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ABSTRACT

Business Cycle Turning Points and Local Labour Markets*

In this paper we consider the predictors of the business cycle in Great Britain, where the claimant count and unemployment rate are found to be key indicators associated with turning points. Next, we consider at a micro-economic level, using disaggregated local authority level data, a number of local labour market issues: (i) the determinants of the claimant count and unemployment rate (both highly correlated with the cycle); (ii) local level economic resilience; and (iii) the likelihood of different states of regional vulnerability. Benefit generosity, unit labour costs and state dependence (hysteresis) are key drivers of local labour market performance.

JEL Classification: E24, E32, J20, R10, R23

Keywords: business cycle dating, local labour markets, resilience, regional vulnerability

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Introduction

Understanding what drives business cycles is important not only in terms of predicting future peaks and troughs in the cycle, but also to ascertain which indicators are those most correlated with turning points, of relevance to central banks and policy-makers alike. Moreover, once such key leading pro-cyclical and/or counter-cyclical indicators have been identified, appreciating the determinants of these indicators at a micro-economic level is a fruitful avenue of research. For example, exploring such indicators may provide further insight into what drives the economic cycle. Hence, in this paper we address the following research questions (RQ). (1) What are the key macroeconomic indicators driving turning points in the growth rate of GDP? (2) What role, if any, does gender play in the business cycle? Specifically, gender in the context of the definition of labour market statistics, e.g., male or female unemployment rates etc. (3) If any labour market indicators are significantly correlated with turning points, then what are their determinants at the micro-economic level? (4) What do labour market indicators imply about regional vulnerability and resilience to economic-shocks? This is important in the context of the potential success of the UK Government mission to drive growth across regions, in order to narrow geographic disparities and improve economic living conditions (Bathelt et al., 2024), which partially relies upon building resilience to economic shocks at a local level.

The analysis commences at the macro-economic level, focusing upon RQ1 and RQ2, considering a basket of aggregate indicators that have previously been found to be associated with business cycle turning points (defined in a number of alternative ways, see below), e.g. Blackburn and Ravn (1992); Millard et al. (1997); Andreou et al. (2000). We do this in the context of the UK economy over a thirty-year period, using quarterly data from 1990 until the advent of the pandemic at the start of 2020. To pre-empt our findings, only a handful of indicators such as gross mortgage lending, and retail sales show a strong and positive association with the UK's business cycle, especially around turning points. On the other hand, several labour market indicators are found to be counter-cyclical and strongly tied to the turning points in the business cycle.

Given the role of labour market characteristics in determining turning points, we proceed to explore in detail at the micro-economic the potential factors associated with these indicators. To achieve this, we use disaggregated local authority level data, addressing RQ3, to examine the determinants of the claimant count and unemployment rate, the two key labour market indicators found to be highly correlated with business cycle turning points. We then focus on RQ4, specifically considering local level economic resilience (relative to the national cycle), following Martin (2012); and we then extend this approach to explore the likelihood of different states of regional vulnerability in a dynamic model allowing for state dependence. The micro analysis shows that benefit generosity, unit labour costs and state dependence are key drivers of local labour market performance. There are also noticeable differences across the sexes and between regions. Exploring the labour market at the local level is pertinent, given that job displacement has been found to subsequently impact upon future work and those affected are typically employed at a lower wage rate, they also often experience a permanent pay reduction across the life-cycle. Moreover, understanding the drivers of the unemployment rate and the claimant count from a micro-economic perspective will help to shed light on what factors one might be able to influence through policy which could have knock-on effects at the aggregate level.

The structure of the paper is as follows: Section 1 focuses upon the definition of turning points in the business cycle, and which macro indicators are associated with peaks/troughs, either pro-cyclically or counter-cyclically; whilst in Section 2 we consider the determinants of the labour market indicators found to be associated with turning points; the final section of the paper offers a summary and discusses implications of the analysis.

1. Macro-economic analysis of turning points in the business cycle

The analysis focuses upon the UK business cycle using quarterly data from 1990Q1 through to 2020Q1, where the end point is selected to avoid any distortion due to the Covid-19 pandemic. We start by defining turning points from the growth in GDP. The identification of turning points in the business cycle is crucial for assessing the probability of future recessions, e.g., Estrella and Mishkin (1998), as well as quantitatively forecasting point estimates of economic activity. It is imperative to examine the association of indicators not only around the entire business cycle but also around the peaks and troughs in the business cycle. Economic indicators that show a strong association with these turning points provide valuable insights into the state of the economy and can inform decision-making.

Various methods have been used to define business cycle peaks and troughs. In the analysis which follows we adopt four approaches: (a) the European Cycle Research Institute (ECRI) dates classical turning points for various countries and has been previously used in the context of the UK e.g., by Sensier et al. (2004) and Taylor and McNabb (2008); (b) similarly, the OECD also provides classical dating of turning points in the business cycle for numerous countries based upon its Composite Leading Indicator approach, where business cycles and turning points are measured and identified in the deviation-from-trend series using GDP; (c) turning points based upon identifying local maxima and minima, with no back-to-back maxima/minima and at least a one quarter gap between a maxima and a minima; and (d) business cycle turning points following Hamilton (2018). The latter approach is based upon identifying the local peaks and troughs using the first and fourth quartiles of the residuals from an OLS regression of GDP growth at some future period (h), g_{t+h}, (t denotes time), conditioned against its lagged values over four periods. Local turning points are identified by parsing out local maxima (+1) and local minima (-1) and applying censor rules to guarantee alternating peaks and troughs. The economy can be in either of two mutually exclusive phases of the cycle, i.e., an up-cycle or a down-cycle.

Figure 1 shows GDP growth, i.e., the business cycle, and the associated turning points based upon (a)-(d). The identification of turning points in the business cycle is crucial for businesses and policymakers to make informed decisions. A consensus emerges from Figure 1 concerning the turning points (based upon alternative definitions a-d), for example trough years are 2008-10 (the financial crash) and 2019/20 (start of the pandemic), whilst peaks in economic growth occur during the mid-1990s, 2003/04 and in 2010.

Next, we explore the relationship between business cycle turning points, as given in Figure 1, and leading pro/counter cyclical indicators. We aim to include indicators that capture the movements in economic activity. Such exercises commonly rely on a set of indicators, with their roots traceable to Burns and Mitchell (1946), which propelled the study of business cycles and eventually led to the creation of a composite index of coincident indicators (Stock and Watson, 1999). We look at the availability of data over the period and shortlist around forty indicators for the UK economy. These indicators represent all major sectors in the economy, such as industry and construction, personal income and consumption, employment, services, external sector, prices, credit and finance, and miscellaneous economic activity.[1]

To ascertain the predictors of turning points we consider the correlation coefficients between the growth in economic activity, g, and each of the $j = 1,2,\dots,J$ potential predictors of turning points over time (x_j), i.e. $\rho_j = \sigma_{gx_j}/\left(\sigma_g \sigma_{x_j}\right)$. Table 1 shows the correlation coefficients, ρ_j, for each relevant indicator around turning points in GDP where those numbers highlighted in red indicate statistical significance at the 5 per-cent level. A negative (positive) correlation denotes a counter-cyclical (pro-cyclical) association with the business cycle. It is noticeable that only a handful of indicators such as gross mortgage lending, production indices

[1] Table A1 in the appendix reports the indicators and the sectors that they represent in the economy.

and retail sales show a strong association with the business cycle. On the other hand, a number of indicators focusing on the UK labour market such as the claimant count rate, both male and female, unemployment rate,[2] are amongst the highest correlates in terms of absolute magnitude being closely tied to the business cycle turning points.[3] Indeed, typically these labour market indicators have the largest counter-cyclical association with the cycle (as shown in bold and underlined in Table 1).[4] Moreover, the role of the labour market in predicting turning points is generally consistent across the alternative definitions of the peaks and troughs in the business cycle, as can be seen across the columns in Table 1 where the shaded cells show the key labour market indicators. Both the unemployment rate and claimant count indicators are also found to be counter-cyclical as revealed by the negative correlation coefficients, hence, turning points in output typically precede those in unemployment perhaps reflecting firm uncertainty over downturns in demand and the desire to hoard skilled labour.

The role of the UK labour market as being a lead predictor for turning points in the business cycle is both an interesting and important finding, particularly the role of gender in the business cycle. As such, in the following section we explore what factors are capable of explaining those labour market metrics found to be of statistical significance, at a micro-economic level. Again, this is policy relevant as access to high level skill, high wage and secure employment is a means to reduce income inequalities across geographical space and between people, having a positive impact on mental and physical health. To date the literature is relatively sparse on the dynamics

[2] Peiró et al. (2012) have argued that several issues may obscure the relationship between output and unemployment. Hence, we also investigate the association between output and the claimant count around turning points, considering both the total count as well as considering gender specific definitions. This is potentially important given that the labour supply curve is typically more elastic among women which may explain existing differences in unemployment across the business cycle (Killingsworth, 1983, Blundell and MaCurdy, 1999).

[3] It is interesting to note that other aspects of the labour market have either smaller, or statistically insignificant, associations with turning points. For example, inactivity rates and employment rates (see Table 1).

[4] Adopting a LASSO approach or a forward-step regression, to consider the relationship between the business cycle and leading indicators, also reveal the importance of the claimant count and unemployment rates in predicting turning points.

of unemployment and/or the claimant count at a micro-level and the existences of differences by gender.

2. Micro analysis of the local labour market, economic resilience, and vulnerability

Having adopted a variety of techniques to identify key macro indicators associated with turning points in the nation's GDP growth rate, our analysis found that labour market indicators in particular the unemployment rate and the claimant count were highly correlated with turning points in GDP growth.[5] This finding is evident across the gender specific definitions. The unemployment rate is based upon the ILO definition, whilst the claimant count is based upon those individuals in the population claiming unemployment-related benefits at a given point in time. However, over time and across local authority districts (LADs) the two measures are highly correlated in both the level and change (i.e., first difference) as shown in Figures 2A and 2B respectively, and statistically significant. In this section we explore the determinants of the claimant count and the unemployment rate, local area economic resilience, and the probability of regional vulnerability, at the micro level using longitudinal data over time at the LAD level.[6] In Great Britain (GB) there are of 378 local authority districts (LAD).[7] We create an unbalanced panel in Great Britain over the period 2004 to 2019, hence incorporating different points in the business cycle including the Great Financial Crisis and Brexit (see

[5] There is a long debate over the use of the claimant count and the ILO definition of unemployment, e.g., Gregg (1994) and Bartholomew et al. (1995). Moreover, Iammarino et al. (2019) argue that unemployment rates should be interpreted with caution especially when considering regional inequalities.

[6] LADs have been chosen as the geographical level of analysis due to both the data availability of variables used in the empirical analysis, but more importantly because they are the lowest administrative level in which policies can be implemented both for the mitigation of economic crisis effects and also for preparing for the recovery from recessionary impacts. Based upon population density figures, i.e. the number of people per square kilometre, in 2019 the smallest LAD was South Somerset, conversely, the largest LAD was County Durham (source: https://www.ons.gov.uk/peoplepopulationandcommunity/populationandmigration/populationestimates/datasets/populationestimatesforukenglandandwalesscotlandandnorthernireland).

[7] Note that this part of the empirical analysis focuses upon Great Britain, excluding Northern Ireland due to reasons of data availability over the period.

previous section and Figure 1).[8, 9] In what follows we firstly model both the claimant count and the unemployment rate, then consider local area resilience following the approach of Martin (2012), and finally extend this approach by exploring the likelihood of different states of regional vulnerability (whilst allowing for state dependence).[10]

2.1 Modelling the unemployment rate and the claimant count

Understanding job displacement is important as workers who lose their jobs and experience a spell of unemployment have been found to subsequently work at a lower wage rate and also often suffer a permanent pay reduction, e.g., see Nickell et al. (2002), Gregg and Tominey (2005) and De Fraja et al. (2021).[11] To understand joblessness across localities and time we employ a system GMM approach (Arellano and Bover, 1995; Blundell and Bond, 1998), to model the claimant count (CC_{it}) and the unemployment rate (UE_{it}) across LADs ($i = 1,2, \ldots, n$) and time ($t = 1,2, .., T$). Defining y_{it} to denote either the claimant count or the unemployment rate, two key correlates of turning points in the business cycle (see Section 1), the empirical model is as follows:

$$y_{it} = \phi y_{it-1} + \boldsymbol{\pi}'\boldsymbol{X}_{it} + \lambda_t + \alpha_i + \epsilon_{it} \quad (1)$$

Our empirical specification follows Taylor and Bradley (1997) and Lee (2014), where the matrix of covariates $\boldsymbol{X}_{it}$ includes: the replacement ratio (equal to the ratio of the LAD average benefit payment to the average wage), which measures benefit generosity where higher benefits

[8] As in the macro-analysis, we exclude the period of the recent pandemic, 2020 onwards, for two reasons. Firstly, data availability for the covariates used in the analysis (see below); and secondly, recently, Brewer et al. (2020) concluded that neither the claimant count nor the ILO unemployment rate are reliable indicators to the true level of unemployment during the recent Covid-19 pandemic.

[9] Both the unemployment rate and the claimant count show substantial variation around their respective means of 5.7% and 3,030. The minimum and maximum values for the unemployment rate (claimant count) are 1% and 21.6% (5 and 52,135) respectively. The highest unemployment rate (claimant count) was in Thanet in the South-East in 2011 (Birmingham in the West Midlands in 2012). Moreover, the variation around the mean has fallen over time for both labour market metrics.

[10] Note that in the results which follow sample sizes differ depending upon whether the claimant count or the unemployment rate is adopted. This is due to several different reasons, e.g.: (i) for some LADs figures are suppressed as they are statistically unreliable; (ii) the LAD estimate is based upon a small number of observations and hence could be disclosive; or (iii) figures are simply missing.

[11] For the effects of job loss in other countries see, e.g.: Bell and Blanchflower (2011); Eliason and Storrie (2010); Genda et al. (2010), and; Mroz and Savage (2006).

may reduce labour supply;[12] jobs density in the LAD which is defined as the number of jobs per resident aged 16-64;[13] unit labour costs (ULCs) measured by the ratio of the LAD specific average wage to gross value added (GVA), where higher worker costs are likely to reduce the demand for labour; the proportion of the working age population in the LAD with NVQ4 or above educational attainment;[14] the proportion of the working age population in the LAD with no qualifications; sector specific productivity is defined as LAD specific industrial sector GVA as a proportion of the working age population; and the natural logarithm of gross disposable income per capita in the LAD, where more prosperous areas are likely to have a lower claimant count and unemployment rate.[15] LAD and time fixed effects are denoted by α_i and λ_t respectively.[16, 17]

All covariates are treated as endogenous and appear with one lag, using an additional lag as an instrument. The results are shown in Tables 2A and 2B for the claimant count and unemployment respectively. There are three columns, for the full sample and then split by gender – where the claimant count and unemployment rate in equation (1) is gender specific as are the replacement ratio and unit labour costs. For each measure of labour market activity and across samples the Sargan test that the over-identifying restrictions are valid cannot be rejected

[12] Although benefit rates are set a national level, regional wages vary substantially (and across the sexes), and hence in lower-wage local authorities disability benefits are relatively more attractive. As such there is large spatial variability in the replacement ratio, see Roberts and Taylor (2022). Consequently, the relative attractiveness of disability benefits at a local level may partially explain geographic variation in the claimant count. Milligan and Schirle (2019) refer to the 'push' of weak labour markets and the 'pull' of more generous benefits.
[13] For example, a job density of 1.0 would mean that there is one job for every resident of working age.
[14] It should be noted that the regulatory framework supporting NVQs was withdrawn in 2015 and replaced by the Regulated Qualifications Framework (RQF). Similar to NVQs, the RQF is comprised of eight levels. However, RQFs differ from NVQs because they are supported by multiple entry levels (this is because it is not possible to assign all these qualifications to a single level). For brevity, in what follows we refer to NVQ levels for reasons of consistency and also because the data was obtained for NVQ levels rather than RQFs.
[15] Long run effects for the x_k covariate can also be calculated in this framework as $\pi_k/(1-\phi)$, see below.
[16] When considering the claimant count, we convert the dependent variable into natural logarithmic format.
[17] Time controls are pertinent in the context of gender decomposition in the claimant count and unemployment rate. For example, Razzu and Singleton (2016) show that during economic recessions, the male unemployment rate increases at a swifter rate compared to females, leading to a reduction in the gender employment gap. Conversely, during the recovery phase the male unemployment rate declines at a faster pace.

at conventional levels of statistical significance, and higher-order lags of the error terms are serially uncorrelated, as desired.

There is clear evidence of state dependence in both the claimant count (Table 2A) and the unemployment rate (Table 2B), this result also holds when split by gender. The overall effect of the lagged claimant count in GB is much larger than that found by Lee (2014), whilst conversely the lagged unemployment rate in GB is marginally smaller. Labour market dynamics are clearly important for both the local area claimant count and the unemployment rate. In terms of unemployment dynamics for the UK and for a set of European countries Smith (2011) and Petrongolo and Pissarides (2008), respectively, found that the inflow rate (i.e., separation from employment) explains a substantial part of the unemployment dynamics over time. The finding of a dynamic process in modelling the unemployment rate is consistent with the persistence of unemployment leading to a higher natural rate of unemployment, similar to the hysteresis effect in the unemployment literature (Blanchard and Summers, 1992). A higher long-term unemployment rate may not only discourage further job search as individuals become disillusioned about finding employment, e.g. Bean et al. (1986), and "*The long-term unemployed have largely given up hope*" (Layard, 1986, p.96), but in addition those geographical areas which persist in states of high unemployment can develop a jobless culture, e.g. Layard and Nickell (1986). Moreover, Arulampalam (2001) found that joblessness can leave permanent scars and increases the risk of future unemployment. Interestingly, for unemployment (Table 2B) the estimate of the autoregressive process is far larger for males than females, this is consistent with the findings of Arulampalam et al. (2000); whilst for the claimant count (Table 2A) the female elasticity on the lagged dependent variable is marginally larger than that found for males.[18]

[18] This may reflect the different gender mix in the proportion of claimants and how the composition has changed over time, see: https://www.gov.uk/government/publications/universal-credit-statistics-background-information-and-methodology/universal-credit-statistics-background-information-and-methodology.

A higher replacement ratio is associated with both a higher claimant count (Table 2A) and a higher unemployment rate (Table 2B), consistent with theory, and the former is much larger for males than females (although it is statistically insignificant in explaining the male local area ILO unemployment rate) – perhaps reflecting lower attachment to the labour market due to women's dual labour market and domestic roles, e.g., Roberts and Taylor (2022). Interestingly, the more jobs there are per resident of the working age population in a LAD the lower claimant count and the unemployment rate (see Tables 2A and 2B, respectively), although there are some differences between the economy overall and gender specific definitions. This result is at odds with the findings of Taylor and Bradley (1997) but consistent with *a priori* theoretical expectations. Moreover, Smith (2011) shows that the job finding rate has an influential effect on UK unemployment dynamics. Overall, this suggests that job creation could help to limit negative labour market shocks, although raising the Beveridge Curve may push down job creation by simultaneously harming productivity.[19]

Higher unit labour costs drive up the claimant count, i.e., a one percent increase in ULCs results in 1.7% (3.1%) more individuals claiming benefits on average in the short-run (long-run), see Table 2A. Similarly, a one percent in labour costs results in a 0.25% (0.44%) higher unemployment rate (Table 2B). These findings are consistent with the analysis of Taylor and Bradley (1997), and for the claimant count the effect is much larger for females than males.

In terms of educational attainment, in line with the findings of Lee (2014) areas having a higher proportion of people with no qualifications, where statistically significant, is associated with both a higher claimant count and higher unemployment rate, whilst conversely NVQ4 or above qualifications are associated with both a lower claimant count and unemployment rate (see Tables 2A and 2B). LADs with higher disposable income per head are found to have a

[19] There is evidence on both sides of the Atlantic of recent upward shifts in the Beveridge curve, see ONS (2022) for the UK and Barlevy et al. (2024) for the US, implying inefficiency in matching unemployed workers to job vacancies.

lower claimant count, i.e., a 1% increase in disposable income is associated with a fall in the number of claimants by 0.89% (1.67%) in the short-run (long-run), Table 2A, but the estimated magnitudes are income inelastic. Similarly, higher disposable income is also associated with a lower unemployment rate, where a 1% increase in disposable income decreases unemployment by 0.11% (0.18%) in the short-run hence income inelastic, Table 2B.

Whilst the results of the analysis of the determinants of the local area claimant count and the unemployment rate in GB are generally consistent, there are some differences in the impact of sectoral specific productivity effects. Over the period higher productivity in manufacturing and construction reduces both the claimant count and the unemployment rate (Tables 2A and 2B) at the national level and across the sexes. Interestingly, productivity in construction is found to have a much larger impact than that of manufacturing, e.g., a 1 per cent increase in productivity in each sector reduces the male claimant count by 0.98% and 0.22% respectively, (see Table 2A). The same sectoral productivity differential is also found for the unemployment rate, although the disparity is not as pronounced, see Table 2B.

Productivity in the distribution sector has differing effects on the claimant count and unemployment, increasing the number of male claimants (with no effect on the male unemployment rate, Table 2B), whilst decreasing the number of female claimants and the female unemployment rate. This perhaps reflects the different allocation of the sexes across sectors. Noticeably, the largest productivity elasticities are for the public sector where higher productivity increases the claimant count of females, with a 1 per cent increase in productivity associated with 2% higher claims (Table 2A). Similar effects are also found for the unemployment rate (Table 2B). This may be because regions with a poor economic performance are more likely to depend on the public sector for employment. Moreover, productivity in the financial sector is found to have a positive impact on both the claimant count (Table 2A) and the unemployment rate (Table 2B), and for the latter is larger in economic magnitude for females. This finding may stem from the fact that the recession following the financial crash of 2008 was founded in the financial services sector, and hence the labour market impact was likely to be largest in those local areas which were most specialized in those industries.

Next, we show the contrast in the point estimates for each covariate differentiating between the 'North' and 'South' of England, where Figures 3A and 3B provide the analysis for the determinants of the claimant count and the unemployment rate respectively.[20] Considering the claimant count, Figure 3A, benefit generosity has a slightly larger effect in Northern English regions.[21] Moreover, the number of jobs per resident and education attainment also had a larger effect on the claimant count in Northern regions. The largest positive differential to influence the claimant count is productivity in the financial sector, consistent with the analysis shown of Table 2A. Potentially reflecting industrial concentration and historical composition, productivity in the manufacturing sector is the only covariate to have a negative impact on the claimant count in Northern regions.[22] Turning to the unemployment rate, Figure 3B reveals that greater benefit generosity has a larger impact on the unemployment rate in the North, consistent with the findings for the claimant count (Figure 3A), as does educational attainment and productivity in the construction sector. Beatty and Fothergill (2005) show that the number of people claiming incapacity benefits was greater in the old industrial areas, typically the North, where regions were characterized by higher unemployment rates. Overall, evidence exists of clear spatial disparity between the North and South of England in the determinants of both the claimant count and the unemployment rate, especially the effect of the replacement

[20] Northern regions are defined as: North-East; North-West; Yorkshire & Humber; East Midlands and West Midlands. Southern regions are defined as: East of England; London; South-East and South-West. Scotland and Wales are dropped from this analysis.
[21] Figures 3A and 3B are constructed by interacting each of the continuous covariates in equation (1) with a binary indicator for whether the LAD is in the North of England. The GMM regressions underlying the figures pass standard over-identification and higher-order autocorrelation tests.
[22] It should be noted that structural change, that is the reallocation of labour across different industrial sectors in the economy, has been slowing down in recent years. In addition to this the rate at which workers move between jobs and sectors has also slowed down (Cominetti et al., 2021).

ratio. Addressing regional disparities and the factors determining these discrepancies is arguably fundamental to boosting productivity and prosperity throughout the economy.

The above analysis has shown that both the claimant count and unemployment rate are dynamic processes and revealed the importance of benefits, labour costs, local area skills (as proxied by educational attainment) and sector specific productivity. There are also clear differences across gender specific definitions of labour market metrics, and between Northern and Southern regions of the economy, in terms of statistical significance and economic magnitude of the covariates, and impacts differ between the short-run and long-run. Having considered the determinants of the claimant count and the unemployment rate, we now turn to look at local area resilience in LADs over time compared to the GB economy.

2.2 Modelling local area economic resilience

Several papers in the literature have examined regional economic resilience, e.g., Martin (2012), Fingleton et al. (2012) and Sensier and Artis (2014). We compute a resilience index, β_{it}, based upon the indicators which were found to be key determinants of business cycle peaks and troughs – namely the claimant count and the unemployment rate (see Section 1). The resilience index, β_{it}, gauges the proportional change in claimant count (or the unemployment rate) in a LAD (i) over time (t), Δy_{it}, compared with national change (GB), Δy_t, as follows:

$$\beta_{it} = \frac{(\Delta y_{it}/y_{it})}{(\Delta y_t/y_t)} \tag{2}$$

Where, $\beta > 1$ this indicates that a LAD is less resilient than the economy (GB) as a whole, i.e. the proportional change in the regional claimant count (unemployment rate) is greater than the nation and so is likely to be more sensitive to exogenous shocks. Conversely, if the above index has a ratio of less than unity then the LAD has a high (relative to GB) resistance (low sensitivity) to recessionary shocks. Hence, at a micro-level this reveals how regions fair according to different phases of the economic business cycle (linking back to our initial macro level analysis). The metric in equation (2) follows a similar definition to Martin (2012), Fingleton et al. (2012) and Sensier and Artis (2014). However, previous analysis was at a higher level of regional aggregation, based upon employment figures where the focus was upon a subset of years when the economy was in recession. In the following, we analyse the resilience index over the entire period 2004-2019 covering a number of peaks and troughs in the business cycle (see Figure 1). This is important as regional resilience to recession can vary and change over time, due to differences in the causes and nature of individual recessionary shocks but also because the factors and mechanisms that shape economic resilience may themselves evolve and change. The index in equation (2) when defined by the claimant count (unemployment rate) has a mean of 1.14 (1.32).

We model the natural logarithm of economic resilience (equation 3) conditional on the covariates, $\boldsymbol{X}_{it} = (x_{1it}, x_{2it}, \cdots, x_{kit})$, as defined above, using a two-way fixed effects specification explicitly incorporating LAD and time fixed effects, hence allowing for unobserved local area heterogeneity and common macro-shocks. The model also incorporates interaction effects between the key covariates and aggregate geographic identifiers, denoted by r,[23] in GB which allows us to obtain regional specific effects:

$$\log(\beta_{it}) = \pi_0 + \sum_{k=1}^{K} \pi_k x_{kit} + \sum_{k}^{K} \sum_{j=1}^{9} \phi_{kr}(x_{kit} \times r_j) + \lambda_t + \alpha_i + \epsilon_{it} \qquad (3)$$

The resilience index is defined by the claimant count and unemployment, where the results of the analysis are shown in Tables 3A and 3B respectively, and also show differences by gender specific definitions of variables, where equation (3) is estimated without the interaction term so: $\phi_r = 0$. In Figures 4A and 4B we plot the point estimates for the parameters of interest across each aggregate geographical region (r) of GB for the claimant count and unemployment rate definition of the resilience index respectively, where the estimate for the k^{th} covariate in a given region r is given by: $\{\pi_k + \phi_{kr}\}$.

[23] The Government Offices for the Regions (GORs) were established in 1994 and they are the highest tier of sub-national division. In England there are nine such regions.

Across both definitions of β, i.e., based upon either the claimant count or unemployment, shown in Tables 3A and 3B respectively, a positive (negative) estimate of π_k denotes the LAD being less (more) resilient than the economy overall. As benefit generosity increases and/or unit labour costs become higher local area resilience is reduced, i.e., the value of the 'sensitivity index' increases reducing resistance to economic shocks. The effect of the replacement ratio is also apparent across the sexes. Having a skilled local economy is seen to increase resilience as evidenced from higher qualification attainment, where statistically significant, whereas conversely those LADs with a higher proportion of individuals in the working age population with no qualifications have less resilience. Interestingly, higher disposable income is also associated with lower levels of economic resilience, i.e., regions becoming more susceptible to economic shocks. This might reflect the fact that regions which are better off, e.g., London, may also have high levels of income inequality (see Agrawal and Phillips, 2020). The only statistically significant productivity effects stem from the construction sector increasing economic resilience, but only when economic resilience is defined by the male unemployment rate.

Considering regional heterogeneity and defining the resilience index from the claimant count, Figure 4A shows that greater benefit generosity (higher unit labour costs) reduces (increases) economic resilience in the North-West. Focusing upon the resilience index defined by unemployment, see Figure 4B, higher unit labour costs across all regions, with the exception of Yorkshire and the Humber, show that these areas are less resilient than GB (as implied by the positive estimates, i.e., $\{\widehat{\pi_k + \phi_{kr}}\} > 0$). This is most noticeable for the North-East, North-West and the East Midlands, where a 1 per cent increase in unit labour costs results in these regions being around 1% less resilient. Higher educational attainment (NVQ4 or above) increases economic resilience in the North-East and West Midlands, see Figure 4A, showing the importance of skill acquisition in alleviating area exposure to shocks.

From the above analysis, it would appear, that labour costs and benefit generosity are the two key metrics which influence LAD resilience in terms of the economic magnitude and statistical significance of the estimates. Ultimately, building local economic resilience may be key to an enduring revival in GB's productivity and help shield regional economies from negative macro events as well as local area adverse shocks.

2.3 A taxonomy of the probability of different states of vulnerability – balanced panel

Next, we model the probability of a LAD being in a given state of vulnerability, whereby we define an ordered index, $s_{it} = 1,\ldots,4$, based upon the taxonomy shown in Figure 5, where the states of vulnerability are constructed from the claimant count and the unemployment rate respectively. Clearly, based upon either definition the most prevalent case is that of severe vulnerability. The advantage of this approach is that we explicitly account for state dependence. This is estimated in a dynamic binary framework using a correlated random effects (CRE) approach with the incorporation of a lagged dependent variable (see Wooldridge 2005, 2010):

$$\text{prob}(s_{it} > q|\mu, s_{it-1}, \boldsymbol{X}_{it}, \lambda_t, \alpha_i) = \Phi\left(\gamma s_{it-1} + \boldsymbol{\pi}'\boldsymbol{X}_{it} + \lambda_t + \alpha_i - \mu_q\right) \quad (4)$$

for $i = 1,2, \ldots, n$ panels (i.e., LADs), where $t = 1,2,.., n_i$, α_i are independent and identically distributed $N(0, \sigma_\alpha^2)$, and μ is a set of threshold parameters (where with four outcomes, see Figure 5, there are three cut-points: $\mu_1, \mu_2 \mu_3$). The standard normal cumulative distribution function is denoted by $\Phi(\cdot)$. Local area (LAD) and time fixed effects are given by α_i and λ_t, respectively. The probability of observing outcome q for the vulnerability index s_{it}, i.e., $\text{prob}(s_{it} = q|\mu, s_{it-1}, \boldsymbol{X}_{it}, \lambda_t, \alpha_i)$, is given as:

$$\Phi\left(\mu_q - \gamma s_{it-1} - \boldsymbol{\pi}'\boldsymbol{X}_{it} - \lambda_t - \alpha_i\right) - \Phi\left(\mu_{q-1} - \gamma s_{it-1} - \boldsymbol{\pi}'\boldsymbol{X}_{it} - \lambda_t - \alpha_i\right) \quad (5)$$

where μ_0 is $-\infty$ and μ_q is $+\infty$. Given the model in equation (4) is dynamic, the estimator has to be based upon a balanced panel of LADs, $i = 1, \ldots, 168\ (151)$,[24] over the period, $t =$

[24] There are 168 LADs when the vulnerability index s_{it} is defined by the claimant count, and 151 when defined by the unemployment rate.

$2005, \ldots 2019$. Equation (4) is estimated as a random effects dynamic ordered probit model, where the correlation between the LAD fixed effect α_i and the lagged dependent variable s_{it-1} yields an endogeneity problem that will result in inconsistent estimates.

We follow Wooldridge (2005) and specify the fixed effect in equation (4) conditional on the initial state of vulnerability s_{i0}, that is, when first observed in the panel, and the group means of individual-level time-varying covariates, $\overline{\boldsymbol{X}}_i$, i.e., Mundlak (1978) fixed effects, as shown in equation (6).

$$\alpha_i = \alpha_0 + \alpha_1 s_{i0} + \boldsymbol{\psi}'\overline{\boldsymbol{X}}_i + v_i \tag{6}$$

Substitution of equation (6) into equation (4) yields an augmented CRE model where the parameters, $\boldsymbol{\pi}$, will approximate those of a fixed effects estimator. v_i denotes a random error term. State dependence in terms of the statistical significance of s_{it-1} and the magnitude of γ is investigated by estimating equations (4) and (6), where unobserved LAD heterogeneity is also considered. The results of this analysis are shown in Tables 4A and 4B, where the vulnerability index is defined from the claimant count and the unemployment rate respectively.

The four columns in Tables 4A and 4B give the order of magnitude of the (conditional) correlation stemming from each covariate on the level of vulnerability, ranked from the highest (outcome category 1) to the lowest (category 4). The two extreme categories denote "*severe*" and "*no*" vulnerability respectively. Each of the threshold parameter estimates in Tables 4A and 4B, i.e., $\hat{\mu}_1, \ldots, \hat{\mu}_3$, are found to be statistically significant thus endorsing the ordered modelling approach. Noticeably, where the covariates ($\boldsymbol{X}_{it}$) are found to be statistically significant there is clear evidence of monotonicity in the order of magnitude of the effects found across the states of vulnerability (see Tables 4A and 4B).

For example, a 1 per cent increase in unit labour costs is associated with a 1.3 (0.4) percentage point higher probability of a LAD exhibiting a state of severe vulnerability; and a 1.7 (0.9) percentage point lower probability of a LAD having no vulnerability, Table 4A (4B).

Consistent with *a priori* expectations a higher replacement ratio increases the likelihood that a LAD is in a state of severe vulnerability, and the effect dissipates and changes sign at the other extreme of the vulnerability index, this is evident from both definitions of the vulnerability index (see Tables 4A and 4B). A higher number of jobs per resident of working age within a LAD is found to decrease (increase) the probability of severe (no) vulnerability by 0.6 (0.8) percentage points. However, this effect is only evident when the vulnerability index is based upon the claimant count – Table 4A, no statistically significant estimates are found in Table 4B.

Those LADs with more highly skilled individuals, proxied by the proportion of the population who have obtained an NVQ level 4 or above, are found to be more resilient than the GB average, with negative and positive educational effects at the two extremes of vulnerability (severe and no vulnerability) respectively. This concurs with the analysis of Lee (2014) and Kitsos and Bishop (2018), implying that regions with higher levels of human capital may have been more able to mitigate recessionary effects due to the attributes associated with transferable knowledge and skills. However, the educational effects are only evident when the vulnerability index is based upon the claimant count, Table 4A, no effects are found from the unemployment rate based definition of the states of vulnerability (see Table 4B).

Interestingly, no effect is found from disposable income per head in Table 4A, but when the vulnerability index is based upon the unemployment rate a 1% increase in the regional standard of living decreases (increases) the probability of severe (no) vulnerability by 1.1 (1.4) percentage points. Generally, there are no significant effects from sectoral productivity contrary to the analysis of the claimant count (see Table 2A), consistent with the analysis of modelling the resilience index. The exception to this latter finding is LAD productivity in the financial sector, where higher GVA per head is found to increase (decrease) the probability of severe (no) vulnerability, albeit at the 10 percent level of statistical significance (see Table 4A).

The lack of sectoral effects on economic vulnerability is generally consistent with the findings of Kitsos and Bishop (2018).

Although the results reported are conditional correlations, not causal estimates *per se*, they are effects over and above that stemming from the LADs' previous state of vulnerability as we explicitly condition the probability of the current state of vulnerability on that in the previous year (see equation 4). The first three rows of Tables 4A and 4B report the effects of state dependence on the probability of the current vulnerability threshold (i.e., at time t), where the omitted category is severe vulnerability in the previous year ($t-1$). As found when modelling the claimant count and the unemployment rate (see Tables 2A and 2B) there is clear evidence of state dependence, s_{it-1}, and the effects, $\hat{\gamma}$, are relatively large. For example, based upon the claimant count definition of the vulnerability index – Table 4A, on average if a LAD exhibited no vulnerability in the previous period, then the probability of currently being in a state of severe (no) vulnerability decreases (increases) by 15 (19) percentage points, relative to a lagged state of severe vulnerability. The effects from a previous state of low vulnerability have similar effects in terms of sign and economic magnitude, although the latter are marginally larger at the two extremes of vulnerability compared to that found from lagged "*no*" vulnerability. No effects are found from a previous state of moderate vulnerability. Similar findings are revealed based upon the alternative definition of the states of regional vulnerability, as shown in Table 4B. However, the magnitudes of the lagged state of vulnerability are noticeably larger and in contrast to where vulnerability was defined by the claimant count are also statistically significant for a prior state of moderate vulnerability.

2.4 The probability of a severe state of vulnerability – unbalanced panel

A potential issue with the analysis of section 2.3, is that a requirement of the CRE dynamic ordered probit model is that it is estimated on a balanced panel, and hence data points and information are lost as the sample size becomes noticeably reduced. Moreover, a selection issue is also introduced where the resulting sample may be biased if those LADs in the panel for the entire duration are non-random. In the final part of our analysis, we estimate a CRE dynamic binary probit model considering the likelihood that the LAD is in a severe state of vulnerability. We do this by adopting the recent approach of Albarran et al. (2019) which is an estimator specifically for unbalanced data (i.e., no observations are lost):

$$s_{it} = \mathbf{1}(\gamma s_{it-1} + \boldsymbol{\pi}'\boldsymbol{X}_{it} + \alpha_i + \lambda_t + \epsilon_{it} \geq 0) \quad (7)$$

Where $s_{it} \in (0,1)$ and is equal to unity if the LAD is in the top left quadrant of Figure 5, i.e., in a "*severe*" state of vulnerability, and zero otherwise. We briefly explain how to estimate the dynamic nonlinear panel data model in equation (7) in the Appendix.

The results are shown in Table 5, where in columns 1 and 2 severe vulnerability is defined by the claimant count, whilst in columns 3 and 4 it is defined by the unemployment rate. Columns (1) and (3) are based upon estimating equation (4) on a balanced panel ($NT = 2{,}158$) using the Wooldridge approach described above, and columns (2) and (4) on unbalanced longitudinal data ($NT = 4{,}121$) employing the Albarran et al. (2019) estimator. The analysis reveals positive state dependence across both balanced and unbalanced panels, and across the claimant count and unemployment rate definitions of vulnerability, hence the results are consistent with that of the dynamic ordered probit models. For example, based upon the Albarran et al. (2019) estimator, a LAD which was in a severe state of vulnerability at $t - 1$ has between an 18 and 13 percentage point higher probability of currently experiencing severe vulnerability. Greater benefit generosity (i.e., the replacement ratio) and higher unit labour costs increase the probability of the LAD currently being in a severe state of vulnerability. The noticeable difference compared to the analysis of Tables 4A and 4B is that productivity effects are statistically significant in the unbalanced samples, where higher sectoral productivity decreases the probability of being in a severe state of vulnerability (where statistically significant). The productivity impacts are most apparent for the distribution, construction and financial sectors; where a 1 per cent increase in sector specific GVA per capita is associated with a decrease in the likelihood of a LAD being in a severe state of vulnerability by 5, 11 and 2 percentage points respectively (see column 4). Interestingly, there are no productivity effects from the manufacturing sector which likely reflects the changes in industrial composition in the economy since the 1980s with a move away from traditional industries towards services and finance.

Next, explore broad regional heterogeneity by showing the contrast in the point estimates differentiating between the 'North' and 'South' of England (as defined above), where Figures 6A and 6B provide the analysis for the determinants of the probability of severe vulnerably using the Albarran et al. (2019) estimator based upon the claimant count and unemployment definitions respectively. Clearly, higher income and sectoral productivity (more noticeable in Figure 6A) lead to a lower probability of the North of England experiencing a state of severe vulnerability (relative to the South of England). State dependence is more severe in northern locations, whilst greater benefit generosity and higher labour costs increase the likelihood of severe vulnerability in Northern economies relative to those in the South. Skills are also important in explaining differentials in severe vulnerability across regions.

3. Conclusion

Our analysis has considered key drivers of turning points in the business cycle over the last three decades. We selected key macroeconomic indicators from a broad set typically used in the literature to identify turning points in the GDP growth rate, where the analysis revealed that the claimant count and unemployment rate are both highly correlated with turning points in the economic cycle, a finding that is generally evident for gender specific definitions of the aforementioned labour market metrics. Next, the analysis moved to the microeconomic level to consider the determinants of these key labour market indicators across both male and female definitions. This part of the research utilised local authority district (LAD) level data covering

378 local authority districts over the period 2004 to 2019, hence incorporating different points in the business cycle. The results showed that benefit generosity, unit labour costs and state dependence, i.e., there is clear evidence of hysteresis, are key drivers of local labour market performance.[25] There are also noticeable differences by gender and evidence of broad regional heterogeneity, where to date the literature is relatively sparse on the dynamics of unemployment and/or the claimant count at the micro-level and the existences of differences across the sexes. Our analysis also considered local area economic resilience and regional vulnerability based upon defining these concepts from the above labour market metrics which were found to predict business cycle turning points. This revealed novel evidence across aggregate regions again revealing the importance of hysteresis, benefit generosity, skills (i.e., educational attainment), and in some specifications productivity across different sectors of the local economy.

The results from the micro-level analysis exhibit important findings which are relevant for the UK Government's agenda of eradicating regional disparities, where access to high level skill and secure jobs will help to reduce inequality across geographical space.[26] Moreover, a higher quality workforce across all regions will yield greater productivity across many sectors, lowering dependency on welfare and state benefits. In addition, a more highly skilled workforce along with a decrease in welfare payments, across geographical space will culminate in greater accumulation of income from taxes for the treasury, which will help to enhance strategic investment and increase research and development capacity in regional infrastructure. However, decreasing welfare dependency may be difficult given prior research has shown it also exhibits strong state dependence, i.e., there is clear evidence in the literature of persistence

[25] Although the UK national minimum wage (NMW) increased during period of our analysis, the labour market impacts of the NMW in terms of job loss have been negligible. Riley and Bondibene (2017) provide evidence that firms managed to contain unit labour costs through increases in the efficiency of production.

[26] Full-time permanent employment fluctuated between 40% and 48% from 1983-2024, whilst over the same period employment in less secure jobs, e.g.: temporary contracts; self-employment; zero-hours contracts (ZHC), varied from 18% to 25%, Wadsworth (2024). ZHCs doubled over the period of our analysis.

in the likelihood of benefit receipt at the micro-level in GB in recent years (see Roberts and Taylor, 2022).

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FIGURE 1: Turning points in the UK business cycle

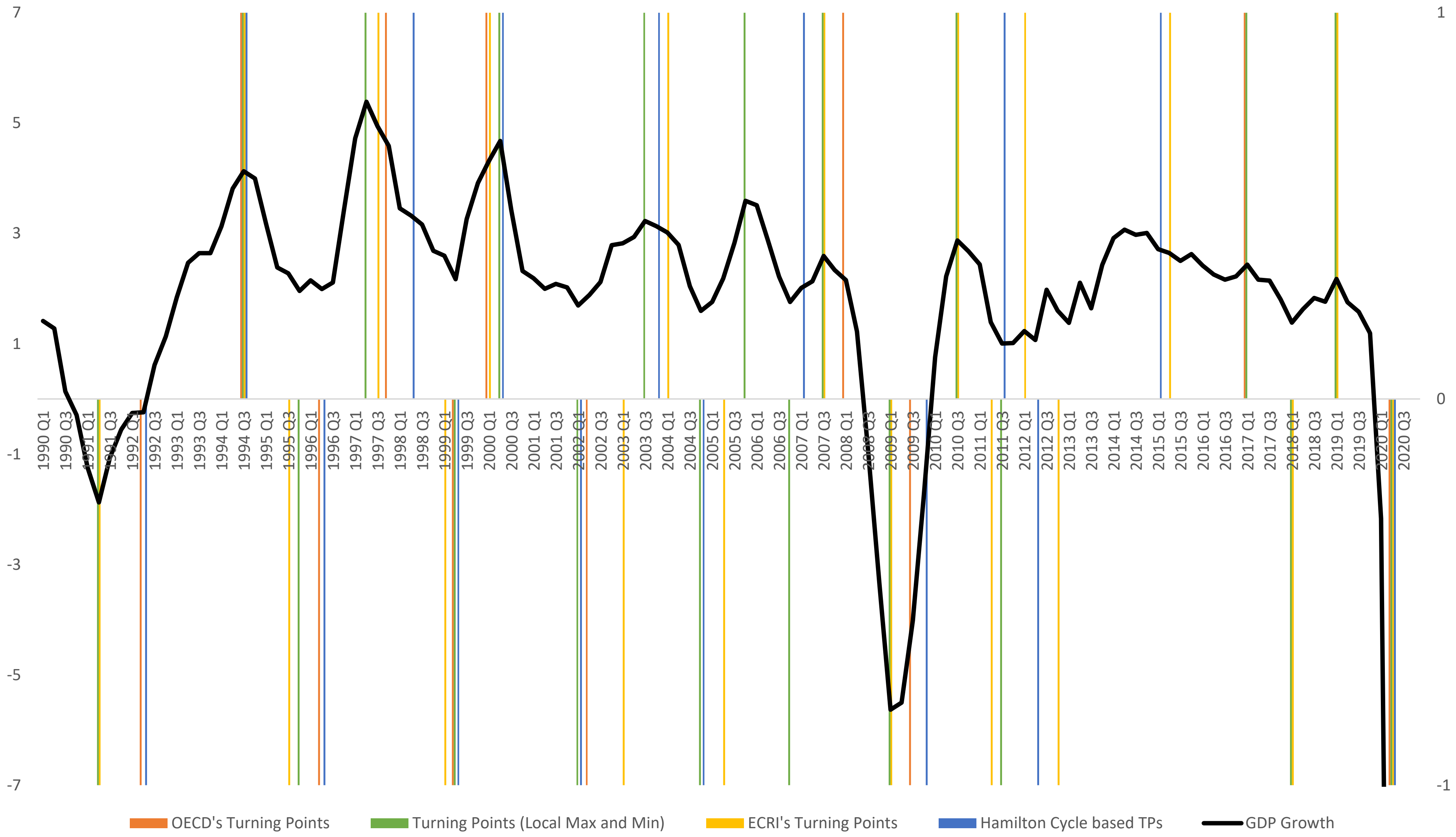
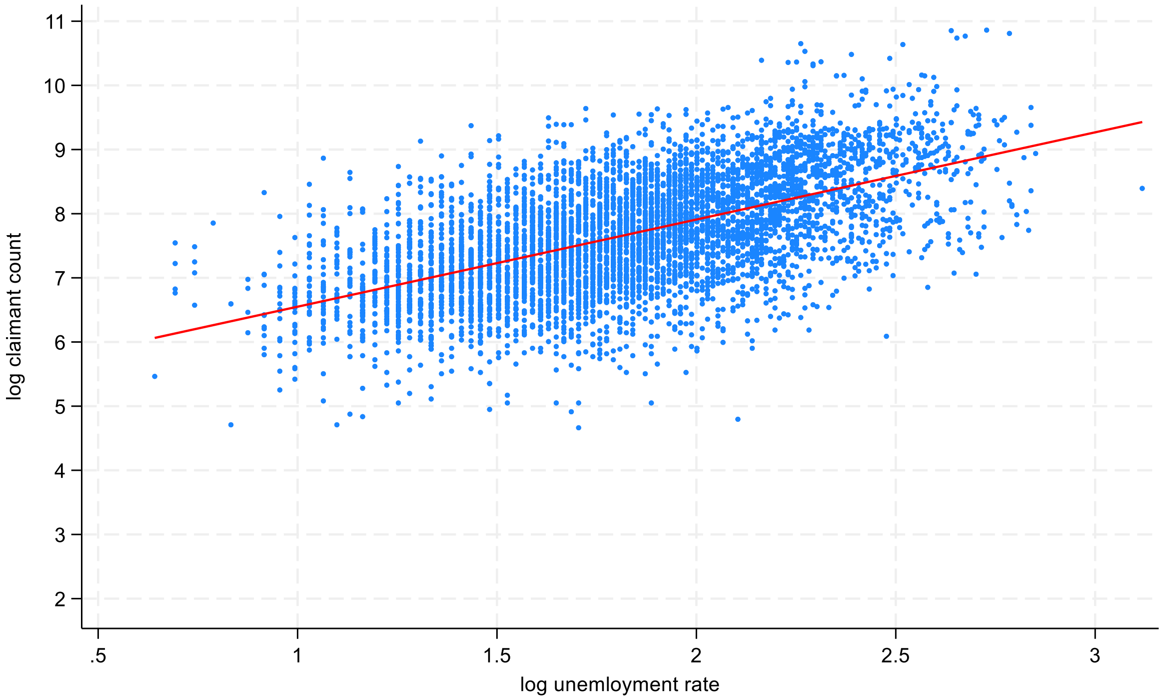
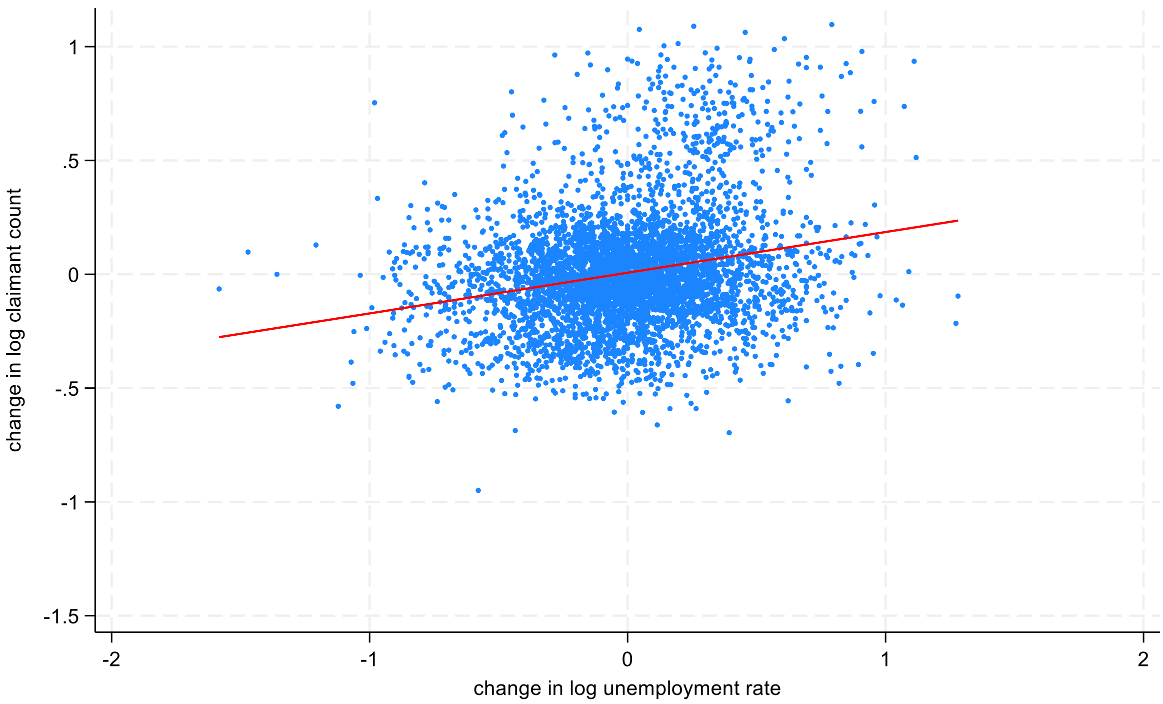


FIGURE 2A: Scatter plot between the claimant count and unemployment rate



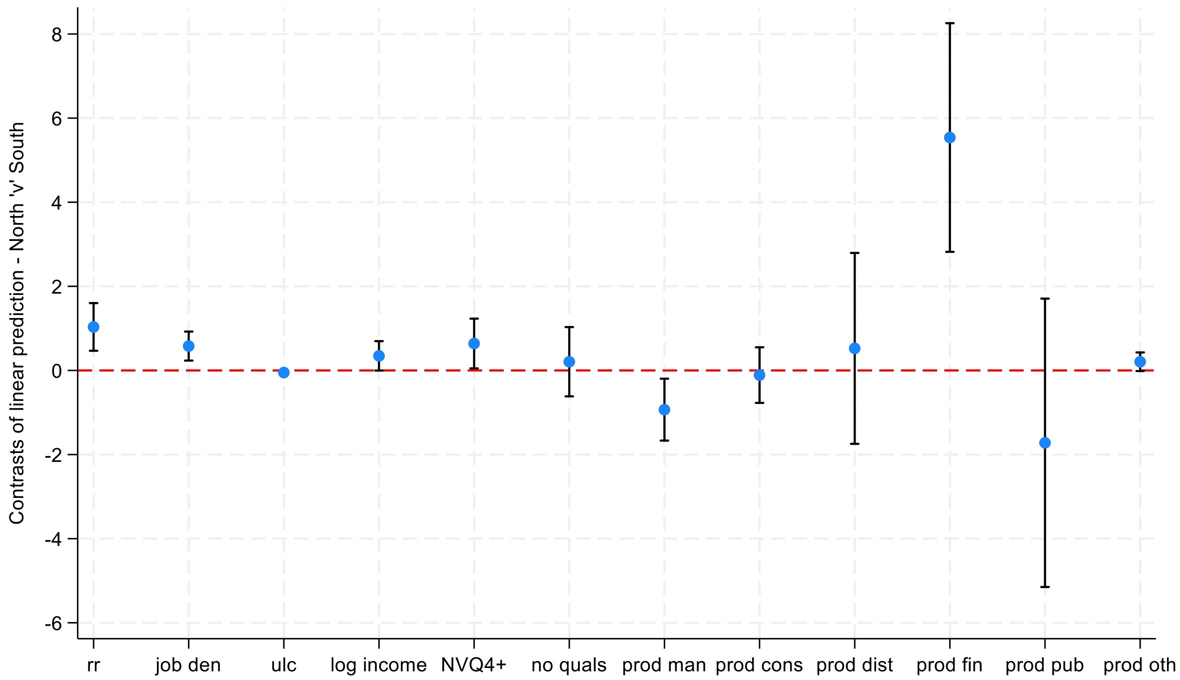
Notes: (i) the claimant count and unemployment rate are both in natural logarithmic units; (ii) the red line shows the linear line of best fit from OLS, where the slope estimate is 1.359 (t-statistic = 52.72), R-squared=0.341.

FIGURE 2B: Scatter plot between changes in the claimant count and unemployment rate



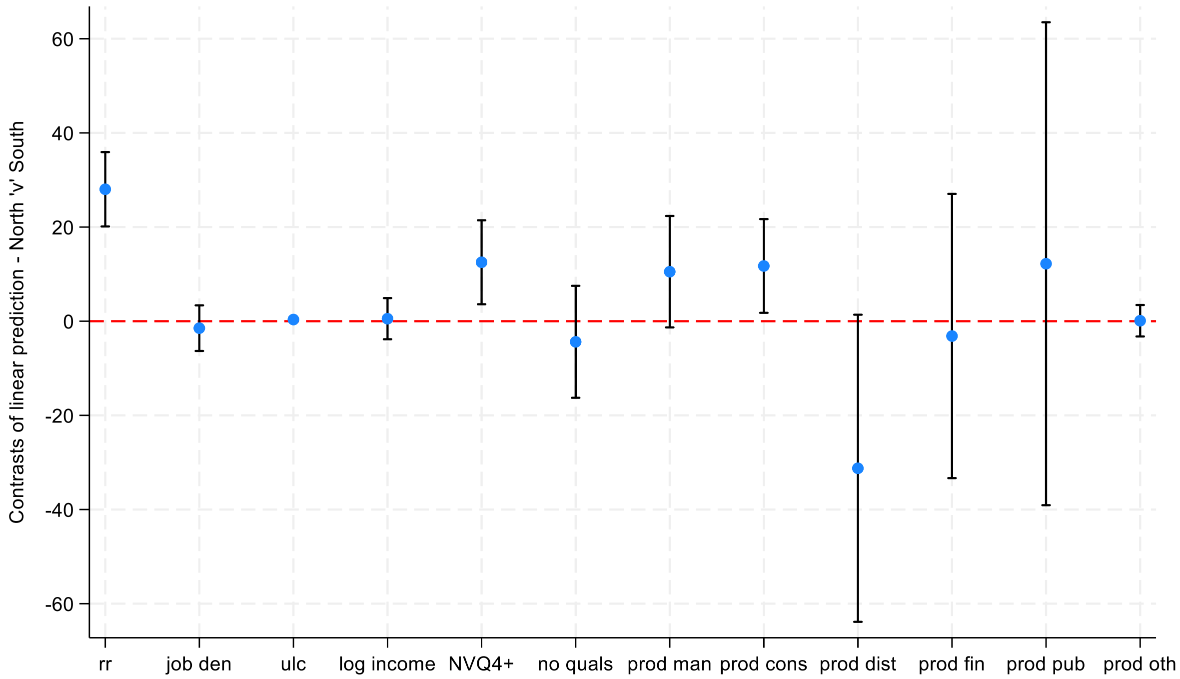
Notes: (i) the claimant count and unemployment rate are both in natural logarithmic units, plots are between the first difference in each series; (ii) the red line shows the linear line of best fit from OLS, where the slope estimate is 0.179 (t-statistic = 16.07), R-squared=0.051.

FIGURE 3A: Determinants of the claimant count, North ‘v’ South England



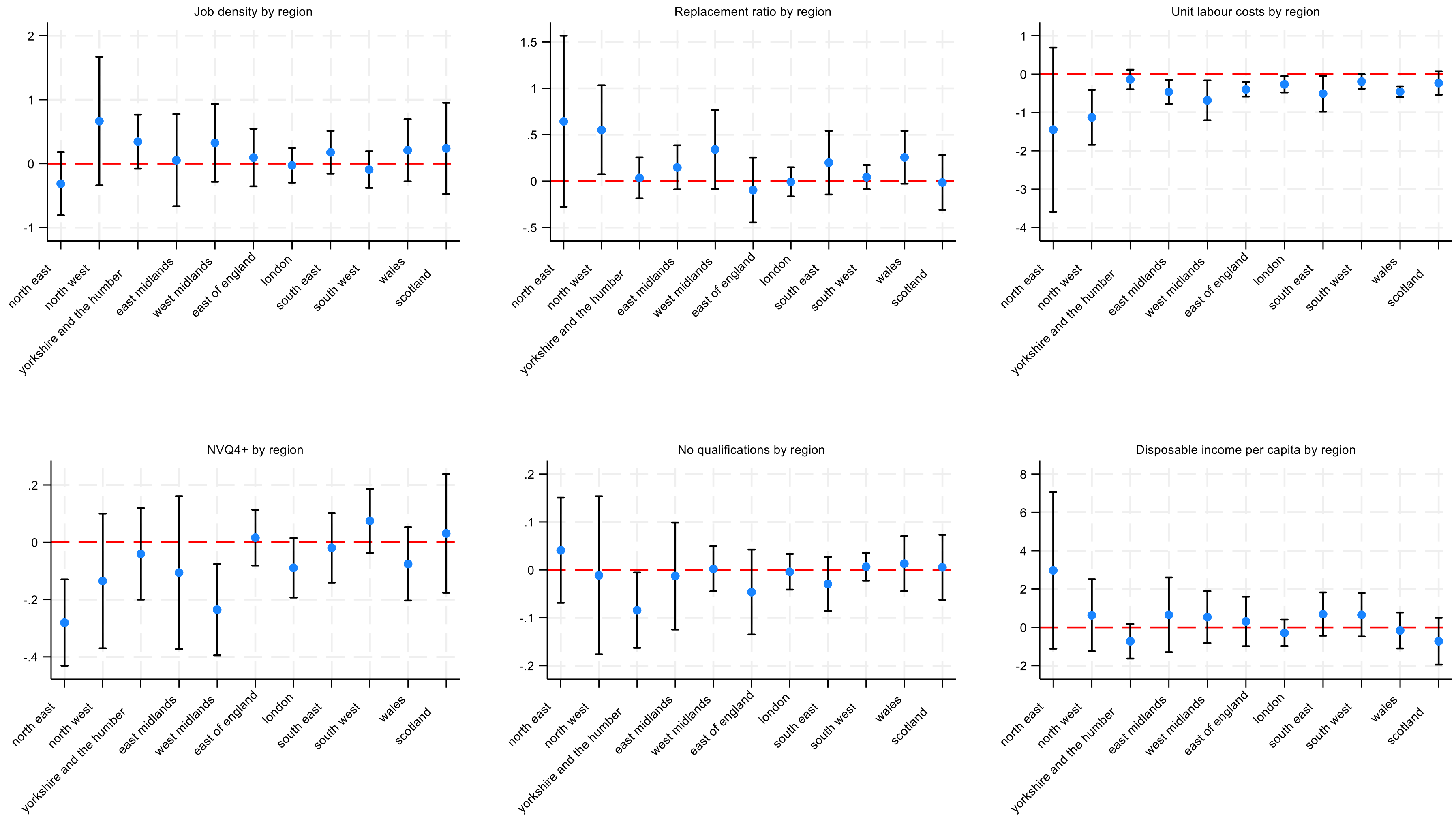
Notes: (i) contrasts in point estimate between North-South of England from GMM analysis shown by blue circles for each covariate; (ii) 95% confidence intervals in black.

FIGURE 3B: Determinants of the unemployment rate, North ‘v’ South England



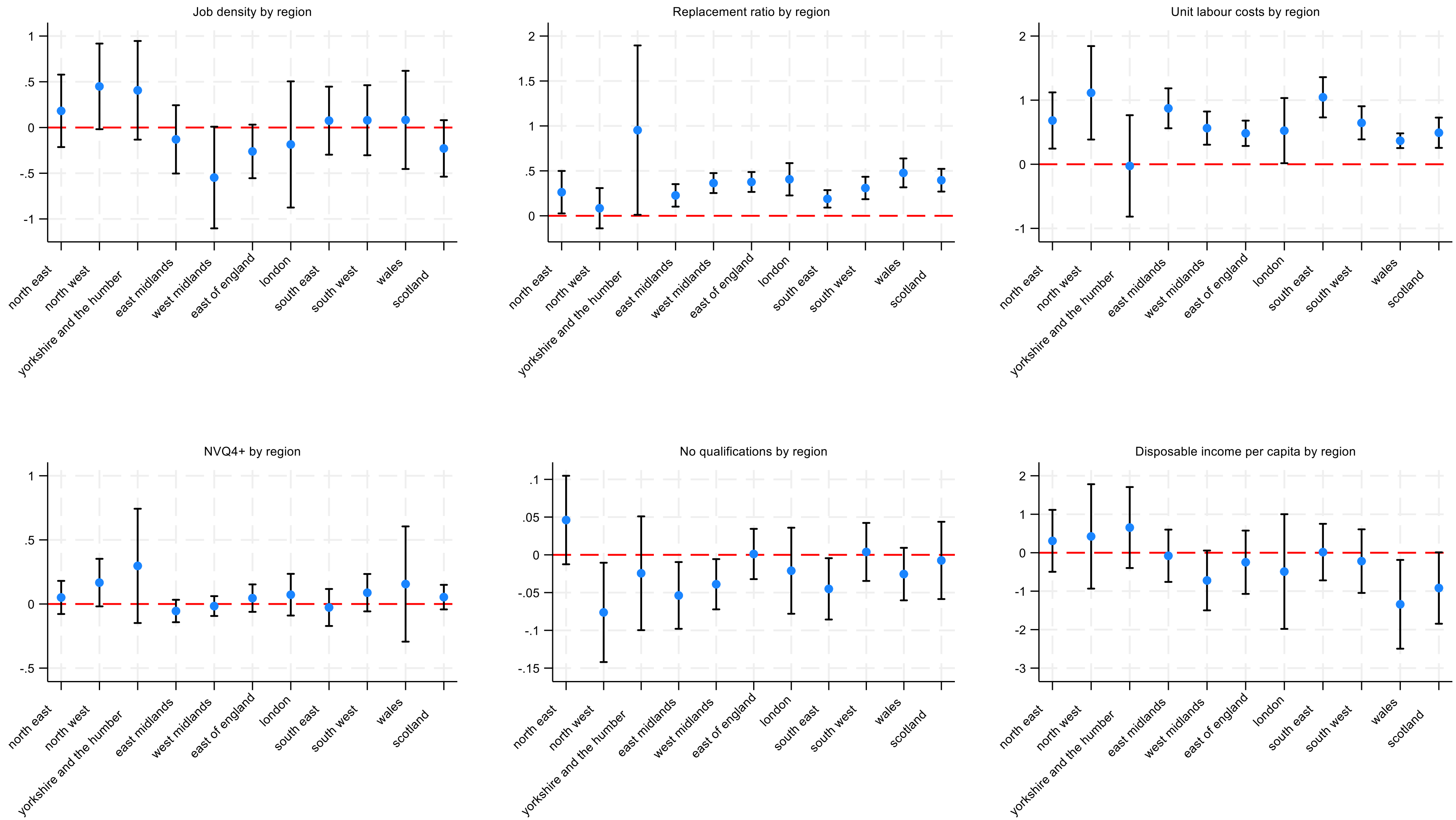
Notes: (i) contrasts in point estimate between North-South of England from GMM analysis shown by blue circles for each covariate; (ii) 95% confidence intervals in black.

FIGURE 4A: Determinants of the resilience index by region, defined from the claimant count



Notes: (i) point estimates shown by blue circles for each region; (ii) 95% confidence intervals in black.

FIGURE 4B: Determinants of the resilience index by region, defined from unemployment



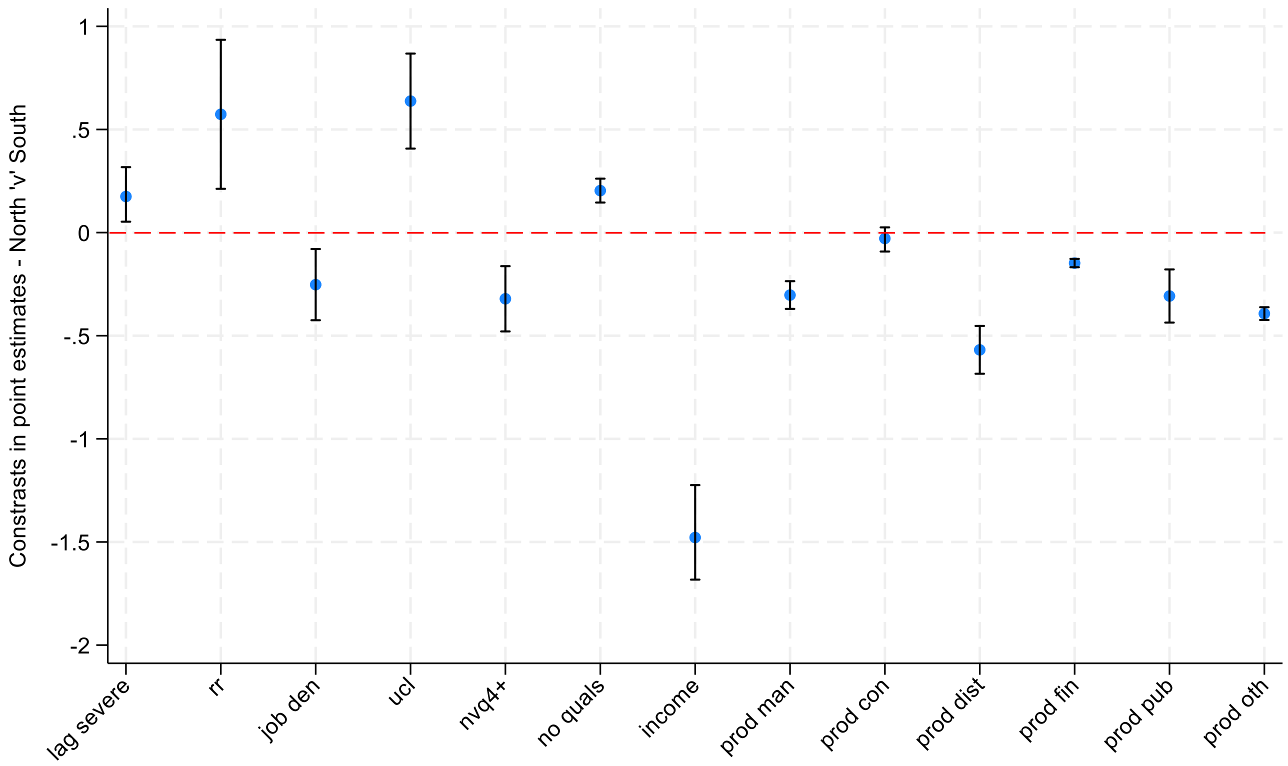
Notes: (i) point estimates shown by blue circles for each region; (ii) 95% confidence intervals in black.

FIGURE 5: Taxonomy of vulnerability

Severe Vulnerability; $s_{it} = 1$ $\Delta y_R > 0$, i.e., $\Delta y_{it} > 0$ $\Delta y_{GB} < 0$, i.e., $\Delta y_t < 0$ 34% (42%)	Moderate Vulnerability; $s_{it} = 2$ $\Delta y_R > 0$, i.e., $\Delta y_{it} > 0$ $\Delta y_{GB} > 0$, i.e., $\Delta y_t > 0$ $\Delta y_R > \Delta y_{GB}$, i.e., $\Delta y_t > \Delta y_{it}$ 18% (15%)
Low Vulnerability; $s_{it} = 3$ $\Delta y_R < 0$, i.e., $\Delta y_{it} < 0$ $\Delta y_{GB} < 0$, i.e., $\Delta y_t < 0$ $\Delta y_R < \Delta y_{GB}$, i.e., $\Delta y_{it} < \Delta y_t$ 25% (29%)	No Vulnerability; $s_{it} = 4$ $\Delta y_R < 0$, i.e., $\Delta y_{it} < 0$ $\Delta y_{GB} > 0$, i.e., $\Delta y_t > 0$ 23% (14%)

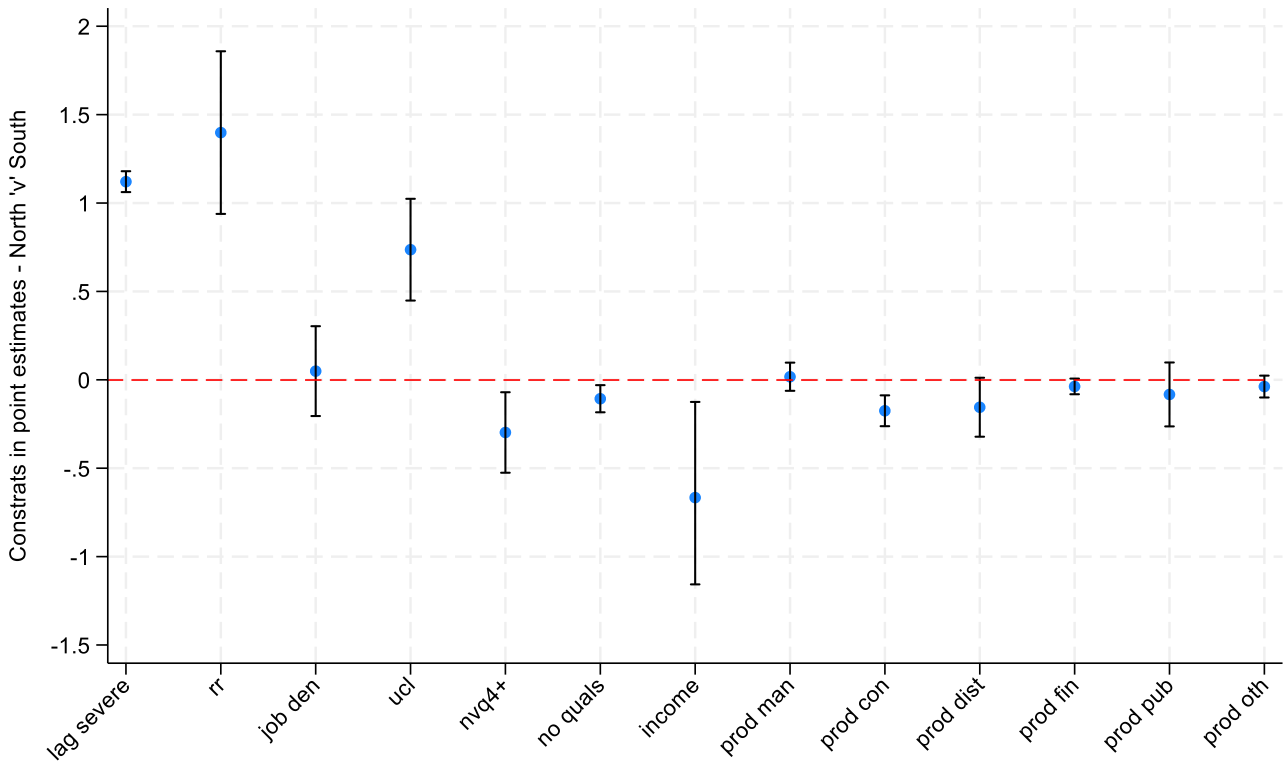
Note: Δy is defined by the first difference in either the claimant count or the unemployment rate at the regional (R), i.e., LAD (Δy_{it}), or national, i.e., GB (Δy_t) level. The figures in each quadrant represent the proportion in each state of vulnerability based upon the claimant count definition of vulnerability, with figures in parenthesis defining the index from the unemployment rate.

FIGURE 6A: Determinants of the probability of severe vulnerability, defined from the claimant count



Notes: (i) contrasts in point estimate between North-South of England from Albarran et al. (2019) estimator are shown by blue circles for each covariate; (ii) 95% confidence intervals in black.

FIGURE 6B: Determinants of the probability of severe vulnerability, defined from the unemployment rate



Notes: (i) contrasts in point estimate between North-South of England from Albarran et al. (2019) estimator are shown by blue circles for each covariate; (ii) 95% confidence intervals in black.

TABLE 1: Association between business cycle turning points (TP) and economic indicators

INDICATOR	OECD TP	ECRI TP	LOCAL MAX/MIN TP	HAMILTON CYCLE TP
UK GBP STERLING EFFECTIVE EXCHANGE RATE INDEX NADJ	-0.01	0.39	0.45	0.16
UK REAL EFFECTIVE EXCHANGE RATES - CPI BASED NADJ	-0.06	0.30	0.35	0.12
UK NOMINAL EFFECTIVE FX RATE (NEER) BASED ON CONSUMER PRICE INDEX	-0.04	0.40	0.42	0.14
UK REAL EFFECTIVE FX RATE (REER) BASED ON UNIT LABOUR COSTS NADJ	0.16	0.50	0.52	0.39
UK NEER: 19 TRADING PARTNERS EA, GBR NADJ	-0.02	0.32	0.41	0.18
UK BOP: IMPORTS - TRADE IN GOODS - TOTAL EXTRA EU28 (REST OF WORLD)	0.19	0.47	0.49	0.24
UK BOP: IMPORTS - MANUFACTURES CURA	0.58	0.62	0.49	0.40
UK BOP: IMPORTS - TOTAL TRADE IN GOODS CURA	0.51	0.59	0.55	0.37
UK BOP: EXPORTS - TRADE IN GOODS-TOTAL EXTRA EU28 (REST OF WORLD)	0.72	0.65	0.71	0.69
UK BOP: EXPORTS - MANUFACTURES CURA	0.67	0.63	0.47	0.48
UK BOP: IMPORTS: TOTAL TRADE (IMPLIED DEFLATOR) VOLA	-0.06	0.04	0.12	-0.17
UK IMPORTS - TOTAL MANUFACTURES (BOP BASIS) CURA	0.58	0.62	0.49	0.40
UK LONG TERM INDICATOR: CONSUMER GOODS & SERVICES (JAN 1974=100)	0.07	0.47	0.55	-0.03
UK RPI - DOMESTIC SERVICES NADJ	0.24	0.26	0.21	0.19
UK UNEMPLOYMENT CLAIMANT COUNT VOLA	-0.40	-0.63	-0.64	-0.34
UK CLAIMANT COUNT RATE, FEMALES SADJ	-0.36	-0.56	-0.58	-0.24
UK CLAIMANT COUNT RATE, MALES SADJ	-0.48	**<u>-0.67</u>**	**<u>-0.68</u>**	-0.43
UK LFS: UNEMPLOYMENT RATE, ALL, AGED 16 & OVER SADJ	-0.49	-0.63	-0.50	-0.32
UK LFS: ECONOMIC INACTIVITY RATE, MALE, AGED 16-64 SADJ	-0.13	0.08	0.05	0.07
UK LFS: EMPLOYMENT RATE, MALE, AGED 16-64 SADJ	0.33	0.42	0.42	0.17
UK MORTGAGE LENDING BY MAJOR UK LENDERS HOUSE PURCHASE, GROSS	0.05	-0.05	-0.02	0.07
UK LFS: ECONOMIC INACTIVITY RATE, FEMALE, ALL AGED 16 & OVER SADJ	0.55	0.29	0.24	0.54
UK LFS: ECONOMIC INACTIVITY RATE, MALE, ALL AGED 16 & OVER SADJ	-0.12	0.01	-0.04	0.08
UK RETAIL SALES: PREDOMINANTLY NON-FOOD STORES - ALL BUSINESS VOLA	0.81	0.62	0.61	**<u>0.69</u>**
UK RETAIL SALES: PREDOMINANTLY FOOD STORES - ALL BUSINESS VOLA	**<u>-0.60</u>**	-0.31	-0.33	**<u>-0.57</u>**
UK RETAIL SALES: OTHER NON-FOOD STORES - ALL BUSINESS VOLA	0.69	0.67	0.60	0.67
UK RETAIL SALES: HOUSEHOLD GOODS STORES - ALL BUSINESS VOLA	0.48	0.26	0.42	0.09
UK RPI: PERSONAL EXPENDITURE NADJ	-0.24	0.08	0.09	-0.21
UK RPI: HOUSING & HOUSEHOLD EXPENDITURE NADJ	0.33	0.57	0.56	0.23
UK RPI: MOTORING EXPENDITURE - PETROL & OIL NADJ	0.15	0.41	0.49	-0.05
UK BUILDING SOCIETIES - NET RETURN INDEX ON UK INVESTMENTS (M) NADJ	0.29	0.19	0.21	0.29
UK GROSS MORTGAGE LENDING CURN	0.23	0.60	0.61	0.04
UK INDUSTRIAL PRODUCTION INDEX - MANUFACTURING VOLA	0.66	0.73	0.68	0.49
UK INDEX OF PRODUCTION - ALL PRODUCTION INDUSTRIES VOLA	**<u>0.82</u>**	**<u>0.77</u>**	**<u>0.74</u>**	0.63
UK RPI: HOUSING - MORTGAGE INTEREST PAYMENTS NADJ	0.28	0.61	0.57	0.22
UK PERSONAL BORROWING OUTSTANDING (SA) CURA	0.39	0.42	0.44	0.30
UK CONSUMER CREDIT: NET LENDING - CREDIT CARD CURN	0.59	0.41	0.41	0.24
UK COMPOSITE LEADING INDICATOR - TREND RESTORED SADJ	0.33	0.29	0.28	0.44
UK ECONOMIC ACTIVITY RATE: UK: ALL: AGED 50-64 SADJ	0.28	0.05	-0.02	0.06
UK PUBLIC SECTOR NET DEBT (AS PERCENTAGE OF GDP AT MARKET PRICES)	-0.45	-0.55	-0.57	-0.25

Notes: (i) statistics shown are correlation coefficients, i.e., ρ_j; (ii) numbers highlighted in red indicate statistical significance at the 5 per-cent level; and (iii) the largest pro-cyclical and counter-cyclical effects are shown in bold and underlined.

TABLE 2A: Determinants of claimant count in Great Britain – by gender

	(1) ALL		**(2) MALES**		**(3) FEMALES**	
	AME	*SE*	AME	*SE*	AME	*SE*
Lagged claimant count, CC_{it-1}	0.4698***	*0.018*	0.4423***	*0.021*	0.4656***	*0.030*
Replacement ratio	0.5105**	*0.234*	2.0118***	*0.402*	0.6617***	*0.216*
Jobs density	-0.1132**	*0.056*	0.0509	*0.102*	-0.0841	*0.065*
Unit labour costs	0.0172***	*0.002*	0.0178***	*0.005*	0.0373***	*0.010*
NVQ4+ education	-0.4208***	*0.099*	0.0757	*0.099*	-0.1290	*0.118*
No qualifications	0.4361***	*0.138*	-0.2568	*0.167*	0.5865**	*0.231*
(GVA/pop) in manufacturing	-0.2072**	*0.105*	-0.2160**	*0.107*	-0.2013*	*0.106*
(GVA/pop) in construction	-0.5988***	*0.070*	-0.9798***	*0.119*	-0.2755***	*0.071*
(GVA/pop) in distribution	-0.2641***	*0.069*	0.4532**	*0.185*	-0.2754***	*0.103*
(GVA/pop) in financial	0.4592***	*0.171*	1.0351***	*0.294*	0.2830	*0.253*
(GVA/pop) in public	1.0289***	*0.315*	0.4565	*0.540*	2.0336***	*0.360*
(GVA/pop) in other sectors	0.1281***	*0.030*	0.1660***	*0.041*	0.0639***	*0.030*
Natural logarithm gross disposable income per capita	-0.8889***	*0.031*	-0.9341***	*0.212*	-0.9269***	*0.190*
Observations	4,732		4,519		4,115	
Time fixed effects	✓		✓		✓	
Region fixed effects	✓		✓		✓	
Wald $\chi^2(37)$; p-value	88,694.34; p=0.000		64,364.21; p=0.000		45,095.74; p=0.000	
Sargan; p-value	p=0.6642		p=0.8113		p=0.6641	
AR test; p-value	p=0.1130		p=0.1006		p=0.1726	

Notes: (i) GMM analysis based upon an unbalanced panel of 378 local authority districts (LAD) in Great Britain over the period 2004 to 2019; (ii) the claimant count is gender specific in columns 2 and 3; (iii) we model the natural logarithm of the claimant count; (iv) the replacement ratio is equal to the ratio of the LAD average benefit payment to the average wage. The average wage used in the calculation of the replacement ratio is gender specific in columns 2 and 3; (v) jobs density is the numbers of jobs per resident aged 16-64. For example, a job density of 1.0 would mean that there is one job for every resident of working age; (vi) unit labour costs are the ratio of the LAD specific average wage to gross value added (GVA); (vii) sector specific productivity is defined as LAD specific industrial sector GVA as a proportion of the working age population (pop); (viii) ***, **, * denotes statistical significance at the 1%, 5% and 10% level respectively.

TABLE 2B: Determinants of the unemployment rate in Great Britain – by gender

	(1) ALL		**(2) MALES**		**(3) FEMALES**	
	AME	*SE*	AME	*SE*	AME	*SE*
Lagged unemployment rate, UE_{it-1}	0.4225***	*0.032*	0.2570***	*0.037*	0.0083***	*0.028*
Replacement ratio	7.8396**	*3.558*	7.0788	*6.594*	7.6740***	*3.192*
Jobs density	0.3532	*0.702*	-4.2854***	*1.737*	-5.2624***	*0.695*
Unit labour costs	0.2538***	*0.060*	0.1485***	*0.010*	0.0918	*0.150*
NVQ4+ education	-5.4449***	*1.899*	-13.9304***	*2.057*	0.9606	*2.008*
No qualifications	3.8873*	*2.204*	-2.2933	*3.503*	12.6634***	*3.288*
(GVA/pop) in manufacturing	-5.5539***	*1.784*	-7.6243***	*2.971*	-2.1088*	*1.248*
(GVA/pop) in construction	-6.4952***	*0.867*	-8.1639***	*1.604*	-6.8406***	*0.641*
(GVA/pop) in distribution	-0.4634	*1.178*	1.3111	*2.999*	-14.070***	*1.061*
(GVA/pop) in financial	12.0656***	*2.328*	22.2845***	*4.635*	33.4711***	*2.784*
(GVA/pop) in public	14.4479***	*3.796*	13.6212	*8.559*	6.3007***	*3.306*
(GVA/pop) in other sectors	0.7095**	*0.368*	0.7763	*0.726*	0.2514***	*0.332*
Natural logarithm gross disposable income per capita	-10.6500***	*2.210*	-9.3071***	*3.186*	-7.2748***	*2.175*
Observations	4,338		3,445		3,058	
Time fixed effects	✓		✓		✓	
Region fixed effects	✓		✓		✓	
Wald $\chi^2(37)$; p-value	885,334.93,694.34; p=0.000		4,150.07; p=0.000		3,208.20; p=0.000	
Sargan; p-value	p=0.7321		p=0.9030		p=0.6306	
AR test; p-value	p=0.0970		p=0.4835		p=0.1904	

Notes: (i) GMM analysis based upon an unbalanced panel of 378 local authority districts (LAD) in Great Britain over the period 2004 to 2019; (ii) the unemployment rate is gender specific in columns 2 and 3; (iii) the replacement ratio is equal to the ratio of the LAD average benefit payment to the average wage. The average wage used in the calculation of the replacement ratio is gender specific in columns 2 and 3; (iv) jobs density is the numbers of jobs per resident aged 16-64. For example, a job density of 1.0 would mean that there is one job for every resident of working age; (v) unit labour costs are the ratio of the LAD specific average wage to gross value added (GVA); (vi) sector specific productivity is defined as LAD specific industrial sector GVA as a proportion of the working age population (pop); (vii) ***, **, * denotes statistical significance at the 1%, 5% and 10% level respectively.

TABLE 3A: Determinants of economic resilience in Great Britain defined by the claimant count – by gender

	(1) ALL		(2) MALES		(3) FEMALES	
	COEF	*SE*	COEF	*SE*	COEF	*SE*
Replacement ratio	0.1594***	*0.058*	0.0758***	*0.023*	0.0191*	*0.010*
Jobs density	-0.2072**	*0.098*	-0.0204	*0.069*	0.0012	*0.026*
Unit labour costs	0.5090***	*0.074*	0.0172	*0.051*	0.0316***	*0.010*
NVQ4+ education	-0.0584**	*0.030*	-0.0289	*0.020*	-0.0273**	*0.011*
No qualifications	-0.0094	*0.015*	-0.0111	*0.007*	0.0061	*0.004*
(GVA/pop) in manufacturing	0.0095	*0.011*	0.0028	*0.008*	0.0014	*0.004*
(GVA/pop) in construction	-0.0021	*0.010*	0.0085	*0.007*	-0.0001	*0.003*
(GVA/pop) in distribution	0.0300	*0.045*	0.0090	*0.017*	-0.0067	*0.008*
(GVA/pop) in financial	-0.0082	*0.013*	0.0052	*0.010*	-0.0013	*0.004*
(GVA/pop) in public	-0.0143	*0.033*	0.0036	*0.017*	-0.0075	*0.010*
(GVA/pop) in other sectors	-0.0001	*0.011*	-0.0003	*0.008*	0.0639**	*0.003*
Natural logarithm gross disposable income per capita	0.4270***	*0.028*	-0.0699	*0.142*	0.2780***	*0.063*
Observations	3,527		3,503		2,960	
Time fixed effects	✓		✓		✓	
Region fixed effects	✓		✓		✓	
R-squared	0.1088		0.0861		0.2278	

Notes: (i) the value of the resilience index, β_{it}, is based upon the claimant count (see equation 2); (ii) fixed effects analysis based upon an unbalanced panel of 378 local authority districts (LAD) in Great Britain over the period 2004 to 2019; (iii) the resilience is gender specific in columns 2 and 3; (iv) the replacement ratio is equal to the ratio of the LAD average benefit payment to the average wage. The average wage used in the calculation of the replacement ratio is gender specific in columns 2 and 3; (v) jobs density is the numbers of jobs per resident aged 16-64. For example, a job density of 1.0 would mean that there is one job for every resident of working age; (vi) unit labour costs are the ratio of the LAD specific average wage to gross value added (GVA); (vii) sector specific productivity is defined as LAD specific industrial sector GVA as a proportion of the working age population (pop); (viii) ***, **, * denotes statistical significance at the 1%, 5% and 10% level respectively.

TABLE 3B: Determinants of economic resilience in Great Britain defined by the unemployment rate – by gender

	(1) ALL		**(2) MALES**		**(3) FEMALES**	
	COEF	*SE*	COEF	*SE*	COEF	*SE*
Replacement ratio	0.3306***	*0.038*	0.4702***	*0.055*	0.2530***	*0.042*
Jobs density	-0.0287	*0.080*	0.2297***	*0.096*	0.0160	*0.096*
Unit labour costs	0.6994***	*0.085*	0.3922***	*0.081*	0.2467***	*0.069*
NVQ4+ education	-0.0543**	*0.020*	-0.0148	*0.037*	-0.0190	*0.044*
No qualifications	0.0229***	*0.009*	-0.0001	*0.012*	0.0235**	*0.011*
(GVA/pop) in manufacturing	0.0071	*0.009*	0.0054	*0.010*	0.0209	*0.013*
(GVA/pop) in construction	0.0184	*0.009*	-0.0191**	*0.011*	0.0150	*0.011*
(GVA/pop) in distribution	0.0244	*0.029*	0.0028	*0.023*	0.0311	*0.026*
(GVA/pop) in financial	0.0065	*0.007*	0.0172	*0.013*	-0.0042	*0.007*
(GVA/pop) in public	0.0231	*0.025*	0.0313	*0.029*	0.0217	*0.029*
(GVA/pop) in other sectors	0.0012	*0.008*	0.0009	*0.009*	0.0158*	*0.009*
Natural logarithm gross disposable income per capita	-0.2149	*0.171*	1.0688***	*0.171*	0.0450	*0.235*
Observations	3,289		2,223		1,782	
Time fixed effects	✓		✓		✓	
Region fixed effects	✓		✓		✓	
R-squared	0.0845		0.0807		0.0356	

Notes: (i) the value of the resilience index, β_{it}, is based upon the unemployment rate (see equation 2); (ii) fixed effects analysis based upon an unbalanced panel of 378 local authority districts (LAD) in Great Britain over the period 2004 to 2019; (iii) the resilience index is gender specific in columns 2 and 3; (iv) the replacement ratio is equal to the ratio of the LAD average benefit payment to the average wage. The average wage used in the calculation of the replacement ratio is gender specific in columns 2 and 3; (v) jobs density is the numbers of jobs per resident aged 16-64. For example, a job density of 1.0 would mean that there is one job for every resident of working age; (vi) unit labour costs are the ratio of the LAD specific average wage to gross value added (GVA); (vii) sector specific productivity is defined as LAD specific industrial sector GVA as a proportion of the working age population (pop); (viii) ***, **, * denotes statistical significance at the 1%, 5% and 10% level respectively.

TABLE 4A: Determinants of the level of vulnerability in Great Britain – definition based upon the claimant count

	SEVERE ($s_{it} = 1$)		**MODERATE** ($s_{it} = 2$)		**LOW** ($s_{it} = 3$)		**NO** ($s_{it} = 4$)	
	AME	*SE*	AME	*SE*	AME	*SE*	AME	*SE*
Lagged no vulnerability, s_{it-1}	-0.148***	*0.019*	-0.059***	*0.011*	0.013***	*0.003*	0.194***	*0.027*
Lagged low vulnerability, s_{it-1}	-0.190***	*0.019*	-0.095***	*0.012*	0.006**	*0.003*	0.279***	*0.028*
Lagged moderate vulnerability, s_{it-1}	0.035	*0.027*	0.003	*0.003*	-0.007	*0.005*	-0.032	*0.024*
Replacement ratio	0.730***	*0.072*	0.276***	*0.029*	-0.050***	*0.011*	-0.957***	*0.092*
Jobs density	-0.626***	*0.197*	-0.237***	*0.016*	0.043***	*0.016*	0.822***	*0.254*
Unit labour costs	1.299***	*0.112*	0.492***	*0.043*	-0.089***	*0.018*	-1.702***	*0.139*
NVQ4+ education	-0.230**	*0.102*	-0.012**	*0.006*	0.067**	*0.029*	0.176**	*0.078*
No qualifications	-0.024	*0.027*	-0.009	*0.010*	0.002	*0.002*	0.031	*0.035*
(GVA/pop) in manufacturing	0.017	*0.027*	0.006	*0.010*	-0.001	*0.002*	-0.022	*0.035*
(GVA/pop) in construction	0.018	*0.024*	0.007	*0.009*	-0.001	*0.002*	-0.024	*0.031*
(GVA/pop) in distribution	0.067	*0.054*	0.025	*0.020*	-0.005	*0.004*	-0.087	*0.071*
(GVA/pop) in financial	0.048*	*0.029*	0.018*	*0.010*	-0.003	*0.002*	-0.065*	*0.040*
(GVA/pop) in public	0.078	*0.077*	0.029	*0.029*	-0.005	*0.005*	-0.103	*0.100*
(GVA/pop) in other sectors	0.029	*0.021*	0.011	*0.008*	-0.002	*0.001*	-0.038	*0.027*
Natural logarithm gross disposable income per capita	-0.346	*0.408*	-0.131	*0.154*	0.024	*0.029*	0.453	*0.533*
Observations	2,352							
LR $\chi^2(51)$; p-value	380.47; p=0.000							
ρ; p-value	0.321; p=0.000							
μ_1; p-value	-0.361; p=0.000							
μ_2; p-value	-0.172; p=0.050							
μ_3; p-value	0.971; p=0.000							
Initial condition, s_{i0}	✓							
Time fixed effects	✓							
Region fixed effects	✓							
Mundlak fixed effects	✓							

Notes: (i) Correlated random effects dynamic ordered probit analysis based upon a balanced panel of 168 local authority districts (LAD) in Great Britain over the period 2004 to 2019; (ii) the replacement ratio is equal to the ratio of the LAD average benefit payment to the average wage; (iii) jobs density is the numbers of jobs per resident aged 16-64. For example, a job density of 1.0 would mean that there is one job for every resident of working age; (iv) unit labour costs are the ratio of the LAD specific average wage to gross value added (GVA); (v) sector specific productivity is defined as LAD specific industrial sector GVA as a proportion of the working age population (pop); (vi) the omitted lagged state of vulnerability is "*severe vulnerability*"; (vii) ***, **, * denotes statistical significance at the 1%, 5% and 10% level respectively.

TABLE 4B: Determinants of the level of vulnerability in Great Britain – definition based upon the unemployment rate

	SEVERE ($s_{it} = 1$)		**MODERATE** ($s_{it} = 2$)		**LOW** ($s_{it} = 3$)		**NO** ($s_{it} = 4$)	
	AME	*SE*	AME	*SE*	AME	*SE*	AME	*SE*
Lagged no vulnerability, s_{it-1}	-0.200***	*0.017*	-0.209***	*0.015*	-0.025***	*0.005*	0.434***	*0.026*
Lagged low vulnerability, s_{it-1}	-0.133***	*0.014*	-0.086***	*0.012*	0.003	*0.002*	0.217***	*0.022*
Lagged moderate vulnerability, s_{it-1}	-0.157***	*0.027*	0.117***	*0.013*	-0.002	*0.003*	0.276***	*0.028*
Replacement ratio	0.217***	*0.042*	0.248***	*0.046*	0.015***	*0.006*	-0.480***	*0.088*
Jobs density	-0.027	*0.105*	-0.031	*0.120*	-0.002	*0.007*	0.060	*0.232*
Unit labour costs	0.411***	*0.066*	0.470***	*0.074*	0.029***	*0.010*	-0.910***	*0.138*
NVQ4+ education	0.027	*0.044*	0.031	*0.050*	0.002	*0.003*	-0.060	*0.097*
No qualifications	0.012	*0.016*	0.014	*0.019*	0.001	*0.002*	-0.026	*0.036*
(GVA/pop) in manufacturing	0.015	*0.014*	0.017	*0.016*	0.001	*0.001*	-0.033	*0.030*
(GVA/pop) in construction	-0.007	*0.015*	-0.007	*0.017*	-0.001	*0.001*	0.014	*0.032*
(GVA/pop) in distribution	-0.039	*0.032*	-0.044	*0.036*	-0.003	*0.002*	0.086	*0.070*
(GVA/pop) in financial	0.009	*0.014*	0.010	*0.017*	0.001	*0.001*	-0.019	*0.032*
(GVA/pop) in public	-0.033	*0.039*	-0.037	*0.044*	-0.002	*0.003*	0.072	*0.087*
(GVA/pop) in other sectors	-0.001	*0.012*	-0.001	*0.014*	-0.001	*0.001*	0.003	*0.026*
Natural logarithm gross disposable income per capita	-1.089***	*0.231*	-1.247***	*0.258*	-0.077***	*0.029*	1.413***	*0.491*
Observations	1,735							
LR $\chi^2(51)$; p-value	382.77; p=0.000							
ρ; p-value	0.097; p=0.000							
μ_1; p-value	-2.191; p=0.000							
μ_2; p-value	-1.824; p=0.000							
μ_3; p-value	-0.592; p=0.050							
Initial condition, s_{i0}	✓							
Time fixed effects	✓							
Region fixed effects	✓							
Mundlak fixed effects	✓							

Notes: (i) Correlated random effects dynamic ordered probit analysis based upon a balanced panel of 151 local authority districts (LAD) in Great Britain over the period 2004 to 2019; (ii) the replacement ratio is equal to the ratio of the LAD average benefit payment to the average wage; (iii) jobs density is the numbers of jobs per resident aged 16-64. For example, a job density of 1.0 would mean that there is one job for every resident of working age; (iv) unit labour costs are the ratio of the LAD specific average wage to gross value added (GVA); (v) sector specific productivity is defined as LAD specific industrial sector GVA as a proportion of the working age population (pop); (vi) the omitted lagged state of vulnerability is "severe vulnerability"; (vii) ***, **, * denotes statistical significance at the 1%, 5% and 10% level respectively.

TABLE 5: Determinants of the probability of severe vulnerability

	CLAIMANT COUNT				UNEMPLOYMENT			
	BALANCED		UNBALANCED		BALANCED		UNBALANCED	
	AME	*SE*	AME	*SE*	AME	*SE*	AME	*SE*
Lagged severe vulnerability, s_{it-1}	0.194***	*0.021*	0.182***	*0.015*	0.127***	*0.023*	0.131***	*0.007*
Replacement ratio	1.100***	*0.077*	0.981***	*0.064*	0.795***	*0.086*	0.809***	*0.027*
Jobs density	0.076	*0.253*	0.017	*0.061*	0.235	*0.256*	0.281***	*0.069*
Unit labour costs	1.730***	*0.126*	1.678***	*0.109*	0.870***	*0.133*	0.876***	*0.038*
NVQ4+ education	-0.138	*0.102*	-0.174***	*0.027*	0.005	*0.109*	0.017	*0.028*
No qualifications	0.024	*0.035*	0.010	*0.009*	-0.018	*0.038*	-0.019*	*0.010*
(GVA/pop) in manufacturing	-0.013	*0.031*	-0.014	*0.079*	0.012	*0.033*	0.013	*0.008*
(GVA/pop) in construction	-0.030	*0.031*	-0.024**	*0.080*	-0.055	*0.034*	-0.050***	*0.009*
(GVA/pop) in distribution	-0.082	*0.032*	-0.102***	*0.019*	0.170*	*0.076*	-0.106***	*0.020*
(GVA/pop) in financial	-0.065	*0.069*	-0.051***	*0.008*	0.036	*0.035*	-0.022**	*0.009*
(GVA/pop) in public	-0.021	*0.031*	-0.053**	*0.022*	0.026	*0.093*	0.003	*0.023*
(GVA/pop) in other sectors	-0.027	*0.086*	-0.029**	*0.007*	-0.026	*0.030*	-0.033	*0.008*
Natural logarithm gross disposable income per capita	0.767	*0.497*	-0.729***	*0.142*	-3.299***	*0.540*	-3.317***	*0.157*
Observations	2,158		4,121		2,158		4,121	
LR $\chi^2(35)$; p-value	258.38; p=0.000				156.76; p=0.000			
Log-likelihood			-16,702.78				-15,228.07	
Time fixed effects	✓							
Region fixed effects	✓							

Notes: (i) Columns 1 and 3 correlated random effects dynamic probit analysis based upon a balanced panel of 166 local authority districts (LAD) in Great Britain over the period 2004 to 2019; (ii) columns 2 and 4 correlated random effects dynamic probit analysis based upon an unbalanced panel of 355 LADs in Great Britain over the period 2004 to 2019; (iii) the replacement ratio is equal to the ratio of the LAD average benefit payment to the average wage; (iv) jobs density is the numbers of jobs per resident aged 16-64. For example, a job density of 1.0 would mean that there is one job for every resident of working age; (v) unit labour costs are the ratio of the LAD specific average wage to gross value added (GVA); (vi) sector specific productivity is defined as LAD specific industrial sector GVA as a proportion of the working age population (pop); (vii) ***, **, * denotes statistical significance at the 1%, 5% and 10% level respectively.

APPENDIX

The following outlines the dynamic nonlinear random effects model for unbalanced panels by Albarran et al. (2019), used to estimate equation (7). Start by defining the following $S_i = (s_{i1}, \cdots, s_{iT})'$, $X_i = (X'_{i1}, \cdots, X'_{iT})'$ and $Z_i = (z_{i1}, \cdots, z_{iT})'$, where s_{it} is the scalar outcome and X_{it} is a row vector of covariates. Having an unbalanced panel is captured by selection indicators $z_{it} \in (0,1)$, equal to unity if s_{it} and X_{it} are observed and zero otherwise, in a balanced panel $z_{it} = 1 \; \forall \; i, t$. Let M_i be the $(T_i \times T)$ matrix that selects the set of observed X_i, i.e., $M_i X_i = \left(X'_{it_i}, \cdots, X'_{iT_i}\right)'$, where in the case of a balanced panel M_i is an identity matrix I. The log-likelihood function is given by:

$$\mathcal{L} = \sum\nolimits_{i=1}^{N} \log \int_{\alpha_i} \left[\prod\nolimits_{t=t_i+1}^{t_i+T_i-1} f(s_{it} | s_{it-1}, M_i X_i, Z_i, \alpha_i; \theta) h\left(\alpha_i \middle| s_{it}, M_i X_i, Z_i; \omega_{\alpha Z_i}\right) \right] d\alpha_i$$

where $f(\cdot)$ is the density and the log-likelihood is maximised with respect to a set of parameters $\lambda = (\theta', \varphi')'$, where θ are parameters common across all subpanels and $\varphi = (\varphi'_1, \cdots, \varphi'_P)$ are a set of subpanel specific parameters. The specific parameters to subpanel p are $\varphi_p = \omega_{\alpha Z^{(p)}}$.

To estimate the model, in the first step a CRE model is estimated for each subpanel and then secondly, the parameters $\lambda = (\theta', \varphi')'$ are recovered by minimum distance (MD). Define $\hat{\delta} = \left(\hat{\delta}'_1, \hat{\delta}'_2, \cdots, \hat{\delta}'_P\right)$ as the estimated parameters of the model after the first step. Each $\hat{\delta}'_p$ includes two estimates, those parameters θ that are common across all subpanels denoted by $\hat{\delta}_p^{[c]}$, and estimates of the non-common parameters φ_p i.e., $\hat{\delta}_p^{[nc]}$. Now the structural parameters λ can be consistently and efficiently estimated by MD, by minimising the following quadratic function:

$$\hat{\lambda}^{MD} = \arg\min_{\lambda} Q(\lambda) = \left[\hat{\delta} - h(\lambda)\right]' V^{-1} \left[\hat{\delta} - h(\lambda)\right]$$

where V is the block diagonal variance-covariance matrix of $\hat{\delta}$ and $\delta = h(\lambda)$, with $h(\cdot)$ restricting all of the $\hat{\delta}_p^{[c]}$ to be estimates of the same θ parameters. The model is asymptotically equivalent to the maximum likelihood estimator, see Albarran et al. (2019) for full details.

TABLE A1: Summary of selected indicators representing various sectors of the UK economy

<table>
<tr><th>Industry and Construction</th><th>Income and Consumption</th><th>Employment</th><th>Services</th><th>External</th><th>Credit and Finance</th><th>Miscellaneous Activity</th></tr>
<tr><td rowspan="4">UK BUILDING SOCIETIES - NET RETURN INDEX ON UK INVESTMENTS (M) NADJ</td><td rowspan="2">UK RETAIL SALES: PREDOMINANTLY NON-FOOD STORES - ALL BUSINESS VOLA</td><td rowspan="2">UK UNEMPLOYMENT CLAIMANT COUNT VOLA</td><td rowspan="5">UK LONG TERM INDICATOR: CONSUMER GOODS & SERVICES (1974=100)</td><td>UK GBP STERLING EFFECTIVE EXCHANGE RATE INDEX NADJ</td><td rowspan="2">UK MORTGAGE LENDING BY MAJOR UK LENDERS HOUSE PURCHASE, GROSS</td><td rowspan="4">UK COMPOSITE LEADING INDICATOR - TREND RESTORED SADJ</td></tr>
<tr><td>UK REAL EFFECTIVE EXCHANGE RATES - CPI BASED NADJ</td></tr>
<tr><td rowspan="2">UK RETAIL SALES: PREDOMINANTLY FOOD STORES - ALL BUSINESS VOLA</td><td rowspan="2">UK CLAIMANT COUNT RATE, FEMALES SADJ</td><td>UK NOMINAL EFFECTIVE FX RATE (NEER) BASED ON CONSUMER PRICE INDEX</td><td rowspan="3">UK GROSS MORTGAGE LENDING CURN</td></tr>
<tr><td>UK REAL EFFECTIVE FX RATE (REER) BASED ON UNIT LABOUR COSTS NADJ</td></tr>
<tr><td rowspan="3">UK INDUSTRIAL PRODUCTION INDEX - MANUFACTURING VOLA</td><td rowspan="2">UK RETAIL SALES: OTHER NON-FOOD STORES - ALL BUSINESS VOLA</td><td rowspan="2">UK CLAIMANT COUNT RATE, MALES SADJ</td><td>UK NEER: 19 TRADING PARTNERS EA, GBR NADJ</td><td rowspan="4">UK PUBLIC SECTOR NET DEBT (AS PERCENTAGE OF GDP AT MARKET PRICES)</td></tr>
<tr><td rowspan="6">UK RPI - DOMESTIC SERVICES NADJ</td><td>UK BOP: IMPORTS - TRADE IN GOODS - TOTAL EXTRA EU28 (REST OF WORLD)</td><td rowspan="3">UK RPI: HOUSING - MORTGAGE INTEREST PAYMENTS NADJ</td></tr>
<tr><td rowspan="2">UK RETAIL SALES: HOUSEHOLD GOODS STORES - ALL BUSINESS VOLA</td><td>UK LFS: UNEMPLOYMENT RATE, ALL, AGED 16 & OVER SADJ</td><td>UK BOP: IMPORTS - MANUFACTURES CURA</td></tr>
<tr><td rowspan="4">UK INDEX OF PRODUCTION - ALL PRODUCTION INDUSTRIES VOLA</td><td>UK LFS: ECONOMIC INACTIVITY RATE, MALE, AGED 16-64 SADJ</td><td>UK BOP: IMPORTS - TOTAL TRADE IN GOODS CURA</td></tr>
<tr><td>UK RPI: PERSONAL EXPENDITURE NADJ</td><td>UK LFS: EMPLOYMENT RATE, MALE, AGED 16-64 SADJ</td><td>UK BOP: EXPORTS - TRADE IN GOODS - TOTAL EXTRA EU28 (REST OF WORLD)

UK BOP: EXPORTS - MANUFACTURES CURA</td><td>UK PERSONAL BORROWING OUTSTANDING (SA) CURA</td><td rowspan="3">UK ECONOMIC ACTIVITY RATE: UK: ALL: AGED 50-64 SADJ</td></tr>
<tr><td>UK RPI: HOUSING & HOUSEHOLD EXPENDITURE NADJ</td><td>UK LFS: ECONOMIC INACTIVITY RATE, FEMALE, ALL AGED 16 & OVER SADJ</td><td>UK BOP: IMPORTS: TOTAL TRADE (IMPLIED DEFLATOR) VOLA</td><td rowspan="2">UK CONSUMER CREDIT: NET LENDING - CREDIT CARD CURN</td></tr>
<tr><td>UK RPI: MOTORING EXPENDITURE - PETROL & OIL NADJ</td><td>UK LFS: ECONOMIC INACTIVITY RATE, MALE, ALL AGED 16 & OVER SADJ</td><td>UK IMPORTS - TOTAL MANUFACTURES (BOP BASIS) CURA</td></tr>
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