted by the pandemic, the situation in the UK was exacerbated by Brexit which restricted international trade flows and also potentially enhanced linkages between Northern Ireland and the Republic of Ireland. New models and methods were required to understand regional macroeconomies and aid the design and delivery of regional and national policy.

The neglect of the regional dimension in the development and implementation of national macroeconomic models continues. In the collection of articles assembled by Vines and Wills (2018), four major foci were articulated in the development of a template for rebuilding macroeconomic models to address major flaws and shortcomings exposed by the Great Recession.[1] However, the regional or spatial dimension was missing from consideration. The present paper outlines some first steps on a path to a more successful integration of spatial heterogeneity in outcomes from macroeconomic models while at the same time providing some important insights into the combined heterogeneity of household agents mapped onto geographical locations. Covid-19, Brexit and the current cost of living crisis have highlighted the heterogeneous nature of the spatial impacts and the need to incorporate this aspect into future modelling work.

Spurred by the need to understand the effects that aggregate shocks such as Covid-19 and Brexit have brought about for the UK economy and, specifically, impacts on the different regions in the UK, the National Institute of Economic and Social Research (NIESR) has been developing a new regional model – NiReMS (National Institute Regional Modelling System). Faced with the above disruptions, the conventional multi-regional generalized RAS approaches to update input-output tables were felt to be inadequate; however, see Haddad et al. (2021). Instead, NiReMS uses an approach based on aggregate national input-output tables and estimated

[1] Donaghy (2021) has provided a valuable contribution that explores the implications of the Rebuilding Macroeconomic Theory Project for regional science research.

latent spatial weights (Bhattacharjee and Holly, 2013). This spatial econometric approach highlights core interdependencies and channels of transmission of shocks between the regions of the UK (Bhattacharjee and Lisauskaite, 2021). Providing feedback between the regional and the national model is an important further step that is retained for future work.

Since the Covid-19 shock affected some households much more severely than others by exacerbating extreme poverty and destitution, the regional analysis needs to pay greater attention to impacts at the household level. Carrascal-Incera and Hewings (2022) develop one way of doing this, building upon Miyazawa's framework to endogenise the household sector and compute the so-called spatial income multipliers combining direct and indirect spatial effects. However, further enhancements were required to move beyond a representative agent model towards a collection (even a continuum) of heterogenous agents within each region and cohort by income, household demographics etc. In the new generation macroeconomic theory, this is typically achieved by considering HANK (Heterogenous Agent New Keynesian) models. At the computational level, this is incorporated in NiReMS by relying upon dynamic microsimulation. Here, individuals and households drawn from an initial representative sample of the UK population are followed through time, through changes in household circumstances, births, education, work and finally death. Income/consumption and labour/leisure decisions are evaluated by dynamic optimisation of their utility functions through time (Bhattacharjee and Szendrei, 2021). While the analysis in this paper is centred at the NUTS-1 level, there will probably be a high level of concordance between the region of origin and income and expenditures. With smaller spatial units (NUTS-2 of local authority areas), this mapping is likely to be disrupted by daily/weekly commuting patterns and propensity of households to exploit their love of variety by shopping for some goods and services in other spatial units.[2]

A key component of this integrated macro-micro model is a regional macroeconomic model (at the NUTS-1 level) incorporating spatial interdependence that are modelled using an estimated spatial weights matrix. The common assumption of symmetric spatial weights inherent in geographical contiguity- or distance-based spatial weights or even in some estimates of spatial weights (Bhattacharjee and Jensen-Butler, 2013; Bailey et al., 2016) is not useful here because of likely core-periphery relations. A hierarchical tree structure is often useful when the network connections only run in one direction (Bhattacharjee and Holly, 2013). As evident from figure (1), such a hierarchical structure is approximately supported by our data. However, there are

[2]Hewings and Parr (2007) provide an example of the complexity of flows of goods and services, journey to work, income and consumption flows within a metropolitan region.

local deviations in parts of the network, which means we need to instrument validity tests to ensure there are no strong causal cycles. This methodology is based on Bhattacharjee and Holly (2013) and discussed in further detail later in the paper.

An important feature of the model is that it tracks individuals through time in line with dynamics in their regional and national economies and can provide short-run projections of the impacts of regional (local) and national (global) shocks, as well as government policy (see, for example, Bhattacharjee et al. (2022)). Here, we describe the model and methodology and illustrate its use in developing socio-economic projections for the UK regions. The combination of spatial econometrics and microsimulation, in line with structural macroeconomic models, provides a very useful tool for analysing consumption across groups and counterfactual policy exercises. We are able to clearly quantify consumption loss due to Covid-19 and the current cost of living crisis, and the impact of policy (for example, energy cost caps and benefit payments). However, an important characteristic should be the impact not only of national and regional shocks on consumption but also the feedback effects of that consumption on the paths of the regional economies. As Carrascal-Incera and Hewings (2022) demonstrate, there are not only important spillover effects but it is also the case that the structure of the goods and services flows are different from the income-generated flows. In addition, the microsimulation exercise, described below, is more flexible since most models assume limited activity status options (employed, unemployed) while in this system, there are households with more than one earner (potentially in part-time employment) whose income may determine the labour force participation decision of the second member. Note, however, that the proposed framework is not a model with full micro-macro feedbacks since only the spatial-macroeconometric model informs the microsimulation model but not vice-versa.

The rest of the paper is organised as follows. Section 2 develops and describes our proposed model, focusing first on modelling the regional macroeconomies and their interconnections, and next heterogeneous household behaviour and outcomes. Section 3 presents some findings, focusing on a counterfactual policy experiment of extending a specific welfare scheme, and Section 4 concludes, including some areas of potential further development.

2 Methodology

Understanding impacts of shocks and policy at the household level in a timely manner is a major challenge for evidence-based policy and research. Conventional macroeconomic models are relatively impotent here, lacking adequate modelling of inter-regional and household-level externalities and heterogeneities. Household surveys take time to conduct and while econometric analyses of such surveys often provide the best picture of the impact of a macroeconomic shock (such as a recession or pandemic) or specific policy, policymakers often do not have the privilege of waiting for the data and analyses to become available. As such, there is clearly a demand for methods that allow for household level analysis before survey data during/after the shock become available.

Microsimulation is one way to model households in their fullest heterogeneity (Orcutt et al., 1961; Sefton and van de Ven, 2004; Aaberge and Colombino, 2014; NIESR, 2016). When the goal is to analyse policy outcomes, dynamic microsimulation has been a useful tool in the arsenal of policymakers (Li et al., 2013). As opposed to static microsimulation, dynamic microsimulation allows some aspects of household decisions to be based on rational expectations utility maximising behaviour using dynamic optimisation over a long-time horizon. This allows realistic modelling of heterogeneity together with close adherence to conventional macroeconomic principles. While building such models has become easier, thanks to tools such as SIDD (van de Ven, 2017a), the macroeconomic path that these models generate do not necessarily match those implied by current generation macro-econometric models.[3]

The question then is whether macro-econometric models can be combined effectively with dynamic microsimulation models in a way that both objectives are fulfilled – credible macroeconomic (regional) projections and counterfactual analysis accounting for heterogeneities implied by real data. This paper offers an easy to implement alternative if one desires to analyse household impacts of macroeconomic shocks and policy given a macroeconomic path.[4] The proposed framework has two building blocks: (a) a spatial model for regional macroeconomies and inter-regional connections; and (b) a dynamic microsimulation model addressing heterogenous households (and individuals). The spatial model decomposes the national macroeconomic trajectory into regional forecasts together with adequate modelling of global and local shocks and their spillovers. This provides projections for each region of the economy. These projections are then used within a microsimulation model to simulate households' consumption-saving and

[3]This is not surprising since the objective of dynamic microsimulation is often to analyse the lifetime impacts of policies rather than to provide medium-run macroeconomic forecasts.

[4]Since our policy focus here lies on understanding the impact of welfare policy on individuals and households, we model heterogenous individuals and households. However, the approach itself is more general and can accommodate firm-level heterogeneities. This will be important in understanding impacts of industrial or job-skills policy. This is retained for future work.

labour-leisure decisions. To showcase the model, we use UK data: the base path of the UK macroeconomy is generated by a dynamic general equilibrium macro-econometric model – the National Institute Global Econometric Model (NiGEM) (NIESR, 2018), while the microsimulation model is based on data from Round 6 of the UK Wealth and Assets survey (WAS).

2.1 Spatial regional macro-econometric model

Our initial step is to build a spatial macro-econometric model at the NUTS-1 Government Office Region (GOR) level for the United Kingdom.[5] The structure of the macroeconomy is based on the popular Smets and Wouters (2007) Dynamic Stochastic General Equilibrium (DSGE) model, restricted to four macroeconomic variables at the NUTS-1 level: real output (Gross Value Added, GVA), real consumption, employment, and real wages. The choice of these state variables is motivated by availability of quarterly data at the GOR level of spatial granularity, together with adequate spatio-temporal variation.[6] Smets and Wouters (2007) do not model unemployment explicitly, hence we use an extension developed in Gali et al. (2012). However, while both these macroeconomic models relate to individual countries, here we need a macroeconomic model with multiple interconnected regions.

Open economy macroeconomic models are promising in the sense that they can model connections between economies through terms of trade. Gali and Monacelli (2005) provide a classic model where a small open economy is connected with all its trading partners. However, there are only two economies in this case – a small economy and a large foreign economy representing

[5]There are 12 GORs, comprising nine English regions (NE: North East, NW: North West, YH: Yorkshire & The Humber, EM: East Midlands, WM: West Midlands, EA: East of England, LON: London, SE: South East, and SW: South West) and the three devolved nations of the UK (WA: Wales, SC: Scotland, and NI: Northern Ireland). These GORs are shown on a map, together with population, on the right panel of figure (1). The left panel of the figure explains the estimated sparse network between the regions. Identification of the network structure is based on the approach of Bhattacharjee and Holly (2013), and described in further detail later.

[6]We use regional GVA data, by sector and region (*Model-based early estimates of regional Gross Value Added (GVA) in the regions of England, Wales, Scotland, and Northern Ireland*), from the ONS (Office for National Statistics) and aggregate this across sectors. Regional consumption data are also available from the ONS (*Regional Household Final Consumption Expenditure (Experimental statistics), by goods and services*), which are then aggregated across all items and imputed to the quarterly level based on trends from aggregate data and output from NiGEM (NIESR, 2018). Similarly we impute regional wage data from ASHE (*Annual Survey of Hours and Earnings*), available at annual frequency, to quarterly using NiGEM aggregates. Employment data are available quarterly at the region level from LFS (*Labour Force Survey*). Regional data on prices and capital are also available; however, they do not show substantial regional variation in growth rates.

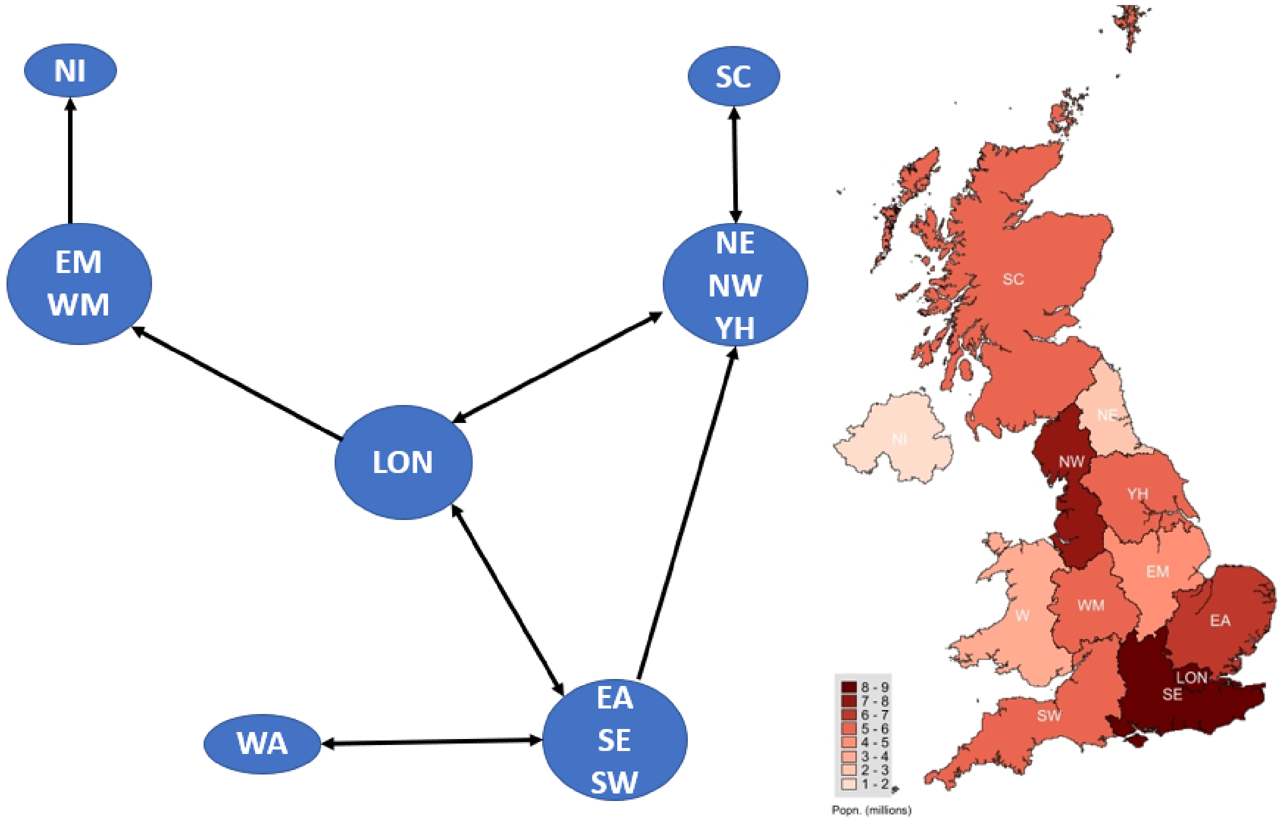


Figure 1: UK: GORs and estimated spatial structure

all other countries. Also, the only connection modelled here is through trade, whereas in reality there are many other potential connections between regions – mobility of factor inputs (labour and capital), technology spillovers, negation of arbitrage opportunities through convergence in prices of output, labour and capital, and so on. In a cross-country setting, Wasseja et al. (2022) take ideas from a classic technology spillover paper by Ertur and Koch (2007) and extend Gali and Monacelli (2005) to include potential multiple sources of interconnection and several alternate spatial models to capture these connections – spatial lag, spatial Durbin, spatial error models and their combinations. Using Bayesian DSGE modelling, they distinguish between alternate spatial models using concepts of local and global identification. However, their context is multi-country, which is very different from our multi-region setting with harmonised monetary and fiscal policy and negligible terms of trade.

Here, we apply the approach of Wasseja et al. (2022) to the model of Gali et al. (2012) specialised and applied to multiple regions of the same country and based on the four state variables as discussed above. In the interests of brevity, we discuss this macroeconomic model at a relatively high level, focusing more on the intuition, conceptual elements and empirics behind its spatial elements. For the moment, we consider a model with representative agents and take this to a heterogenous agent setting later through microsimulation.

A typical small open economy region is inhabited by representative households who seek to maximize

$$\mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t u(C_t, L_t), \tag{1}$$

where $u(.,.)$ is a utility function in consumption flows (C_t) and labour hours (L_t) discounted by the discount rate β and subject to a dynamic budget constraint. Gali and Monacelli (2005) have a composite consumption index combining a home good and a foreign good, where relative consumption is determined by relative prices or effective terms of trade. However, in our case, relative prices are (almost) the same across regions because negligible trading constraints negate arbitrage opportunities. However, trading induces consumption across regional boundaries. Hence, once the model is log-linearised around the steady state, trade between regions is modelled by spatial lags of log-consumption, whereby the representative household in an index region can consume output produced in (neighbouring) regions. Lacking data on trade between regions at sufficient granularity, we estimate neighbourhood using latent spatial weights approaches (Bhattacharjee and Jensen-Butler, 2013; Bhattacharjee and Holly, 2013).

We assume a continuum of firms within each region i where firms produce output using an identical constant returns to scale Cobb-Douglas production function with labour and capital as inputs. We further assume that labour is mobile across regions while capital is not.[7] Then, aggregate output Y_{it} is a function of aggregate capital K_{it} and aggregate labour hours L_{it} as:

$$Y_{it} = \mathbf{A_{it}} K_{it}^{\alpha} L_{it}^{1-\alpha}, \quad 0 < \alpha < 1, \quad i = 1, \ldots, N \tag{2}$$

Following Ertur and Koch (2007), we model technological progress $\mathbf{A}$ accommodating technology spillovers, such that

$$\mathbf{A}_{it} = \Omega_t k_{it}^{\phi} \prod_{j \neq i}^{N} \mathbf{A}_{jt}^{\rho w_{ij}}, \tag{3}$$

where Ω_t represents exogenous technology while technology spillovers are modelled by a cross-region spatial weights matrix $W = ((w_{ij}))_{i,j=1,\ldots,N}$ and spatial autoregressive parameter ρ. Expressing in logarithms and solving for the technology vector $\mathbf{A}$, we have:

[7] Regions within a small country limits consideration of mobile capital. Also, lacking data on capital with sufficient spatio-temporal variation, in our estimation capital is normalised.

$$\mathbf{A} = (I - \rho W)^{-1}\Omega + \phi(I - \rho W)^{-1}k, \tag{4}$$

This motivates a spatial lag model for output (Ertur and Koch, 2007) measured in our case by regional GVA. As above, we depart from Ertur and Koch who assume *a priori* known spatial weights matrix, estimating the weights as structural parameters of our open economy regional macroeconomic model. However, unlike Wasseja et al. (2022), we do not estimate an explicit DSGE model. For identification purposes we further assume that $\rho W \equiv \mathbf{W}$.[8]

Following Smets and Wouters (2007) and Gali et al. (2012), in the log-linearised model wages move over time to equate real wages with the marginal rate of substitution between working and consuming – marginal costs and benefits of working. Then, the "wage mark-up" above the marginal rate of substitution takes the form (Smets and Wouters, 2007):

$$w_{it} - (\gamma l_{it} - \delta(c_{it} - \theta c_{i,t-1})). \tag{5}$$

In addition, the potential for labour mobility implies a degree of wage equalisation across regions to negate arbitrage, hence wages also have a spatial lag.

Similar to consumption, labour is determined by households through dynamic optimisation using an Euler equation. Here too, labour mobility implies a spatial lag. This system of four equations in logarithms of the state variables, in our case, has a finite order VAR (vector autoregression model) representation of the so-called ABCD form (Fernández-Villaverde et al., 2007). The model can now be estimated using, for example, IV-SUR (instrumental variables seemingly unrelated regression) allowing for correlated errors; any cross-equation parameter restrictions as implied by theory can also be accommodated, but we have none in this case.

To estimate $\mathbf{W}$, we use the method in Bhattacharjee and Holly (2013) where network structure is identified by repeated application of the Hansen-Sargan overidentifying restrictions test (Hansen, 1982). The basic idea is that, for an index region, regions that are not its neighbours but are connected through the spatial network can act as instruments for the neighbours, which in themselves are endogenous. This property helps identify the weights matrix and avoids the endogeneity problem common when purely exogenous "classic" (typically geographic) spatial weight matrices are not used. Note that symmetric weights are untenable in our context because of potential core-periphery relationships.[9]

[8]See Bhattacharjee and Jensen-Butler (2013) for details on identification strategies in the estimation of spatial weights matrices.

[9]Spatial weights based on the gravity model is a potential alternative. However, given the complex nature

Before estimating spatial weights, we need to check for (temporal) stationarity. Panel unit root tests reveal that all four variables (logarithm of: output/GVA ($\ln Y$), labour/employment ($\ln L$), consumption ($\ln C$) and wages ($\ln w$)) are nonstationary and integrated of order 1, I(1). We also find two cointegrating relationships: between output and consumption ($\ln Y$ and $\ln C$); and between wages and labour productivity ($\ln w$ and $\ln (Y/L)$. This makes excellent economic sense. Hence, rather than a VAR, we estimate a spatial panel VECM (vector error correction model) with potential partial adjustment to these two cointegrating relations. In line with economic intuition and practice, we also include inflation (at the national level) in the cointegrating relations. Further, we are conscious of potential spatial strong dependence (Pesaran and Tosetti, 2011), even if testing this is inadequate in small N panel (Pesaran, 2015); national aggregates are included to the regression to account for the factor structure. This leads to a spatial VECM model with spatially heterogenous slopes:

$$\Delta R_{it} = \alpha_i + \mathbf{W}\Delta R_{it} + \Gamma \begin{bmatrix} \Delta R_{i,t-1} & \Delta_s R_{it} \end{bmatrix} - \Theta \begin{bmatrix} -\gamma & 1 & 0 & 0 \\ -\theta & 0 & 1 & \eta \end{bmatrix} R_{i,t-1} + \Lambda \begin{bmatrix} \Delta R_t^* & \pi_{t-1} \end{bmatrix} + \epsilon_{it}, \tag{6}$$

where $R_{it} = \begin{bmatrix} \ln Y_{it} & \ln C_{it} & \ln w_{it} & \ln L_{it} \end{bmatrix}'$, Δ and Δ_s are the (temporal) first difference and seasonal (fourth) difference operators respectively, $R_t^* = \begin{bmatrix} \ln Y_t^* & \ln C_t^* & \ln w_t^* & \ln L_t^* \end{bmatrix}'$ is a vector of national aggregates to account for factor structure and potential strong dependence (Pesaran and Tosetti, 2011), and π_{t-1} denotes lagged inflation (at the national level).

Using the VECM model (6) the network between UK GORs identified has a sparse structure (left panel in figure (1)). London has only limited connections with regions across the country, particularly the devolved nations of Wales, Scotland and Northern Ireland. Finally, based on the above estimated neighbourhood structure, we estimate by IV-SUR spatial panel VECM models for all four variables. Motivated by the literature on GMM for dynamic panel data and spatial regression models, we use higher-order spatial and temporal lags as excluded instruments, validating instrument choice by overidentifying restrictions tests (Bhattacharjee and Holly, 2013). The model is estimated using data for 12 GORs (NUTS-1 regions) over 84 quarters (1997Q1 to 2017Q4).[10]

of spatial interactions implied by our regional macroeconomic model, we prefer an estimated spatial weights matrix.

[10]We have further periods of data, all the way to 2021Q4, that are not used in the estimation. They are used to verify out-of-sample performance of the estimated model. The reason we use data till 2017Q4 is because

Our macro-econometric model, estimated as above, is based on a representative agent within each region, but allowing for spatial interactions modelled using spatial lags. We take out-of-sample predicted output and employment from this model as inputs into our microsimulation exercise. Thus, our microsimulation is informed by macroeconomic aggregates (both for the UK and all its NUTS-1 regions) but extends analysis to a heterogenous agent setting.

2.2 Heterogenous Agents and Dynamic Microsimulation

Macroeconomic models enable counterfactual structural policy analysis, but there are increasing concerns about what is overlooked. One issue is that they are often not able to adequately capture impacts of local shocks and regional/welfare policy, even those (as above) with spatial and regional interlinkages. To gain a better understanding of the distributional impacts of major shocks (like Covid-19) and progressive tax/benefits policy, a heterogenous agent framework is necessary. The recent literature has highlighted strongly the importance of heterogenous agents framework, particularly following the Global Financial Crisis, as conventional economic models and analyses have been criticised for strong focus on a representative agent framework (Kaplan et al., 2018; Challe, 2020; Bunn et al., 2021; Moll et al., 2021; Golosov et al., 2021).

In this paper, we propose the use of microsimulation (Bourguignon and Spadaro, 2006; Figari et al., 2015; NIESR, 2016) as an alternative. In this approach, longitudinal pseudo-panel data on a suitably chosen sample of households and constituent individuals can be simulated over a period of time moving into the future. Our proposed microsimulation model is dynamic (and structural) in the sense that that some aspects of household decisions are based on rational expectations utility maximising behaviour using dynamic optimisation over a long time horizon. Specifically, we optimise the consumption-saving and labour-leisure decisions of households using a life-cycle model, with stochastic income and deterministic pensions. However, some other features, like transitions in household composition through births and deaths, household formation and dissolution, are based on fixed transition probabilities and not as such outcomes of optimising decisions.

To ensure that the microsimulation results are in-line with the aggregate macroeconomic projections in the short- to medium-run, they are aligned to: (a) a structural macro-econometric model (the National Institute Global Econometric Model - NiGEM) (NIESR, 2018); and (b)

our microsimulation exercise is based on survey data for the financial year 2017-18 – April 2017 to March 2018. We make a simplifying assumption that the same spatial weights matrix applies to all the four regional macroeconomic variables; this assumption will be validated in future work.

sectoral growth rates from input-output analyses (the National Institute Sectoral Economic Model - NiSEM) (Lenoël and Young, 2020). Microsimulation requires some suitable large surveys that capture households (and individuals) in their fully representative heterogeneity – by observed socio-economic-demographic characteristics as well as latent preferences and tastes. These households are impacted by aggregate regional output growth and employment dynamics as reflected in projections from our regional macroeconomic model described above. But this impact is only on average. Individual households react to these aggregate regional shocks in their full heterogeneity and this generates a profile of heterogenous behaviours in response to shocks and policy. This way, the microsimulation model and its outcomes are tied in with short- and medium-run macroeconomic dynamics.[11]

2.2.1 Life Cycle model

Microsimulation models critically depend on how behavioural decisions (such as consumption-savings and labour-leisure) are made. In static microsimulation, they are modelled in reduced form, where typically an estimated regression model determines behavioural decisions. Alternatively, they can be modelled more structurally, where either an Overlapping Generations model or a Life-Cycle model helps impute the decision variables conditional on household characteristics – this is the key domain of dynamic microsimulation models. Our proposed microsimulation model is structural utilising a Life-Cycle model to capture behavioural decisions. Nevertheless, we keep the baseline model relatively simple so as to allow for flexibility in analysing a multitude of alternate counterfactual policy or shocks. Thus, the model can be expanded depending on what the researcher deems to be important in the short- and medium-run. Importantly, we utilise the VFI toolkit for MATLAB which ensures that setting up such models is simple and computation times are reasonable (Kirkby, 2017, 2022). Computation resources can be conserved by preparing tables for behavioural responses *a priori* and looking up values for each household in the sample.

Our analysis is implemented at the household (benefit unit) level, where each household is defined as a single adult or a couple together with children (under 18 years of age); when persons reach the age of 18, they form their own benefit unit. This is done to align analysis to the way that the benefit system in the UK works. A household so constructed can have dual-

[11]Since microsimulation /generates pseudo-panel data on a collection of households across time, it is important that the initial sample of households are representative of the UK economy. Discussion about the initial sample of households is included in the Appendix.

earners, which our Life-Cycle model accommodates. When interpreting the policy functions we refer to adult 1 in the household as the "reference" adult, and adult 2 as the "spouse". When determining who is a reference adult in a household, we simply designate the individual with the higher wage.

Dynamic Budget constraint. The first building block of the life-cycle model is the dynamic budget constraint. This constraint is modelled as:

$$x_{t+1} = (1+r)x_t + E_t(y_{t+1}) - C_t \tag{7}$$

where r is the interest rate, which is currently set at its long-term average of 5%, x_t are household assets/wealth in period t, C_t the consumption in period t, and $E_t(y_{t+1})$ is the expected household income in the next period. We restrict C_t to be above 0 for all periods t, which is equivalent to allowing agents a minimum degree of subsistence consumption and makes sense in a welfare state context. In our current implementation, borrowings are not allowed in the dynamic optimisation, since the finance sector is not explicitly modelled and as such anyone with a loan request would be granted one. This would in turn lead to a situation where agents would take up as much loans as possible as long as the No-Ponzi condition ($x_T \geq 0$) binds. However, borrowing potential can be accommodated in the income/wage model.

Income Process. The model assumes that the agents expect to live up to a maximum age of 105 years. This is split into working years of up to 51 years, during which their income earned is stochastic, and retirement years of up to 37 years, when deterministic pensions are earned. The income process is modelled as:

$$y_t = \begin{cases} \kappa_t L_{1t}\pi(z_t)w + \mathbb{I}_{n>1}\kappa_t L_{2t}\pi(z_t)0.95w & \text{if } 18 \leq t \leq 68 \\ Pen & \text{if } 69 \leq t \leq 105 \\ 0 & \text{otherwise} \end{cases} \tag{8}$$

where Pen is a deterministic pension,[12] and κ_t is a hump-shaped deterministic function reflecting earnings over the life time (calibrated to UK data), L_{1t} and L_{2t} are fractions of time spent on work by the first and second adult in the household respectively, w is average labour income in

[12]Pensions are currently set at UK average as estimated from WAS. Modelling heterogeneity in pensions is retained for future work. We experimented with different deterministic levels, but it does not make a big difference. While pensions are assumed constant over time (in real terms), that does not mean that all pensioners will have the same consumption profile – we assume that they can liquidate a fraction of their assets at any time without cost.

the market, and n is the number of adults in the household. Note that $\mathbb{I}_{n>1}$ determines whether there are two wage earners in the household or only one. If $n = 1$, then the second part of the wage equation drops out. Further, note that we multiply the second earners income in the household by 0.95. This was done simply because of how we designate reference adults – the individual with the higher wage in the household.[13] Finally $\pi(z_t)$ is a 2-state Markov process determining whether the individual is employed in a specific period, given their employment status last period, where U is a binary variable demoting unemployed or economically inactive:

$$\pi(z_t) = \begin{bmatrix} P(z_t = 1 - U|z_{t-1} = 1 - U) & P(z_t = 1 - U|z_{t-1} = U) \\ P(z_t = U|z_{t-1} = 1 - U) & P(z_t = U|z_{t-1} = U) \end{bmatrix} \tag{9}$$

Importantly, we normalise wages w at 1. As such the policy grid is constructed relative to average wages for the household, subject to household socio-economic-demographic characteristics, including education, location, etc. To obtain average wages we can simply use WAS to calculate the average labour income for any specific household. On average, w is £24,000 in wages which is approximately the average income of a household where the household head is aged between 18 and 68 years, calibrated to round 6 of the UK WAS data. The deterministic κ_t function ensures that there is heterogeneity in earnings by age of the individual.

Growth rates can be modelled in one of several alternate ways. First, one can reformulate the problem and include a growth term in the wages. While this is technically possible, in implementation one would need to increase the grid points dramatically to account for the non-stationary nature of the new profiles. Second, one can simply rerun the dynamic optimisation routine after the microsimulation projects one year forward, taking the average labour income from the previous year. The advantage of this approach is that it allows not only that wages are updated but also employment transition matrix as well as pensions (relative to wage). With the VFI toolkit, computations are fast and therefore this option is feasible. Nevertheless, the more complex the model becomes, the longer this option will take to run. The third and final option is to simply multiply the policy grid with the growth rates, similar to Gourinchas and Parker (2002). The advantage of this method is that it is quick and requires no complex computations. The disadvantage is that the fit will deteriorate the more years we iterate forward, especially at parts of the grid where grid points are more sparse, typically the higher asset classes. Our objective being rich inference at the household level with the combination of simple models, we

[13]This does not affect findings much and if one wishes to define reference adults in a different way, this parameter can be set to 1.

have currently opted for option 3.

Utility and Value function. The model uses a version of the nonseparable CES utility similar to NIESR (2016):

$$\begin{aligned} u(C/m, L) =& \frac{1}{1-\gamma}\Big[\Big(\Big(\frac{C}{1+0.5n+0.3m}\Big)^{1-\frac{1}{\epsilon}} + \alpha^{\frac{1}{\epsilon}}[(1-L_1)^{1-\frac{1}{\epsilon}} + \mathbb{I}_{n>1}(1-L_2)^{1-\frac{1}{\epsilon}}]\Big)^{\frac{1}{1-\epsilon}}\Big]^{1-\gamma} \\ & - \mathbb{I}_{n>1}\mathbb{I}_{L_2>0}\mathbb{I}_{\frac{c}{1+0.5n+0.3m}>C_{min}}(2L_2) \end{aligned} \tag{10}$$

where m is the number of dependent children in the household. To retain comparability by household composition, we equivalised the consumption of the household depending on the number of adults and children: we discount household consumption by 0.5 for an additional adult in the household, and 0.3 for each of the first 3 children in the household. The final term in the utility function is a cost to the labour hours of the second earner. Importantly this cost only enters the equation if the consumption of the household is above some threshold C_{min}. We set $C_{min} = 0.8$, so that when equivalised consumption is above 80% of average labour income, there is a cost associated with the second earner taking on labour hours. The reason behind this, is that once a household has enough earnings to maintain a steady and comfortable living, it is not necessary for the second earner to enter the labour market. We think the inclusion of such a cost on the utility function is warranted as it covers the situation where the spouse in a dual-earner household supplies zero hours to the labour market.

The parameters for the CES utility are taken from van de Ven (2017b); see table (1). The one parameter that we change is the discount factor for couples for which we use 0.95 rather than 0.93. This change was made because for the marginally higher discount factor the second earners labour force participation has no “islands” on the grid.

The agents in the model live for only finite time which leads to a nonstationary Bellman

Table 1: Utility parameters

	Singles	Couples
Relative risk aversion, γ	1.55	1.55
Intertemporal elasticity, ϵ	0.6	0.6
Utility price of leisure, α	2.2	1.034
Discount factor, β	0.97	0.95

equation[14] that the agents solve in each period t:

$$
\begin{aligned}
V(x_t, z_t, t) = \max_{C_t, x_{t+1}, L_t} \; & u(C_t/m, L_t) + s_t \beta E_t[V(x_{t+1}, z_{t+1}, t+1)|z_t], \\
& 0 \le L_t \le 1,\ C \ge 0,\ x_{t+1} \ge -B,\ x_T \ge 0 \\
& z_t = \pi(z_t)
\end{aligned}
\tag{11}
$$

Here, L_t is potentially a vector when $n > 1$. In this value function we include a probability of survival s_t to age $t+1$ which is age dependent. This ensures that when agents optimise their consumption and labour choices, they also factor in the probability of surviving to the next period. Note that while we do not implement a preference for leaving inheritance, agents will still leave assets behind due to the uncertainty of age at death. In the microsimulation model when an agent dies, their assets are distributed equally among surviving household members; otherwise, if they have no surviving household members, this just gets liquidated.[15]

2.2.2 Microsimulation

An important innovation in our microsimulation model is that it is tied into projected economic growth (or contraction) over the short- and medium-run. This enables greater alignment of household income, wealth and consumption trajectories to reflect the effect of large economic shocks, for example, Covid-19 or the Global Financial Crisis, and of policy measures, such as the Universal Credit uplift of £20 per week for the poorest households.[16] Sectoral growth rates are provided by a dynamic general equilibrium macro-econometric model - the National Institute Global Econometric Model (NiGEM) (NIESR, 2018) - together with an input-output based sectoral model NiSEM (National Institute Sectoral Economic Model) (Lenoël and Young, 2020).[17] Regional Growth rates are provided by the model described in section (2.1).

[14] Note that the equation is a contraction mapping when $\beta < 1$, which means that the simulation gets closer to stationary as the years alive increases.

[15] Some of the policy functions generated by the life-cycle model are presented in the Appendix.

[16] An important motivation of developing this new microsimulation model was to enable study of the impact of the Covid-19 shock and corresponding welfare measures. The NIESR has a previous microsimulation model LINDA (Lifetime INcome Distributional Analysis) (NIESR, 2016; van de Ven, 2017b) which did not allow such alignment to short- and medium-run macroeconomic projections.

[17] NiSEM projects growth rates for 9 sectors while WAS has 10 sectors, where employed persons in WAS work. We match the 9 NiSEM sectors to the closest corresponding WAS sector and take the average growth rate for each corresponding WAS sector. While this is not a perfect match, it is adequate to capture sectoral differences experienced by Households.

Each simulated individual works and lives in a region and can migrate from one region to another. When the individual is retired, they are recorded a growth rate of 1. Note that we are working with real terms, so recording growth rates of 1 for pensioners is equivalent to having a pension scheme that is adjusted for inflation only. Nevertheless, if one wishes to model a Swiss type pension, they can easily adjust this method so that pensioners are recorded the economy-wide growth rate.

Note that since we take labour force participation from the Life-Cycle model, observed wages will be equivalent to the offered yearly wage, multiplied by the proportion of time spent working. This implicitly assumes that agents can choose exactly how much they want to work given their wage offer and assets. As such, in our microsimulation model we will discretize labour decisions accordingly: (1) Full-time employee if labour decision is above 0.3, (2) Part-time employee if labour decision is above 0 but below 0.3, (3) inactive/unemployed if labour decision is 0. The cut-offs for the labour decisions were chosen so as to yield a split between full-time employees and part-time employees that closely matches the WAS data. Nevertheless, one can choose alternate cut-off points.

The key to the microsimulation is that we want to tie the dynamics to the spatial/regional macro-econometric model projections. Namely, we want regional employment growth in the microsimulation model to track regional employment projections of the macro-econometric model, and regional average wage growth to track growth of regional wages. As such, after our Static microsimulation step (that is, sampling an initial set of households), we use the NiREMs growth rates to create projected employment and average wage projections for each region. We then proceed with the microsimulation with an aim to get as close to these projection paths as possible.

While it is feasible and straightforward to ensure that employment numbers in the microsimulation match projected employment of the spatial macro-econometric model, average wage growth is more difficult. This is because as wages are adjusted, households re-optimise their labour decisions which influences the average wage of the region. For this reason, one has to allow for some discrepancy between the two: E_w. Formally we want the difference between wage growth in the two models to be:

$$\Delta w_{i,t} = \left| \frac{\sum_{i=1}^{N_t} w_{i,t,n}}{N_1} - \frac{GVA_{i,t} - GVA_{i,t-4}}{GVA_{i,t-4}} \times \frac{\sum_{n=1}^{N_1} w_{i,0,n}}{N_0} \right| < E_w \tag{12}$$

Note that we use year-on-year growth rates for the regional projection. This is because temporal frequency of regional projections and the microsimulations frequency do not have to match. In our application, the macro-econometric model is at quarterly frequency and the microsimulation at annual frequency.

Importantly, these differences are region specific, which allows the spatial regional macro-econometric model projections to guide the microsimulation exercise. The goal is to adjust households' labour force status and wages in such way as to get as close to the projected paths as possible. In particular, we want the absolute value of the difference to be below E_w.

Microsimulation determines individuals' employment status and wages stochastically. Nevertheless, we want to mimic patterns observed in data. Hiring and firing is done by taking into account an agent's continuous labour market choices. As such, an individual's L can be thought of as determining the probability of being hired and $max(L) \times L_D - L$ as probability of being fired. As such, we will treat L not only as a measure of fraction of time spent working, but also as a measure of job search intensity when the individual is unemployed. When an individual is hired, their "offered wage" w^* will be determined by a reduced form Mincer-type model subject to region, sector, and individual/household characteristics.[18] Note that this is the wage offered to the economic agent but not necessarily what they take home. For the first year, we use the observed disposable income w_{obs} to impute the offered wage using $w_{obs} = \kappa_j L_D w^*$. Note that the policy grid is normalised for the average w^*.

We model decisions on promotion and demotion using a different rule. Recall that in the Life-cycle model the agent's disposable income was $w = \kappa_j L$. While the changes in κ_j with an individual's age is deterministic, the wage offered by their firm is not. Instead, when the agent is employed they are assigned a $\hat{\kappa}_j = \kappa_j$. Note that as the microsimulation progresses through time, differences between the two κ terms will start to emerge. Promotion/demotion probability will be determined by $\kappa_j - \hat{\kappa}_j$: As this term becomes more positive, the agent is more likely to be promoted, as it becomes more negative, the agent is more likely to be demoted.

Since promotion and demotion will only change the κ_j of the individual it will not result in wage growth in the offered wages w^*. As such, to account for overall wage growth we will apply sectoral growth rates to w^*. As the sectors grow at different rates, this induces heterogenous wage dynamics, which will feed into more realistic consumption profiles, even though we assume representative agents for consumption imputation.

Since wage growth is determined at the sectoral level, agents' transition between sectors

[18]It is possible to make this Mincer-type wage determination equation as elaborate as desired, but one has to make sure that determinants (such as education) are also simulated in the microsimulation.

becomes crucial. In our model, this is determined in 2 steps. First, the agent working in a specific sector in a given year has a probability of moving to a different sector the following year, where these transition probabilities are computed from the UK WAS data. The second step is to determine which sector the agent will move into. This is done by taking into account sectoral growth rates.[19]

Microsimulation also allows modelling migration between the regions. Migration is determined by transition probabilities calculated from the UK WAS. Likewise, immigration and emigration are also allowed, with region-specific rates taken from national statistics.[20]

Death is modelled by age and gender-specific death rates and childbirths by age-specific fertility rates (separately for single mothers and those in relationship). Regional fertility rates are not explicitly modelled but this can be done (Zhang et al., 2021). Gender of the child is also allocated based on population statistics. Excess mortality from Covid-19 is explicitly modelled for the year 2020-21, but set to zero for later years.

Rates of household formation (cohabitation) and dissolution are based on UK WAS data. Matches are based on gender, ethnicity and location (exact matches) together with close matches on household wealth quintiles.[21]

The designation of a household in the model is based on the definition of benefit units in the UK tax and benefit systems. On reaching the age of 18, every individual forms his/her own benefit unit separate from the parents. This means that all households (actually benefit units) in the model comprise either a single adult or two adults in a relationship, potentially together with one or more children under the age of 18. Taxes and benefits are calculated according to current UK rates, and tax avoidance is not modelled. The UK government had in the beginning of 2020 introduced a temporary enhanced welfare payment (Universal Credit uplift) for very poor households. One counterfactual exercise we report are the distributional implications of continuing this payment beyond the period it was implemented.

The sequence of steps of the microsimulation are summarised in algorithm (1). Note that

[19] One can make the sector decision be more elaborate incorporating it into a reduced form discrete choice model of sectoral choice, subject to education, household characteristics, age, location, and other determinants

[20] The impacts of Brexit are left for future work. We can model this by limiting immigration and potentially setting London as the region that perhaps attracts relatively more of the immigration post-Brexit. The model will still allow immigrant transition across the country, in time, but largely through London.

[21] The above matching model is restrictive but is adopted without prejudice or ascribing value. While this model is probably more realistic at the current times, alternate more liberal matching models based on fuzzy matches can and should likely be used in future work.

we apply benefits at the end of the microsimulation. As regional labour and wage dynamics are determined earlier, this will imply that there might be some deviation in the final regional projections. Nevertheless, these differences are expected not to be large.

Algorithm 1 Microsimulation algorithm

1. Retirement
2. Death
3. Household Dissolution and Formation
4. Migration
5. Birth of children
6. Sectoral transition and growth rates
7. Calculate difference between spatial regional employment growth and microsimulation regional employment growth and move people in/out of employment until all regional dynamics match
8. Calculate difference between spatial regional GVA growth and microsimulation regional wage growth and promote/demote people until all regional differences are smaller than E_w (labour force choices are run for each promotion/demotion as a change in household income can lead to new labour supply choices)
9. Apply benefit incomes to households that are eligible
10. Use policy grid to impute consumption and update labour supply for each household
11. Move period forward by a year

Running the described microsimulation exercise with an initial WAS sample of 5,000 randomly chosen households across the country yields the wage dynamics described in figure (2). Note that wage projections from the spatial regional macro-econometric model are not inputs to microsimulation – GVA and employment growth are. Then, a comparison of the two serves to demonstrate how much difference the heterogenous agent microsimulation makes from a representative agent spatial macro-econometric setting. The differences in the short- to medium-run

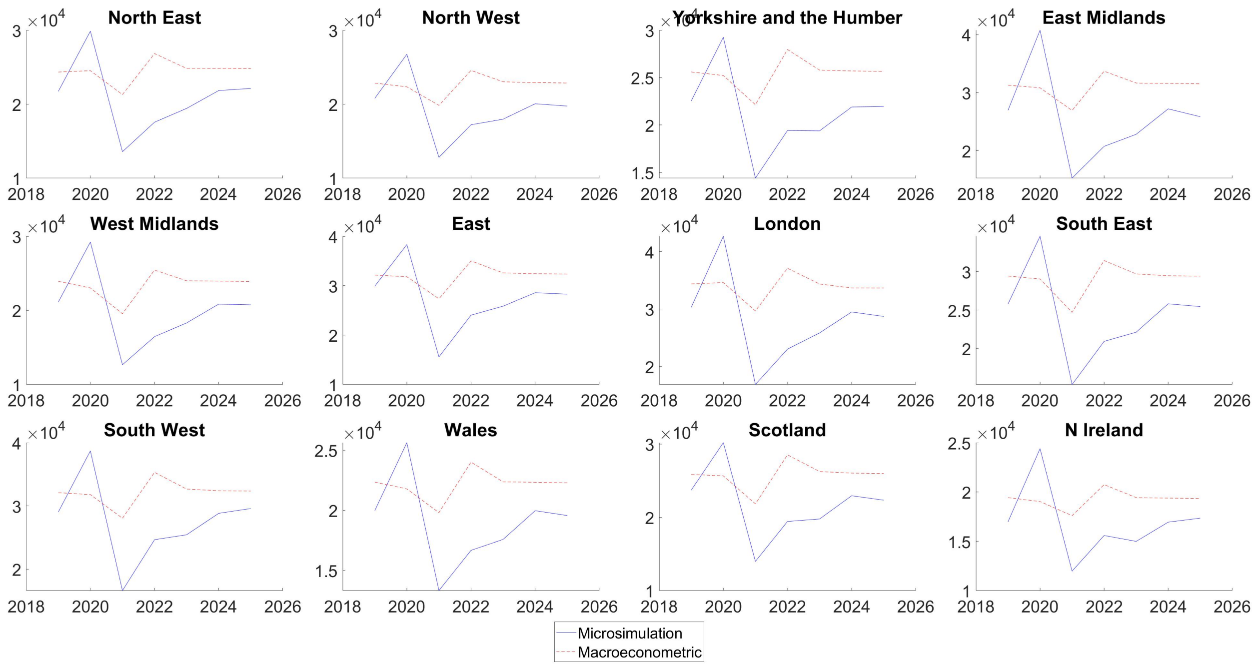


Figure 2: Wage Dynamics

are substantial, thereby demonstrating that microsimulation projects much stronger adverse distributional impacts of the Covid-19, Brexit and cost of living crises. This is in line with other evidence; see, for example, Bhattacharjee et al. (2022). Heterogeneity exacerbates the impacts of global shocks in a way that a representative agent rational expectations model would not. This is because rational agents would anticipate a reversal of shocks (in expectation), and hence their behavioural responses would be moderated (Kaplan et al., 2018; Moll et al., 2021). It is also clear that, in the long run, both approaches converge to a steady state, though microsimulation indicates somewhat more scarring (Bhattacharjee et al., 2021, 2022); this highlights amplification effects also found in HANK models (Kaplan et al., 2018; Moll et al., 2021). Finally, temporal patterns are similar in both cases and regional differences in impacts of shocks and recovery are equally stark.

3 Empirical Application

When the Covid-19 pandemic hit economies and societies around the world, it exacerbated inequalities particularly in regions, demographies and communities that were already left behind. This made it important to promote appropriate policies in order to address the distributional consequences of the Covid-19 shock, which a microsimulation model like ours is intended to deliver. Together, lockdown rules forced people to adjust their behaviour, with huge ramifications for the macroeconomy and a shift in individual and household consumption and savings decisions. As more people were vaccinated governments in Europe transited from lockdowns to recovery management.

In an effort to restore the economies back to pre-pandemic dynamics, policymakers have focused heavily on aggregate macroeconomic outcomes. This has been inadequate, as evident in the United Kingdom (UK) government agenda focus shift to "building back better" and "levelling up". While aggregate recovery is no doubt important, exclusive focus on the aggregate can obscure some impacts of the Covid-19 crisis and policy responses to it. In essence, households in different regions and with different levels of wealth were not affected to the same degree by the Covid-19 shock. This meant that some households were able to weather the adjustments imposed by the Covid-19 economy without major problems, while other households had to liquidate part of their wealth to maintain consumption or even ended up sliding into destitution (Bhattacharjee and Lisauskaite, 2020; Bhattacharjee et al., 2021). As such, "Covid-19 was never the great leveller" (Pabst, 2020) – it has exacerbated economic inequalities in the UK in a way that can be missed by exclusively focusing on aggregate outcomes.

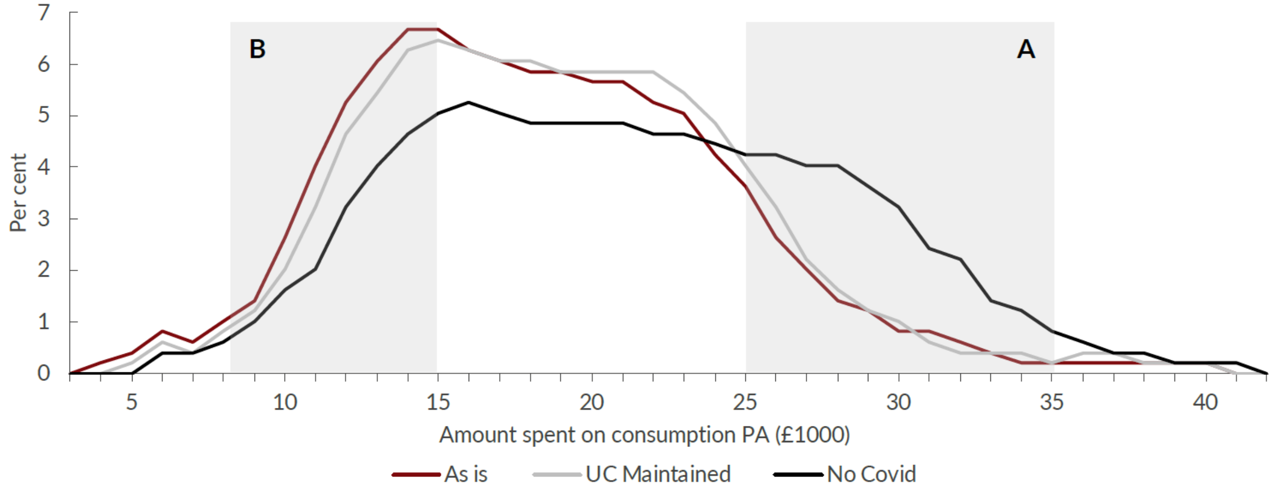
We apply our proposed model to the UK to better understand the impacts of the Covid-19 shock and policy responses upon regions and society. At the start of 2020, the UK government introduced temporarily enhanced welfare payments (the Universal Credit uplift) for very poor households.[22] Together with an employment protection scheme (UK Coronavirus Job Retention Scheme, commonly known as the 'furlough scheme'), enhanced Universal Credit (UC) payments helped shield extremely poor households from the most adverse effects of the pandemic. Note that, the furlough scheme is already accommodated in the regional macroeconomic and microsimulation models by inducing a temporary (time-contingent) disjuncture between productivity and wages. Enhanced UC was terminated in September 2021 (`https://lordslibrary.parliament.uk/universal-credit-an-end-to-the-uplift/`), and the central counterfactual exercise we report are the distributional and regional implications of continuing this payment beyond the period it was implemented. It is also useful to compare outcomes in the factual relative to a counterfactual where the economy was not hit by the Covid-19 pandemic shock.

[22]Means-tested additional welfare payments of £20 per week for households (benefit units) whose weekly (household composition adjusted) income fell below a minimum subsistence threshold (Bhattacharjee and Lisauskaite, 2020).

Note that the microsimulation exercise creates one longitudinal pseudo-panel dataset for each scenario modelled. Bhattacharjee and Szendrei (2021) formulate three scenarios (a) the factual (where the economy has been hit by the pandemic shock and enhanced UC withdrawn in September 2021); and two counterfactuals (b) enhanced UC not withdrawn; and (c) no Covid-19 shock. One can then conduct a variety of modelling and inference procedures on these (pseudo-)data. The authors apply high-dimensional quantile regression to the data and find that regional (location) impact of extended UC payments is moderate relative to the pandemic shock, but being self-employed, a male household head or having low education (lower than university degree) are associated with increased consumption inequality. For the non-pandemic counterfactual, the variables that increase consumption inequality are wage income and being full time employed.

Unsurprisingly, Bhattacharjee and Szendrei (2021) find that consumption at every quantile is higher in the non-pandemic counterfactual by at least 10%; however, the impact is asymmetric across the quantiles. Whereas in lower quantiles, consumption would have been around 10-15% higher if there had not been the Covid-19 shock, this difference is about 15-20% in the upper quantiles. The counterfactual with extended UC payments sees a very steep decline with lower quantiles consuming 5% more, and upper quantiles consuming almost the same as compared to the factual microsimulation. This highlights the way microsimulation informed by a spatial regional macro-ecometric model is capable of imputing household consumption in a manner that inherently incorporates heterogenous agents.

Figure (3) is based on the same information but conveyed in a different way, plotting the estimated density of consumption distribution for the three scenarios. It shows where in the distribution the impact of policy and shocks is the greatest. Households in the upper half of the distribution were able to make lockdown savings which was subsequently helpful during the current cost-of-living crisis (shaded A). This is likely because households with the highest conditional consumption are insulated against the shocks imposed by Covid-19 (for example, having access to more liquid assets can help smooth out consumption). On the other extreme, poor households are likely more constrained by their incomes. Households towards the bottom (shaded B) suffered the most from the Covid-19 shock. However, close to half of this adverse effect would have been mitigated by ending the UC uplift, particularly towards the lowest end of the distribution. As such, while the absence of the pandemic would have yielded additional consumption for all quantiles, the lowest quantiles of consumption were somewhat supported by the extension of the UC payments.



NiGEM, NiReMS and LINDA

Figure 3: Impact of Covid-19 and Universal Credit uplift on distribution of household consumption in 2022-23: Figure 1, Bhattacharjee and Szendrei (2021)

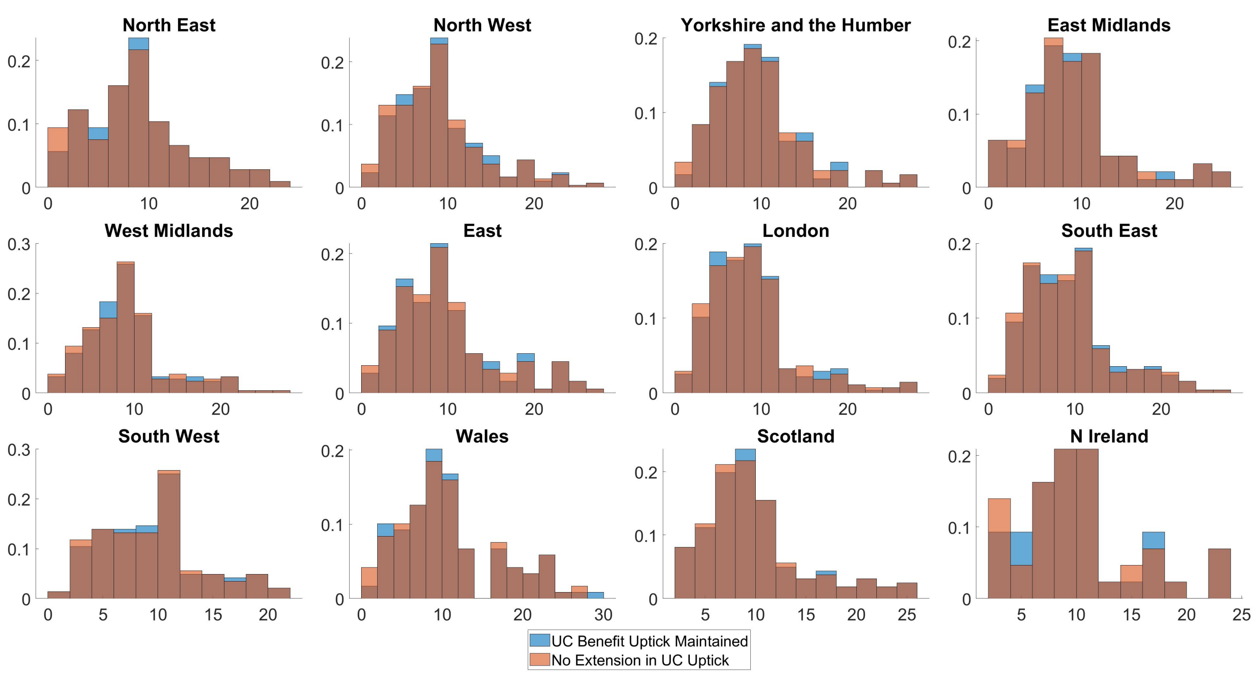


Figure 4: Consumption histogram for low asset households per region (consumption £'000s))

Clearly linking the spatial regional macro-econometric model to microsimulation goes even further. In figure (4), we plot histograms of consumption distribution for poor households (in terms of wealth) by region. Importantly, the analysis at the national level (figure 3) revealed that the difference between the "no extended UC" and the factual is minor, except at the lower end of the consumption distribution. To explore the regional differences further, we look at the consumption profiles of low asset individuals (less than £20,000); this is about 2/3 of median household disposable income – an important measure of poverty.[23] As such, while the impacts of household composition and age are conditioned upon in the subsequent quantile regression step, these effects are confounded in the histograms of figure (4). Nevertheless, the central conclusions from the national analysis carry over, is that without extended UC we find more individuals at the lower end of the consumption spectrum. Importantly, the added insights that our regional macro-econometric model provides is to highlight that not all regions were impacted equally. Our analysis shows that low asset households in the North East, Wales, and Northern Ireland were hit particularly hard, with significantly more households pushed into consumption of £5,000 per annum or less as the UC uplift is not extended.

Our microsimulation model allows individuals to make consumption-saving as well as labour-leisure decisions. This allows us to examine individuals' labour decisions. We are particularly interested in low asset (less than £20,000) and young (younger than 25 years) individuals. Ideally, it is in the best interests of society that young adults to go through education so that their lifetime income profiles improve. However, figure (5) shows that without the additional welfare support in maintaining the UC uptick, young adults' labour hours shifts upwards dramatically across all regions, highlighting that they are more likely to be pushed into full-time work. Note, however, that choice for educational attainment is not modelled explicitly in the current microsimulation. Importantly, the difference between the counterfactuals in labour choices is even starker than consumption which is not surprising given that the utility function is set up in a way that encourages households to smooth consumption over time.

4 Conclusion

In this paper, we propose and document a new model, NIReMS (National Institute Regional Modelling System), as a synthesis of a spatial regional macro-econometric model and dynamic

[23]Note that these histograms are based on the microsimulated sample, while the national analysis used a quantile regression method (Bhattacharjee and Szendrei, 2021).

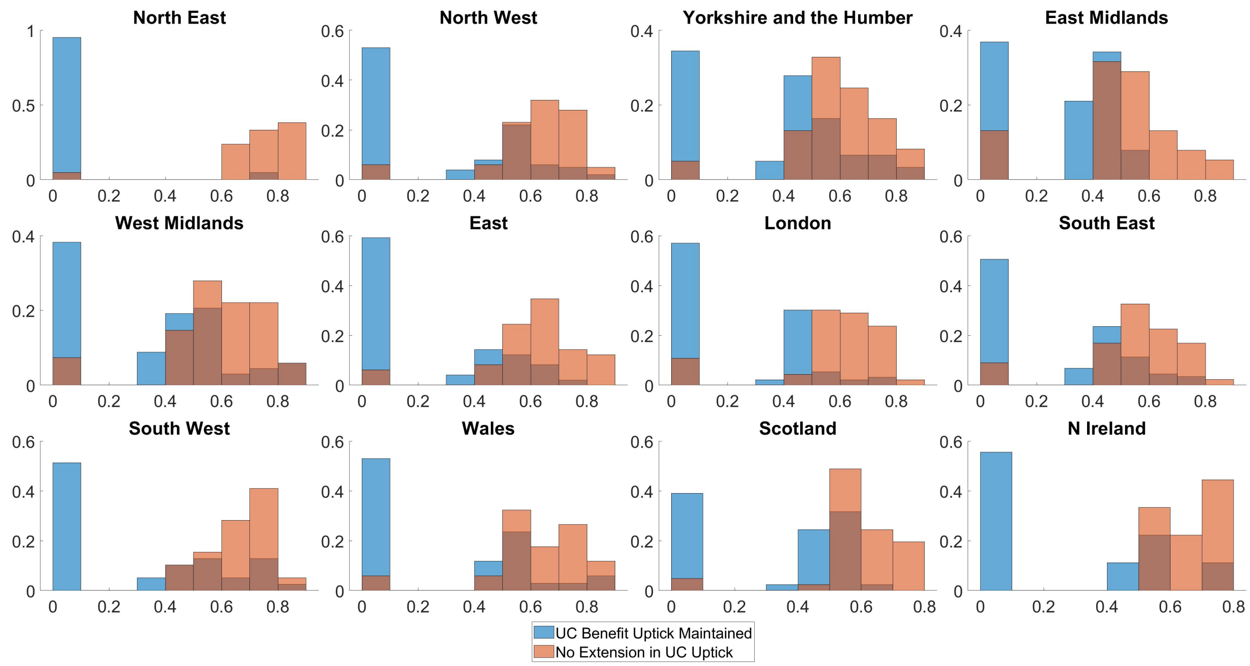


Figure 5: Labour choice histogram for low asset young adults per region (proportion of time compared to highest Labour hour)

microsimulation to account for heterogenous agents. Using this model, we can create counterfactual scenarios to analyse distributional and regional impacts of aggregate (global) and local shocks together with a menu of policy measures to mitigate against such shocks. We consider an application where the microsimulation exercise creates one longitudinal pseudo-panel dataset for each scenario modelled, namely (a) the factual (where the economy has been hit by the pandemic shock and enhanced Universal Credit (UC) withdrawn in September 2021); and two counterfactuals (b) enhanced UC not withdrawn; and (c) no Covid-19 shock.

Unsurprisingly, consumption at every quantile is higher in the non-pandemic counterfactual by at least 10%; however, the impact is asymmetric across the quantiles. Whereas in lower quantiles, consumption would have been around 10-15% higher if there had not been the Covid-19 shock, this difference is about 15-20% in the upper quantiles. The counterfactual with extended UC payments sees a very steep decline with lower quantiles consuming 5% more, and upper quantiles consuming almost the same as compared to the factual microsimulation. This highlights the way microsimulation, informed by a spatial regional macro-econometric model, is capable of imputing household consumption in a manner that inherently incorporates heterogenous agents. Furthermore, the added insights provided by the regional macro-econometric model is that not all regions were affected equally. The analysis shows that low asset households in the North East, Wales, and Northern Ireland were hit particularly hard, with significantly more households pushed into consumption of £5,000 per annum less as the UC uplift was not extended.

As noted earlier, this is an initial step towards the more complete integration of a national macroeconomic model with a regional modelling system that addresses both spatial and agent heterogeneity. As several other analysts have noted, there is a parallel need to incorporate firm heterogeneity. This can be accomplished, in part, by the development and integration of interregional input-output tables with the spatial econometric system that has been used in this paper. One important methodological advance would be the exploration of the way that feedback effects that are derived from the input-output system can be harnessed into the spatial econometric system. An initial exploration has been provided by Kim and Hewings (2012a,b), integrating a metropolitan-wide econometric input-output model with a spatial econometric model at the community level in which a system of equations links aggregate population and employment with formal consideration of the spatial spillover effects.

In addition, agent heterogeneity also has an important activity analysis dimension; following the initial work of Batey and Madden (1981), the microsimulation model used in the present paper could be expanded to capture alternative participation in the labour market – full-time, part-time, unemployed as well as the increasing cohort of retirees accounting for estimated 20% of total population by 2030. Also important in this context is modelling breaks from employment for retraining – an increasingly critical element of achieving better jobs-skills matches – aligned to local needs and the diversity of individuals/households. In addition, access to the WAS will also provide an indication of the speed of recovery by households of different income and asset levels, enriching the quality of forecast of the trajectory of the macroeconomy.

There is a further opportunity, once the macro-spatial integration has been completed, to explore the impacts of addressing spatial heterogeneity on macroeconomic outcomes. As Kim and Hewings (2012a,b) found, admittedly for a two-level system with less than 10 million inhabitants, limitations at the lower (community) level on the ability to house the expected population increase generated by a macroeconomic model created a difference of greater than 5% in the forecast population beyond 2040. In the UK context, regional variations in recovery could generate an important impact of macroeconomic outcomes.

One important and exciting aspect of ongoing and future development is the integration of spatial econometric and interregional input-output analysis to provide micro-macro feedbacks. Following insights from inter-sectoral context, this has the potential for capturing consumption variation in macroeconomic models much more accurately as well as amplified effects of aggregate shocks. Finally, while our spatial weights here are freely estimated, one could well use trade estimates from the SEIM system (?) at the NUTS-2 level and aggregate to the higher level. This might provide us with some quasi-robustness checks of spatial econometric estimates versus Input-Output derived estimates and provide better integration of the two approaches. All of these developments will enhance the understanding of spatial and individual inequality in the UK and provide a much richer set of analytical tools on which to base national and regional policy initiatives.

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A Appendix

A.1 Sampling

The choice of initial sampling frame is key. For this reason, we first discuss how the initial set of households (that are projected across time using microsimulation) is obtained. Two considerations are important here. First, the frame must be reasonably current and representative of the population under study. Second, the coverage of variables in the underlying survey must be adequate in representing heterogeneity. Having said that, the choice need not be exhaustive, and gaps can be filled in with appropriate imputation or simulation. In any case, the central idea of dynamic microsimulation is that the entire dataset moving forward in time generates longitudinal pseudo-panel data, where the values for all variables are simulated. Some of these variables are endogenously populated using dynamic optimisation, and the others are either non-stochastic or take values based on exogenous transition probabilities.

In the case of UK households, there are several base surveys available, from which a suitable choice must be made. We considered 4 such options: the Labour Force Survey (LFS), the UK Wealth and Assets Survey (WAS), Understanding Society (formerly British Household Panel Survey), and the Annual Survey of Hours and Earnings (ASHE); relative merits and demerits are discussed in Ritchie et al. (2014). The LFS is the most current of the four, but its coverage in terms of variables is rather limited focusing mainly on the labour market but with limited household features. The Understanding Society survey is also current, but mainly based on opinion questions rather than nominal currency values, hence not very useful to study intensive margins. ASHE is quite comprehensive in choice of variables, but is based on individuals and only employees, hence its coverage is rather limited.

The WAS (ONS, 2022) has the most comprehensive coverage of the four, very rich in assets and income (and their components) and hence amenable to adequately model taxes and benefits. While the Round 6 data are for 2017-18,[24] we felt that this is not a major limitation because generating pseudo-panel data moving into the future is an essential feature of dynamic microsimulation in any case. It is nationally representative at the individual and household levels (with explicit sampling weights attached to both levels). However, two important limitations remain. First, the data covers all regions of the UK, except Northern Ireland. Second,

[24] More current data is available through Round 7 of WAS but these were collected mostly through telephone interviews on account of Covid-19 lockdowns and distancing. Hence, we choose to use data from Round 6 of WAS to construct or base sample.

consumption is not included, and some variables are not publicly released, perhaps the most crucial for distributional implications being ethnicity. Likewise, detailed location data are not released. We choose WAS for 2017-18 to construct our base sample, but make adjustments to address both the above limitations.

For the first, we draw a random sample of 10,000 households taking sampling weights into account, but add to the data a pseudo-sample representing Northern Ireland. Comparable data from the Family Resources Survey shows that, in 2014-15, average weekly household income in Northern Ireland was £420 compared with £473 for the UK as a whole (ONS, 2017). Therefore, we draw the pseudo-sample for Northern Ireland from a truncated sample of the WAS data, where regions with higher earnings are omitted to the extent that average household earnings are reduced to 89 per cent of the original. We achieved this by drawing a sample of households from Wales and the North East of England. However, this exercise does not yield entirely satisfactory sectoral distribution of employment in Northern Ireland. To address this, we added to the above pseudo-sample, 10% of households from Scotland employed in agriculture, and 10% of households from the English regions of the North West and Yorkshire and Humberside employed in agriculture. Admittedly, this exercise is somewhat subjective, but it yields satisfactory profiles in line with census statistics, hence we think it is reasonably robust.

For the second, lack of consumption data is not, in our view, a critical issue. Our microsimulation exercise is aimed at simulating consumption profiles in any case. We included ethnicity as well. While these data are sensitive and therefore in restricted dissemination, wealth quintiles, education and regional profiles by race are published elsewhere (ONS, 2019, 2020). Based on these data, we imputed race/ethnicity for each household head in our sample by computing conditional probabilities using the Bayes rule. We view the capacity for such imputation as an important advantage of our methodology, whereby one can in principle use any survey to conduct such a microsimulation exercise. Effectively, we have controls in the form of (aggregate) real consumption and the microsumulation exercise allocates these to the continuum of households based on their dynamic optimising behaviours.

A.2 Policy functions of Life-Cycle model

To verify that this model leads to policy functions that look reasonable and can be used in microsimulation, we present the policy function for labour market participation and consumption for a single adult household with no children in figure (6). We also present the endogenous labour market choice of a dual-earner household with no children in figure (7). These patterns of consumption and labour choice/outcomes look very much intuitive.

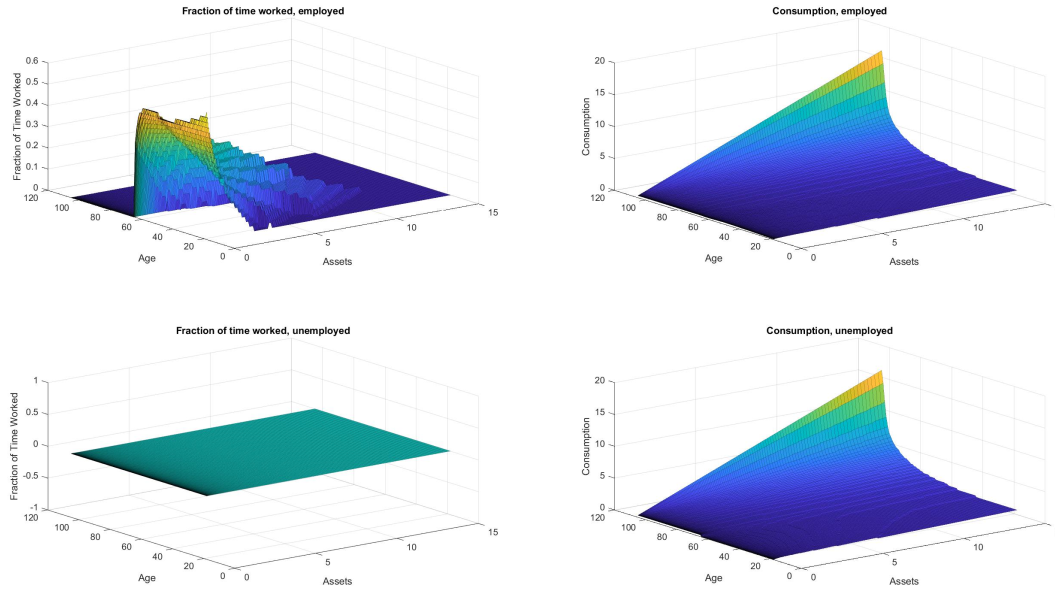

Figure 6: Single adult household labour and consumption decisions (assets/cons. in £'000s)

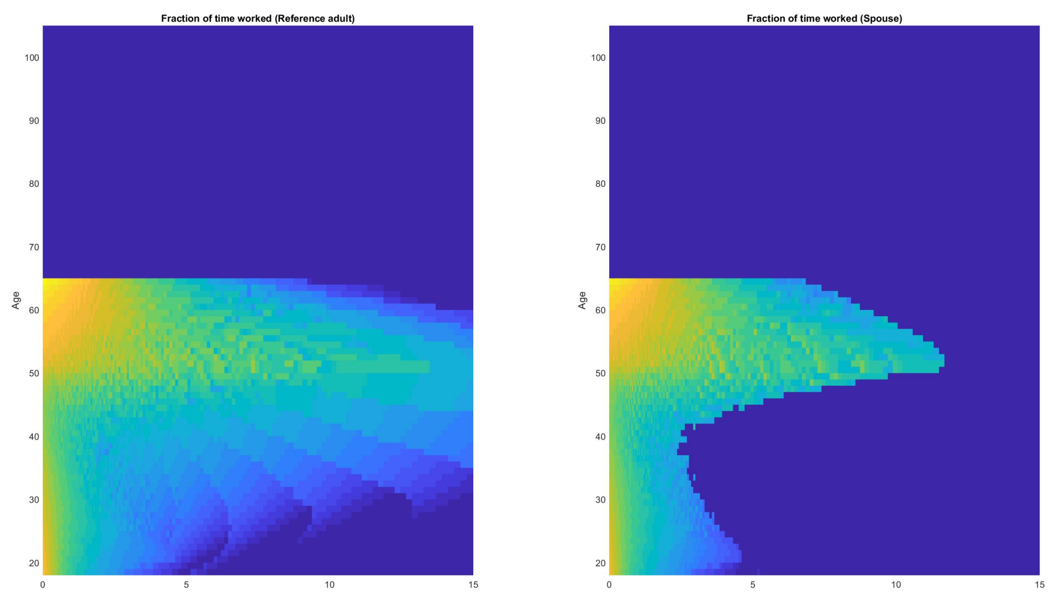

Figure 7: Couple household labour decisions (assets in £'000s; Blue: 0%; Yellow 100%)