ISER Working Paper Series

The scarring effect of unemployment from the early '90s to the Great Recession

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No. 2015-05
March 2015

INSTITUTE FOR SOCIAL
& ECONOMIC RESEARCH

www.iser.essex.ac.uk

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Non-technical summary

In this paper we analyse the extent to which unemployment experiences negatively affect workers' re-employability. The phenomenon, also known as the "Scarring effect of unemployment" or "True State Dependence", is likely to be caused by factors such as human capital depreciation during unemployment, that is the loss of labour market related skills and knowledge; negative signalling to employers, i.e. the use by employers of unemployment experiences to discriminate between "good" and "bad" job applicants; and job rationing, i.e. during a crisis there is a limited number of jobs available while the number of jobs seekers is relatively high.

Our analysis makes use of data from the British Household Panel Survey and Understanding Society and focuses on three periods characterised by very different labour market conditions. First, we study the scarring effect of unemployment during the early '90s, a period of declining unemployment rates. Second, we analyse true state dependence during the early 2000s, a period of low and relatively stable unemployment. Finally, we study to which extent British workers have been scarred by unemployment during the Great Recession. As well as providing evidence on unemployment scarring in the last two decades, our approach allows us to investigate the dynamics of true state dependence across the business cycle.

Taking into account the role of individuals' observed and unobserved characteristics (such as the individual propensity to unemployment), we provide evidence in support of the presence of unemployment scarring in all the periods analysed. Our estimates also suggest that scarring increases when unemployment increases, and the finding holds both between and within sub-periods. We also provide evidence that young people are more scarred than older workers during the Great Recession (the results are less conclusive for the earlier sub-periods).

The evidence provided supports the importance of short run interventions aimed at reducing unemployment especially in periods of adverse labour market conditions. Tackling unemployment would not only reduce the immediate distress associated with unemployment, but also reduce it in the longer term.

The scarring effect of unemployment from the early'90s to the Great Recession

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March 2015

Abstract

This paper addresses two issues of great importance in the current economic climate. First, it analyses the extent to which unemployment experiences have a scarring effect on British men during the Great Recession. Second, it provides an insight into the relation between true state dependence and the business cycle by investigating the role of local unemployment in affecting the persistence of unemployment incidence and by analysing the dynamics of unemployment scarring in the last two decades. Our results support the presence of true state dependence both during the Great Recession and in the other two sub-periods analysed, the early 90s and early 2000s. Moreover, we find evidence of a negative association between the scarring effect of unemployment and the business cycle. From a policy perspective, our findings imply that public interventions aimed at alleviating unemployment in the short term are also likely to have beneficial effects on longer term unemployment, especially during downturns.

Key words: Unemployment, Scarring, Great Recession, True state dependence, Business cycle

JEL classification: J64, J60, J01, R23

Acknowledgment: This research was supported by funding from the UK Economic and Social Research Council (ESRC) under the grant 'Understanding the impact of recession on labour market behaviour in Britain' (grant number RES-062-23-3284and also forms part of the research programme of the Research Centre on Micro-Social Change, also funded by the ESRC (award no. RES-518-28-001). The author is also thankful to Mark Bryan and Andrea Salvatori for the precious advice.

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I. Introduction

Persistence in unemployment incidence is a well-documented phenomenon consisting in a higher propensity to experience unemployment at a given point in time if unemployment has occurred in the past. As pointed out by Heckman and Borjas (1980), evidence on persistence is likely to arise from two different channels. On the one hand, unemployment experiences can have a causal impact on future unemployment probability. The authors define this kind of relationship "true state dependence" and both labour supply factors, such as human capital depreciation, habituation effects or a fall in search intensity, and labour demand factors, such as negative signalling and crowding in the labour markets, are likely to be the underlying causes (Lockwood, 1991; Pissarides, 1992; Blanchard and Diamond, 1994; Clark et. al., 2001; Biewen and Steffes, 2010; Michaillat 2012; Cockx and Picchio, 2013). On the other hand, individual characteristics, observed and/or unobserved, are likely to play a major role in explaining the propensity to experience unemployment both at a given point in time and in the future. In that case previous unemployment experiences would proxy such characteristics and any relationship between past and current unemployment status would hence be spurious (Heckman and Borjas, 1980).

In this work we explore the presence of persistence in unemployment incidence during the last two decades, with a specific focus on the last recession. Our working definition of scarring effect, or true state dependence, hence underlies the existence of a causal relationship between previous unemployment experiences and current unemployment status. The existence of such a relationship is highly relevant for policy makers. As reported by Arulampalam et al. (2000), if true state dependence exists short run policies aimed at reducing unemployment will not only affect the short term unemployment rate but also the long run-equilibrium rate of unemployment. The study of unemployment persistence is hence of great interest in the current economic climate: the extent to which workers have been "scarred" by unemployment experiences during the great recession is in fact relevant both to better understand the long lasting effect of the crisis and to design policies that are able to efficiently foster economic recovery.

Since the '80s a vast literature has explored the existence of state dependence, but its evidence is ambiguous. Heckman and Borjas (1980) describe four main forms of state dependence. The authors define as Markovian dependence the situation in which a difference exists between the probability of becoming unemployed for an employed worker and the probability of remaining in unemployment for an unemployed individual in a short time interval; occurrence dependence exists when the probability of becoming or remaining unemployed is influenced by the number of previous unemployment spells; duration dependence occurs when the probability of remaining unemployed is influenced by the length of the current unemployment spell; finally, authors define lagged duration dependence as the situation in which the probability of remaining or becoming unemployed depends on the lengths of previous unemployment spells. Using data from the National Longitudinal Survey of Young Men for the years 1969-1971, and focusing on the latter three forms of state dependence, the authors find no evidence of lagged duration dependence and occurrence dependence, while they find a weak evidence of the existence of duration dependence.[2]

Arulampalam et al. (2000) analyse Markovian unemployment persistence in the UK using wave 1 to 5 of the British Household Panel Survey (BHPS). Focusing on the respondents' labour market status measured at each consecutive interview, the authors find evidence in support of the "scarring" hypothesis, in particular for mature workers. Stewart (2007) models jointly persistence in low pay and persistence in unemployment, analysing their interrelations. Both low pay jobs and unemployment spells are in fact likely to negatively influence human capital accumulation and to provide adverse signals to potential employers. Using data from the BHPS for the years 1991-1996 the author shows that past low-wage employment is as important as past unemployment in reducing the probability of being employed at a given point in time; moreover, the analysis provides evidence in support of a no pay-low pay cycle as those entering low-wage employment after a spell of unemployment are significantly more likely to re-enter unemployment than those entering in a higher pay employment after the unemployment spell. Consistent evidence emerges also from Böheim and Taylor (2002).

Evidence on the longer term scarring effect of unemployment can be found, among others, in Gregg (2001) and Burgess et al. (2003).[3] Gregg (2001) uses the National Child Development Study (NCDS) to measure the impact of unemployment experiences before age 23 on the

[2] For more US based literature see, among others, Mroz and Savage (2006). Using data from the 1979 National Longitudinal Survey of Youth (NLSY79), the authors find evidence of short term persistence of unemployment for young people, while persistence tend to disappear in the long term.

[3] See also Kalwij (2004). Using UK administrative data, the author shows that a quarter of the sample of young men used in the analysis is not able to find a stable employment by age 35, while this is the case for the rest of the sample. Those failing to enter in stable employment are mainly low-skilled individual, and results suggest the presence of structural employment instability for this group.

probability of experiencing unemployment or inactivity between age 28 and 33. The author provides evidence in favour of a significant scarring effect of unemployment experience during youths, in particular for males. Burgess et al. (2003) use data from six waves of the Labour Force Surveys between 1981 and 1996 to perform a pseudo-cohort analysis of the impact of early career unemployment rate on future employment prospects. The authors find evidence of scarring only for the less skilled, while the more skilled seem to benefit from early career unemployment rates.[4] Unemployment experiences are also shown to have a negative and long lasting impact on outcomes such as salaries (Gregory and Jukes, 2001; Arulampalam, 2001; Mroz and Savage, 2006; Eliason and Storrie, 2006) and wellbeing (Bell and Blanchflower, 2011a, b; Clark et al. 2001).

This work contributes to the rich literature on unemployment persistence in two ways. First, it addresses the extent to which unemployment experiences have scarred British workers during the Great Recession by analysing persistence in unemployment incidence between 2007 and 2011. Second, the paper provides an insight on the dynamics of the "true state dependence" over the business cycle by analysing the extent to which scarring effect varies with local labour market conditions and by comparing estimates relative to the last recession with that of a period of falling unemployment, the early '90s, and of a period of relative stability of unemployment rate such as the early 2000s (Figure 1).

The sign of the association between true state dependence and business cycle cannot in fact be determined a priori, as it is closely related to the nature of the causes of unemployment scarring. Kroft et al. (2013) summarise four possibilities.[5] First, models focusing on human capital depreciation (Pissarides 1992; Acemoglu 1995; Edin and Gustavson 2008) predict that true state

[4] See Eliason and Storrie (2006) and Nordström Skan (2004) for studies using Swedish administrative data. Eliason and Storrie (2006) analyse the unemployment impact on wages and employment patterns for a sample of workers from plants which shout down in 1987 and 1988. The authors find evidence of a recovery both in terms of wage and employment in the years immediately following the plant dismissal. However, convergence stops at the onset of the 1991 recession and a divergence trend occurs until 1993. The authors show that dismissed workers still suffer of a penalty both in term of unemployment incidence and wage 12 years later, concluding that the workers experiencing unemployment are also more sensitive to the macroeconomic climate. Nordström Skan (2004) finds evidence of long term scarring effect of unemployment exploiting the between-sibling variation to control for unobserved heterogeneity.

[5] Although the authors focus on the relationship between duration dependence and labour market conditions, the theoretical predictions are largely applicable to the case of state dependence in unemployment persistence.

dependence should be independent from labour market conditions, as skill depreciation is assumed not to be affected by unemployment levels in the economy.

Second, models focusing on search behaviour predict that discouragement, and hence a fall in search intensity, will occur when employment perspectives deteriorate, with a consequent positive relationship between scarring effect and unemployment cycle (e.g. Ayllón 2013).

Third, models which identify in the negative signalling of unemployment the main source of state dependence predict for unemployment to be less scarring in times of adverse labour market conditions, on the grounds that unemployment experiences are less informative about the unobserved characteristics of job applicants in periods of slack labour markets (Lockwood 1991). Among others, Biewen and Steffes (2010) find supporting evidence analysing unemployment persistence in Germany, while Kroft et al. (2013) and Omori (1997) provide evidence for the US, with a focus respectively on duration dependence and lagged duration dependence.

Fourth, a number of models focus on crowding in labour markets. Among them, Blanchard and Diamond (1994) predict that if the length of the current unemployment spell provides a negative signal to potential employers in the hiring process, then high levels of unemployment are expected to reduce the probability of finding a job as it is more likely that some other worker with a shorter spell of unemployment will apply. Michaillat (2012) proposes a search and matching model in which unemployment due to jobs rationing is likely to arise even in the absence of frictional unemployment. The author shows that rationing unemployment (i.e. unemployment due to a shortage of jobs) quantitatively outweighs frictional unemployment in times of slack labour markets, while the opposite is true in times of favourable labour market conditions. In both cases, the theoretical predictions are that scarring will be worse during adverse labour market conditions because of crowding. Evidence in support of job rationing and crowding in the labour market can be found in Crépon et al. (2013). Analysing the impact of a randomised labour market program aimed at providing job placement assistance to skilled unemployed in France, the authors find that the employability of non-treated workers is significantly worsened by the program especially in times of adverse labour market conditions. The authors identify in job rationing and crowding in the labour market the main source of this negative externality.

Our analysis shows strong evidence in support of the presence of true state dependence during the great recession and, consistent with the crowding and job rationing models, it provides an indication of a negative relation between true state dependence and business cycle both within and between the three time periods analysed. Policy interventions aimed at reducing unemployment are hence likely to have positive longer term effect on the unemployment risk, in particular during downturns. Our estimates are based on random effect dynamic probit models with Wooldridge (2005) solution for the initial condition problem and make use data from the British Household Panel Survey (BHPS) and Understanding Society.[6]

The paper is organised as follows: section 2 introduces the data and the methods used for the analysis; results are presented and commented in section 3; conclusions follow in section 4.

II. Data and Method

II.1 Data and descriptive statistics

Individual unobserved heterogeneity is a potential source of bias for estimates of true state dependence. To correctly disentangle the effect of unobserved individual characteristics, i.e. the individual propensity to be unemployed, from that of past unemployment incidence is a major identification challenge and panel data are powerful tools in achieving consistent estimates of our parameters of interest. For this reason, we make use of two rich sources of panel data collecting detailed information on household and individual circumstances during the last two decades: the British Household Panel Survey (BHPS) and Understanding Society.[7]

The British Household Panel Survey started in autumn 1991 and ran for 18 annual waves. Interviews usually took place during autumn or winter and respondents were typically re-interviewed in the same period each year. After wave 18, BHPS respondents were reabsorbed into Understanding Society, a larger household survey lunched in 2009, and were re-interviewed in 2010/11 and 2011/12. Since we only use Understanding Society to follow former BHPS respondents, we refer to 2010/11 and 2011/12 data respectively as wave 19 and wave 20. In our analysis we use data from three non-overlapping sub-periods: we analyse data from waves 16,

[6] The analysis relative to the early '90 is closely related to Arulampalam et al. (2000). See Gregg and Wadsworth (2010) for an analysis of unemployment during the last two decades.

[7] See Taylor (1996) and https://www.understandingsociety.ac.uk for info respectively on the British Household Panel Survey and Understanding Society.

starting in autumn 2006, to 20 to estimate true state dependence during the Great Recession; waves 9-13, covering the period from autumn 1999 to winter 2004, are used to evaluate the scarring effect of unemployment in a period of low and stable unemployment (see Figure 1); similar to Arulampalam et al (2000), waves 1-5 are used to study the persistence in unemployment incidence during a period of high but declining unemployment.

As well as the original BHPS sample, various subsamples took part in the BHPS over time. In particular, a sample of respondents to the European Community Household Panel Survey (ECHP) was part of the study between wave 7 and wave 11, Wales and Scotland boost sample were included in wave 9 and a Northern Ireland sample in wave 11. With the aim of maximising the sample size, our study makes use of the original BHPS sample, present in all the sub-periods used, and the boost sample for Scotland and Wales, present in the waves 9 -13 and waves 16-20 but not in waves 1-5. We did not include the ECHP subsample because it is not continuously present in any of the sub-periods used, and the Northern Ireland subsample because it would be only part of the analysis relative to waves 16-20.

At the beginning of each of three sub-periods analysed, i.e. waves 1, 9 and 16, we keep full respondent males, aged between 16 and 50, not in full time education and active in the labour market, i.e. either working or in unemployment. With respect to people in work, we classify as labour market active both employees and self-employed who declared that they did paid work last week or had a job which they were away from. Consistent with Arulampalam et al. (2000) and Stewart (2007), we define as unemployed those respondents who were not in work and reported that they looked for a job in the last 4 weeks. All the rest are classified as inactive and hence not included in our estimation sample. As a robustness check we repeat the analysis with a less stringent definition of unemployment which includes also those self-defining themselves unemployed even if the job search criteria are not met. Each respondent stays in our estimation sample until a full interview is missed, or the person becomes inactive or enters full time education, or has a missing value in any of the other variables used in the analysis. Our final sample is hence an unbalanced panel with complete information on the respondents until the end of the sub-period analysed or until the respondent is excluded. A sample of this sort can be defined as “compact” but unbalanced.

Tables 1 to 3 report descriptive statistics for each of the sub-periods analysed. As shown by Table 1, the proportion of unemployed continuously falls between wave 1 and wave 5, being close to 10 percent and just below 4 percent in wave 5. The average proportion over the period is 7 percent. The probability of being unemployed at a given point in time conditional on being unemployed in previous wave is above 56 percent, while 2.8 percent of those employed in the previous wave are observed to be unemployed at the time of interview. These raw data estimates are in line with those reported by Arulampalam and al. (2000), and support the existence of persistence in unemployment incidence.

The majority of the UK based literature finds a positive effect of the local unemployment to vacancy ratio on the probability of being unemployed at a given point in time (e.g. Arulampalam et al. 2000; Arulampalam and Stewart 2009) and Biewen and Steffes (2010) find evidence that the scarring effect is countercyclical in Germany. We control for local labour market conditions trough the claimant proportion, a measure of the proportion of claimants of unemployed related benefits over the population aged 16-64 at the local authority district level.[8] Consistent with the trend of the unemployment rate reported in Figure 1, the claimant proportion increases between wave 1 and wave 2, and start to decrease in later waves.

A higher incidence of full time education among youths, as well as ageing and the fact that we don’t allow new entries in our estimation sample, explains the lower and declining over time proportion of youths aged between 16 and 25 compared with other age groups. Arulampalam et al. (2000) shows that youth has been less affected than adults by scarring in the early ‘90s; we test weather a similar pattern emerges during the Great Recession.

On aggregate, the majority of respondents in our sample are above the CSE education level, and 22.8 percent report no qualifications among the listed ones. Following Arulampalam and Stewart (2009), the education variable is considered time invariant and measured at the beginning of the sub-period because a) observations drop from our estimation sample as soon as they are observed in full time education; b) few changes in qualification occur. The great majority of respondents in our sample are home owners, with a prevalence of social renters on private renters among non-home owners. The proportion of married people increases over time while the average number of children in the household ranges between 0.89 and 0.88 in the period analysed. Only 3

[8] See NOMIS website for more information

percent of respondents report to be in poor health conditions while a 3 percent are from a non-white ethnic group.

Table 2 reports descriptive statistics for waves 9 to 13. On average 3.5 percent of the sample is observed to be in unemployment at the time of the survey, and the proportion is declining over time. Evidence of persistence in unemployment incidence in the raw data emerges, as the probability of being in unemployment conditional on being unemployed in previous wave is about 45 percent, a value considerably higher than the 1.6 percent probability faced by those employed in the previous wave. It should be noted that the claimant proportion shows a slowly declining trend across waves, consistent with the broadly stable unemployment rate in the same period. The use of a boost sample for Scotland and Wales explains the high proportion of people living in these two regions.[9]

With respect to waves 16-20, the number of observation is declining over time as expected, but a significant drop occurs between wave 18, the last wave of the BHPS, and wave 19, the first wave in which former BHPS respondents were interviewed as part of Understanding Society. Table 3 shows that the proportion of unemployed is declining between wave 16 and wave 18, reaching a minimum of 2.1 percent in wave 18, i.e. late 2008 and early 2009, and it rises considerably in wave 19; the aggregate proportion of unemployed is about 3 percent.[10] On aggregate, the probability of being in unemployment at a given point conditional on being unemployed in previous wave is close to 41 percent. The same probability amounts to 1.5 percent for those previously employed. Consistent with previous literature, this evidence confirms the existence of persistence in unemployment incidence in the row data.

Comparing the descriptive statistics across sub-periods, it should be noted that i) the levels of the claimant proportion are considerably higher in this first sub-period than they are during the Great

[9] The item measuring general heath is different in waves 9, 19 and 20 compared with the other BHPS waves. Categories have been re-grouped in order to be as comparable as possible, but this is likely to explain the drop in the proportion of people in bad health that occurs in these waves.

[10] A considerable drop in the proportion of unemployed occurs between waves 1 and 2, 9 and 10, 16 and 17. As well as a declines in the aggregate unemployment rate, also confirmed by figure 1, the drop is likely to be caused to a certain extent by the way our sample is build, as inactivity and missing interview seems to affect more the unemployed than the employed. Although endogenous selection into economic activity could be an issue, in their study on low-pay persistence Cappellari and Jenkins (2008) show that ignoring endogenous selection into employment does not introduce sizable bias into estimates of covariate effects. Moreover, the robustness check in which we estimate our models by defining as unemployed also those inactive respondent who defined themselves as unemployed confirms our findings.

Recession; ii) the age profile varies across sub-periods, with a higher proportion of youths and a lower proportion of adults in the early '90s arguably because of the subsequent expansion in access to further education; and that iii) the level of academic qualification is substantially lower in the wave 1 to 5 sub-period, with a 12.7 per-cents of respondent with a degree or more and more than 22 percent of observations with no qualification. A further improvement in the education profile of respondents also arises when statistics relative to the Great Recession sub-period are compared to those relative to waves 9-13.

Descriptive statistics show the presence of persistence in unemployment incidence in all the sub-samples used. However, controlling for observable and unobservable characteristics is necessary to assess the existence of true state dependence in the data. With respect to observables, for example, tables 1-3 show a high degree of heterogeneity in characteristics of the respondents in the three sub-samples, with people part of the "Great Recession sample" tendentially older and more educated than those part of the early '90s sample. Similar considerations apply to the claimant proportion. The next sub-section introduces the identification strategy that we use to disentangle the effect of previous unemployment from those of observed and unobserved characteristics and to estimate true state dependence.

II.2 Methods

Similar to numerous previous works on persistence in unemployment incidence, we use a dynamic random effect probit to identify the presence of true state dependence in our data (Arulampalam et al., 2000; Biewen and Steffes, 2010; Stewart, 2007) and we adopt the Wooldridge (2005) solution for the initial conditions problem. See Arulampalam and Stewart (2009) for an exhaustive description of the three most commonly used methods to deal with the initial condition problem, i.e. Heckman (1981a,b), Orme (1997; 2001) and Wooldridge (2005).

An individual i at time of interview t is observed to be in unemployment if her unobserved propensity to be unemployd U_{it}^* crosses a threshold of 0. The propensity to be unemployed is assumed to be a function of unemployment status at the time of previous interview, U_{it-1}, a row vector of observable characteristics, $\boldsymbol{X}_{it}$, an individual specific unobserved effect c_i and a random error term e_{it}.

$$U_{it}^* = \boldsymbol{X}_{it}\boldsymbol{\beta} + \gamma U_{it-1} + c_i + e_{it}\,, \qquad i = 1, \dots, n \text{ and } t = 2, \dots, T_i \qquad (1)$$

with $e_{it} \sim N(0,1)$. Following Mundlak (1978) and Chamberlain (1984), we allow for correlation between the unobserved heterogeneity term c_i and observed characteristics $\boldsymbol{X}_{it}$ by assuming a relationship of the form $c_i = \overline{\boldsymbol{X}}_i \boldsymbol{\theta} + \alpha_i$, where $\alpha_i \sim iid\ N(0, \sigma_a^2)$ and independent of $\boldsymbol{X}_{it}$ and e_{it} for all i and t (Stewart, 2007; Arulampalam et al. 2000). We are hence left with an equation of the form

$$U_{it}^* = \boldsymbol{X}_{it}\boldsymbol{\beta} + \gamma U_{it-1} + \alpha_i + \overline{\boldsymbol{X}}_i \boldsymbol{\theta} + e_{it}, \qquad i = 1, \dots, n \text{ and } t = 2, \dots, T_i \tag{2}$$

The model in equation (2) can be consistently estimated only if the initial condition U_{i1} is exogenous. This would be the case, for example, if we had observed individuals since the beginning of the data generating process. In presence of a correlation between initial condition and unobserved heterogeneity, however, the estimate of the parameter of interest γ would be biased upward because part of the effect of the unobserved heterogeneity would be captured by the coefficient on the lag dependent variable (Stewart, 2007).

Following Wooldridge (2005), the problem of the initial condition is addressed in the spirit of Mundlak (1978) and Chamberlain (1984) by controlling for a linear relationship between unobserved heterogeneity and initial condition and estimating the model conditional on the initial value of the variable of interest. In particular, it is assumed that:

$$\alpha_i = a_0 + a_1 U_{i1} + \varphi_i \tag{3}$$

Substituting (3) into (2):

$$U_{it}^* = \boldsymbol{X}_{it}\boldsymbol{\beta} + \gamma U_{it-1} + a_0 + a_1 U_{i1} + \varphi_i + \overline{\boldsymbol{X}}_i \boldsymbol{\theta} + e_{it}, \qquad i = 1, \dots, n \text{ and } t = 2, \dots, T_i \tag{4}$$

Equation (4) can be easily estimated using a random effect probit.

The coefficient on the lagged unemployment status is our coefficient of interest. A positive and significant coefficient implies the presence of true state dependence since, controlling for observed characteristics and unobserved heterogeneity, past unemployment influence current unemployment status. Consistent with other studies on unemployment persistence, the vector $\boldsymbol{X}_{it}$ contains variables such as age, highest academic qualification, marital status, general health, proportion of unemployment benefits claimants in the population aged 16-64 at the local authority district level, region of residence and wave dummies. $\overline{\boldsymbol{X}}_{it}$ contains the within-individual average of time varying covariates. Due to lack of variation in regional mobility, averages of region dummies are not included in the model. The variable age is assumed to be exogenous to the unobserved heterogeneity term, so average age is similarly not included.

Following Wooldridge (2005), average partial affects (APE) are based on

$$\mathrm{E}[\Phi(\boldsymbol{X}_{it}\boldsymbol{\beta} + \gamma U_{it-1} + a_0 + a_1 U_{i1} + \varphi_i + \overline{\boldsymbol{X}}_i\boldsymbol{\theta})] \tag{5}$$

where the expectation is over the distribution of $(U_{i1}, \overline{\boldsymbol{X}}_i, \varphi_i)$

$$APE = \frac{1}{N}\sum_{t=2}^{T_i}\sum_{i=1}^{n}\left\{\Phi\left(\frac{\boldsymbol{X}_{it}\widehat{\boldsymbol{\beta}} + \hat{\gamma}+\hat{a}_0+\hat{a}_1 U_{i1} + \overline{\boldsymbol{X}}_i\widehat{\boldsymbol{\theta}}}{\sqrt{(1+\hat{\sigma}^2)}}\right) - \Phi\left(\frac{\boldsymbol{X}_{it}\widehat{\boldsymbol{\beta}} + \hat{a}_0 + \hat{a}_1 U_{i1} + \overline{\boldsymbol{X}}_i\widehat{\boldsymbol{\theta}}}{\sqrt{(1+\hat{\sigma}^2)}}\right)\right\} \tag{6}$$

where N identify the total number of individual-time observations in our sample. In order to evaluate the extent to which true state dependence varies within the three sub-period analysed, we also compute wave specific APEs by averaging over the wave specific population. We follow the same strategy for the calculation of APEs by age and by level of local unemployment. Standard errors are computed trough bootstrapping with replacement with 500 replications.

In the spirit, respectively, of Biewen and Steffes (2010) and Arulampalam et al. (2000) we also investigate whether true state dependence varies with age and levels of local unemployment. Our model being non-linear, our base specification presented in equation (4) already allows for the average partial effects on the lagged unemployment status to vary with the characteristics of the respondent. In this context, even if the inclusion of an interaction term allows more flexibility in analysing the relationship between true state dependence and individual characteristics, a lack of significance in the interaction term does not necessarily imply a zero gradient in true state dependence with respect to changes in such characteristics. Hence, when we analyse whether true state dependence varies between claimant proportion or age of the respondent we act according to the following strategy. First, we augment our base specification by including an interaction term between the lagged unemployment status and the claimant proportion (model 3) or age (model 4). In model 3 we also we include an interaction term between the unemployment status at first interview and the claimant proportion. If these interaction terms are statistically significant, then we compute APEs using the model including the interactions. Otherwise we compute APEs from model 2 in order to maximise statistical efficiency. [11]

III. Results

In this section we present the results of our analysis. For each sub-period we estimate 4 different models. Model 1 is a pooled probit, which allows us to analyse the relationship between lagged and current unemployment status controlling for the observable characteristics of the respondents, but not for the unobservable ones. Model 2, which consists in a dynamic random effect probit with Wooldridge (2005) solution for the initial condition problem, is our baseline specification as it allows us to also control for unobserved time invariant characteristics of the individual. In model 3 we extend our baseline specification by controlling for the interaction between lagged unemployment status and claimant proportion. The aim of this specification is to allow more flexibility in analysing possible relations between local labour market conditions and true state dependence (Biewen and Steffes, 2010). In model 4 we add an interaction term between our lagged unemployment status and age of the respondent. Arulampalam et al. (2000) show that youths below 25 years old are less scarred by unemployment than adults in the early '90s, and we check if the finding is still valid during the early 2000s and the Great Recession.

After analysing the three sub-periods on their own in the subsections 1 to 3, we also report estimates of true state dependence for an hypothetical individual with fixed characteristics in each of the three sub-periods analysed; this exercise allows us to study the patterns of the scarring effect of unemployment across the three sub-periods analysed holding constant the observable characteristics of the individual. The last subsection discusses a number of robustness checks.

III.1 The early 90's

In this section we focus our analysis on the period ranging from 1991 to 1995, a period of declining unemployment after the early '90s recession. We partly replicate Arulampalam et al (2000), although we use slightly different regressors and a different solution to the initial

[11] We also estimate a model including an interaction term between lagged unemployment status and wave dummies. We do not report estimates from this specification as interaction terms are never statistically significant.

condition problem to obtain estimates of state dependence that are consistent across the three sub-periods used. Our coefficient estimates are reported in Table 4, and APEs in Table 5.

Consistent with previous research, the pooled probit estimates (Model 1) show a positive relationship between lagged and current unemployment status. This result implies that controlling for a number of observed characteristics those unemployed in the previous wave face a higher risk of current unemployment than those previously employed. However, since model 1 does not control for individual unobserved heterogeneity, the finding is not to be interpreted as evidence of true state dependence. Among other regressors, estimates from model 1 show that the claimant proportion is positively associated with unemployment probability, while the sign of the association is negative for age and education, with older and more educated respondents less likely to experience unemployment at a given point in time. Estimated coefficients also show that compared to private renters, home owners face a lower unemployment risk while social renters are more likely to be in unemployment. Finally, being married is associated with a lower unemployment probability, while number of children in the household is positively associated with unemployment risk. Among wave dummies, only the coefficient on wave 5, correspondent to year 1995/96, is statistically significant.

Average partial effects from Model 1 are reported in Table 5. Results show that after controlling for the observable characteristics of the respondent the average partial effect on the lagged unemployment status is close to 0.4, meaning that on average a person who was unemployed last year is 40 percentage points more likely to be unemployed this year than a similar person who was employed last year.

Estimates from Model 2 are based on a random effect dynamic probit with Wooldridge (2005) solution to the initial condition problem. Model 2 represents our preferred specification as it controls both for the effect of observed characteristics as well as unobserved time invariant characteristics. Consistent with previous literature (e.g. Arulampalam et al. 2000; Stewart 2007), the coefficient on the lagged unemployment status is positive and statistically significant. The result is consistent with the existence of true state dependence as past unemployment incidence significantly affects current unemployment probability. In particular, the APE of lagged unemployment is about 8.4 percentage points, while wave specific true state dependence is estimated to decline over time from about 10 percentage points in wave 2 to 6.2 percentage points in wave 5. As expected, estimates of true state dependence from model 2, which controls for individual unobserved heterogeneity, are considerably smaller than those from model 1, and even smaller than raw data state dependence.

With respect to other regressors, estimated coefficients confirm the importance of age and education in affecting the unemployment risk. Also the claimant proportion has a positive and significant coefficient, confirming that adverse labour markets increases the probability of being unemployed.

APEs from model 2 show a declining trend over time, a pattern similar to that followed by unemployment rate in the same period (Figure 1). With the aim of analysing the relationship between state dependence and labour market conditions we include an interaction term between lagged unemployment status and claimant proportion (Model 3). Estimates show that the interaction term is not statistically significant. In a different specification (not reported) we interacted the cyclical component of claimant proportion in the spirit of Biewen and Steffes (2010), but without finding any significant effect. APEs on lagged unemployment after model 3, reported in Table 5, are consistent with those computed after our base specification, and confirm the declining trend in true state dependence over time.

As the interaction term between unemployment status at previous interview and claimant proportion is not statistically significant, for greater statistical efficiency we use estimates from model 2 to evaluate to which extent the scarring effect of unemployment varies among individuals experiencing different labour market conditions. We hence evaluate average partial effects on lagged unemployment over the distribution of claimant proportion discretised in 2 percentage points bands. Estimates, reported in Table 6, show that unemployment experiences scar more those experiencing higher level of local unemployment. A t-test confirms that scarring effect at each subsequent band of claimant proportion is statistically different from the one faced by individuals living in areas where the proportion of active population claiming unemployment related benefits ranges between 2 and 4 percentage points. Unlike the results presented by Biewen and Steffes (2010) for Germany, our findings suggest for state dependence to be higher in periods or areas of high unemployment and hence to be negatively correlated with the business cycle.

Consistent with Arulampalam et al. (2000) the coefficients from Model 4 show that youths below age 26 are less affected by the scarring effect than other age groups. Arulampalam et al. (2000) imputes this result to job shopping, i.e. a propensity to change job several time during youth. APEs after model 4, reported in Table 5, are consistent with the findings of our base specification. APEs averaged across age groups after both models 2 and 4 are reported in Table 7. Following our base specification, youths are the most scarred by unemployment experiences, while estimates of true state dependence for older workers are between 7.1 and 7.9 percentage points. APEs based on model 4, which allows more flexibility in the relationship between age and scarring effect of unemployment, show that youths are less scarred by unemployment experiences than mature workers, although the differences are not statistically significant. Despite the interaction terms between unemployment status at previous wave and age bands are statistically significant, their introduction makes the estimates of APEs over age groups less precise.

Consistent with several UK focused works based on early '90 data (e.g. Arulampalm et al 2000, Stewart 2007), our analysis strongly supports the existence of true state dependence in a period ranging from 1991 to 1995/96. Over the analysed period, the estimated average partial effect following our base model specification is close to 8.5 percentage points and it goes up to 9 when interactions between age categories and lagged unemployment status are included. Our estimates show a counter-cyclical pattern of true state dependence, as unemployment is less scarring if local labour market condition are more favourable. In the following sub-sections we perform our estimations on two different sub-periods, the early 2000's and the Great Recession. As well as providing consistent estimates of true state dependence in those periods, the analysis will contribute to a better understanding of its relationship with the business cycle.

III.2 The early 2000s

This section analyses state dependence in unemployment incidence in the early 2000s. As shown in Figure 1, between 1999 and 2003 unemployment was low and broadly stable. The macroeconomic scenario in this period is hence radically different both from the one analysed above, characterised by declining unemployment rates, and from the one studied in the next subsection, characterised by a considerable increase in unemployment during the Great Recession. Model specifications are the same as in the previous section: model 1 contains a pooled probit analysis, in model 2 we estimate the dynamic random effect probit model with the Wooldridge (2005) solution for the initial condition problem, in models 3 and 4 we modify our base specification by introducing interaction terms between the lagged unemployment status and, respectively, claimant proportion and age categories.

Comparing the estimated coefficients, reported in Table 8, with those relative to the analysis of waves 1-5, three main differences arise: i) a negative but not significant effect of claimant proportion on the probability of being unemployed in model specifications 2-4; ii) in all the model specifications the "none of these" education category becomes the only one with a statistically positive coefficient; iii) in model 4, the coefficient on the interaction term between lagged unemployment status and age categories become not statistically significant with the exception of the 46-55 age category that is just on the margin of statistical significance.

Focusing on the APEs reported in Table 9, for model 1 we estimate an effect of 0.27 overall with an irregular pattern between waves. According to APEs after model 2, those previously unemployed have on average a 6 percentage points higher probability to be currently unemployed than those previously in employment. Despite being irregular, no particular pattern can be identified between waves. APEs from models 3 and 4 show consistent results. In Table 10 we report APEs after model (2) evaluated over the discretised distribution of claimant proportion. Estimates confirm that workers experiencing worse labour market conditions are more scarred than those experiencing lower level of local unemployment.[12]

Table 11 reports APEs by age group estimated after model 2, showing that youths suffer the most from past unemployment experiences. Since the interaction term between lagged unemployment and age dummy is just at the margin of statistical significance in model 4, we also report APEs by age group computed after model 4. The results, reported in the second panel

[12] As a robustness check, we also computed APE on lagged unemployment status by fixing the values of claimant proportion at various increasing values. This method of computing APEs imposes to all the individuals in our sample to experience the same level of claimant proportion, leaving all the other variables at individual values. While we find consistent results with respect to the early '90s and Great Recession sub-periods, i.e. APE increases with level of claimant proportion, this is not the case of the early 2000's sub-period. The result is arguably driven by the lack of precision with whom the coefficients on the claimant proportion and on the average over time of the claimant proportion faced by the individual are estimated. Excluding the average over time of time varying covariates, which are jointly not statistically significant, produce consistent results with those presented in the main sections of the paper, and confirms a positive association between claimant proportion and scarring effect both averaging over the population of people experiencing different levels of unemployment and by exogenously fixing claimant proportion at different values of interest.

of Table 11, shows a U-shaped trend of true state dependence with respect to age, although the lack of statistical significance of the interaction terms makes our APEs for the youngest population group to be not statistically different from those of older groups.

Our analysis hence shows the presence of true state dependence during the early 2000s, and its average over the time period is smaller than the one estimated for the early '90s. In the waves 9-13 estimates of true state dependence show a slightly irregular but overall constant pattern and support a negative relationship between business cycle and scarring effect of unemployment.

III.3 The Great Recession

Table 12 reports the estimates of Models 1-4 for waves 16-20, i.e. the sub-period of the Great Recession. Consistent with findings relative to the other sub-periods analysed, the coefficient on the lagged unemployment estimated by the pooled probit (model 1) is positive and statistically significant. Unlike the early '90s sub-period, local labour market conditions seem not to significantly influence the unemployment risk as the coefficient on the claimant proportion is positive but not statistically significant. The lack of an effect can however be explained by a high degree of correlation between wave dummies and claimant ratio. In all model specifications, in fact, the exclusion of wave dummies from our estimated equation leads to larger in size and statistically significant coefficient on the claimant ratio. Among other regressors, estimates from model 1 confirms both the negative association between age and unemployment risk found for the previous sub-periods and, similar to the wave 9 to 13 sub-period, also the role plaid by lack of education qualification in increasing the unemployment probability. APEs after our pooled probit specification (Model 1), reported in Table 13, show that the effect on the lagged unemployment status is close to 0.2. Wave specific APEs show the presence of a shift in wave 19 and wave 20.

Model 2, which allows us to control for unobserved heterogeneity as well as observed characteristics of the individual, provides evidence in support of existence of true state dependence during the Great Recession. The coefficient on lagged unemployment is in fact positive and statistically significant, while APEs (Table 13) shows that those who were unemployed at a given wave experience a probability of being in unemployment at the following wave that is 7.9 percentage points higher than those previously employed. The scarring effect of unemployment shows an increasing pattern by wave, as our estimates are close to 7 percentage points in 2007/08 and 2008/09 and peak to 8.4 and 7.9 percentage points in wave 2010 and 2011. Among other regressors, the coefficient on the local claimant proportion is not statistically significant, arguably for collinearity with the wave dummies, while age, having no academic qualification and the dummy relative to wave 19 significantly affect the unemployment risk.

In models 3 and 4 we fail to find any significant interaction term between lagged unemployment status and respectively claimant proportion (Model 3) and age (Model 4). APEs relative to these specifications confirm the findings from model 2. As for the previous sub-periods, we report in tables 14 and 15 respectively APEs by claimant proportions and by age after model 2. The estimates confirm the positive association between local unemployment and state dependence, as the APE on lagged unemployment is significantly higher for those experiencing high level of claimant proportion when compared with those experiencing tighter labour market conditions. Consistent with APEs following our base specification for the other sub-periods, the estimated APEs show a decreasing pattern in scarring by age group, with youth more affected by unemployment experiences than adults.

Our analysis thus confirms that unemployment is also a scarring experience during the Great Recession. Moreover, our results suggest the existence of a negative association between business cycle and true state dependence in the years of the Great Recession as well as in the other sub-samples.

Comparing across sub-periods, our results hence show that i) unemployment experiences have had a scarring effect on future employability in the last two decades; ii) workers experiencing worse local labour market conditions are significantly more scarred than those experiencing tighter labour markets and iii) youths are those more at risk of being scarred by unemployment experiences, although allowing more flexibility in the relationship between unemployment status in previous wave and age shows that older workers have been scarred at least as much as youths in the early ‘90s.

Figure 2 reports our wave specific estimates of true state dependence after Model 2 for the three sub-periods analysed together with trends for male annual unemployment rates in Great Britain as reported in Figure 1. Similarly, Figure 3 provides a scatterplot of our estimates unemployment scarring and male unemployment rates. Point estimates are weighted by the inverse of their estimated variance. The plots provide descriptive evidence that the negative association between scarring effect of unemployment and business cycle holds not only within sub-periods, but also between. If confirmed by future research, such results will be consistent with factors such as crowding in the labour markets (Michaillat 2012) at least compensating the beneficial effect of the reduction in the stigma associated to unemployment during recessions.[13]

In the next subsection we further develop the role of business cycle in affecting unemployment experience by analysing the scarring effect of unemployment for an hypothetical person with fixed characteristics across the three sub-periods.

III.4 Cross period analysis

Previous sections have provided evidence in favour of true state dependence in the three sub-periods analysed and have provided evidence supporting that unemployment scarring is basically counter-cyclical, as a positive association between true state dependence and unemployment cycle arises.

In this subsection we report the estimates of true state dependence after model 2 for a reference person across the three sub-periods. The reference person has the following characteristics: age between 16 and 25; O level education; home owner; not married and with no children; not in poor health; from a white ethnic background and living in the Midlands. Claimant proportion is fixed at the wave specific average faced by people living in the Midlands. The exercise allows us to better appreciate the extent to which scarring effect has changed in the past two decades by holding constant the observed characteristics of the individual. As far as unobserved heterogeneity and initial conditions are concerned, following Wooldridge (2005) we use the observation specific values.

Tables 16-18 reports APEs for the reference person across the three sub-periods analysed. Compared to tables 5, 9 and 13, the estimates show that the APEs for the reference person are

[13]While our estimates of true state dependence are wave specific, annual unemployment rates refers to calendar years. We matched the two measures by using the year in which wave-specific interviews officially started to take place (e.g. 1992 for wave 2, etc..). This explains the missing estimate of true state dependence in Figure 2 for year 2010, as we assigned the value of true state dependence relative to wave 18 to the year 2008 and those relative to wave 19 to the year 2010,

usually bigger and less precise than the APEs calculated for the sub-period populations. The results confirm the main findings of our analysis: evidence of true state dependence arises from the whole period analysed, despite being just at the margin of statistical significance for the wave 9-13 sub-period, and its magnitude is negatively correlated with the business cycle as wave specific APEs follow a decreasing pattern during the first sub-period, stable during the late '90s and increasing during the Great Recession.

III.4 Robustness check

We perform a number of robustness checks. First, given that discouraged unemployed who do not meet the job search criterion would be classified as inactive and hence excluded from our estimation sample, we repeat the analysis using an alternative definition of unemployment which relaxes the job search criterion and classifies as unemployed all those who are not employed or self-employed and classify themselves as unemployed.[14] Results, reported in column 1 of Appendix tables A1, A3 and A5, show evidence of state dependence for all the period analysed. APEs, reported in column 1 tables A2, A4 and A6, confirm that scarring effect is negatively correlated with the business cycle. We also find evidence in support of true state dependence being present in all the sub-periods analysed, and of a pattern over time which is consistent with scarring effect being negatively correlated with the business cycle, when we restrict our estimation sample to a balanced panel (column 2) or exclude the Scotland and Wales boost samples (column 3). [15]

A number of previous studies showed that the estimated true state dependence drops considerably when spell of unemployment lasting across two (or more) consecutive interviews are excluded from the estimation sample (Arulampalam et al. 2000; Stewart 2007). The check is performed on the grounds that the coefficient on lagged unemployment status is likely to pick the effect of continuing spells rather than true state dependence (Jenkins 2013). Column 4 of tables A1-A5 reports estimated coefficients and APEs from model 2 after excluding long spells of unemployment and re-compatting the panel. Consistent with previous literature, the size of the

[14] See Arulampalam (2002) for a discussion on the implications of using different definitions of unemployment for the identification of true state dependence

[15] The declining trend in scarring effect observed in sub-period 1991-1995 is less regular using a balanced panel. It should also be noted Scotland and Wales boost samples have been introduced only in 1999, and this explains why estimates for the early '90s sub-period reported in column 3 are the same as to those reported in the main result sub-section.

coefficients on lagged unemployment drops considerably and same applies to APEs. Despite the reduced size, a negative association with the business cycle is still present. It should be noted, however, that the check is costly in terms of observation loss and likely to introduce a negative bias in our calculation. Dropping continuing spells of unemployment implies, in fact, excluding from the estimation sample not only the long spell of unemployment experienced by a respondent, but also all the observations following the long spell as the panel needs to be compact. Although the number of observations lost is not too large in absolute terms, it should be noted that the exclusion only affects those with at least two consecutive unemployment statuses in our estimation sample, i.e. those who contribute to our coefficient of interest. [16] Moreover, from an intuitive point of view, scarring effect of unemployment can manifest itself not only through an increase in the probability of being in a different unemployment spell in the future, but also through a lower probability of finding a job and to end the current unemployment spell. Hence, arguably, excluding from the estimation sample those with long spells of unemployment would introduce a negative bias in our estimates.[17] Finally, excluding long spells of unemployment would be most appropriate if the time distance between two consecutive interviews did not allow a change in employment status. An example can clarify this point. If our models would be applied to a study of prison convictions and the gap between interviews would be smaller than the time that the respondent has to spend in prison, then we would artificially find a positive effect of a past prison experience on a current prison experience, while the prison experience is in fact the same and the respondent would not have had any chance to change her status. In the context of this paper, respondents are allowed to change their labour market status between consecutive interviews and if they do not change it, it is because of individual characteristics, observable and/or unobservable, labour demand factors and past unemployment experiences.

[16] Consistent with Arulampalam et al. (2000), we consider a spell "long" if the respondent is in the same unemployment spell in two consecutive interviews. Stewart (2007) makes the definition stricter by excluding from the analysis all the observations who are unemployed in consecutive interviews and do not have at least one employment spell in between. This specification leads to a loss of statistical significance for the coefficients on lagged unemployment experience for waves 1-5 and waves 16-20, arguably because of an the even higher number of observation with two or more consecutive unemployment spells excluded by the check.

[17] Elements of duration dependence, as well as state dependence, can influence the probability of staying in unemployment for two or more consecutive waves. However, explicitly disentangling between the two sources of dependence goes beyond the scope of this paper.

To conclude, the checks performed confirm the robustness of our results and support the evidence on existence of true state dependence in our data and on its negative correlation with the business cycle.[18]

Conclusions

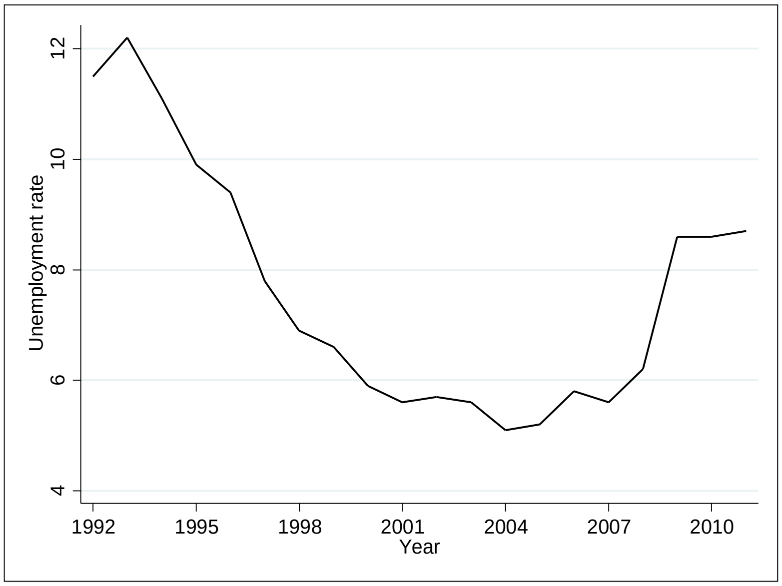
In this paper we analyse the extent to which past unemployment experiences affect current unemployment risk in the last two decades. In the spirit, among others, of Arulampalam et al. (2000) and Stewart (2007), we use data from the BHPS and Understanding Society to estimate a dynamic random effect probit with Wooldridge (2005) solution to the initial condition problem for three sub periods: the early ’90, the early ‘2000 and the Great Recession. Our estimates provide evidence in favour of true state dependence in all the periods analysed. In particular, consistent with Arulampalam et al. (2000), we find that between 1991 and 1995, a period of declining unemployment, those unemployed at a given point in time were on average 8.4 percentage points more likely to experience unemployment in the following wave than those previously employment. Our estimates show a declining pattern of true state dependence in the period analysed, as APEs declines from 9.8 to 6.2 percentage points. We also find evidence of true state dependence between 1999 and 2003/04, a period of low and stable unemployment. In these years, APEs are on average equal to 6.2 percentage points, and the patter of the estimates across waves is tendentially stable over time. Finally, between 2006 and 2011/12, the period which includes the Great Recession, estimates of true state dependence amounts to 7.9 percentage points, but increasing over time from 6.9 percentage points in 2007 to 9.9 percentage points in 2010/11, and reducing to 8.4 percentage points in 2011/12. Consistent with theoretical prediction of job crowding models (Michaillat 2012; Crépon et al. 2013), our results show a negative association between business cycle and true state dependence, as estimates increase when unemployment increases, and fall when unemployment fall. Finally, while in the early ‘90s we find evidence of scaring effect of unemployment affecting adults at least as much as youths, the evidence suggests that youths have been affected the most by state dependence during the early 2000s and the Great Recession.

[18] We do not report p-values based on bootstrap for concerns relative to computational time.

Our findings therefore support the existence of a scarring effect of unemployment during the great recession, and a positive association arise with levels of unemployment. The Great Recession has hence not only increased the current stock of unemployed, but also has negatively influenced the future employment chances of those experiencing unemployment. Short-term intervention aimed at reducing the number of unemployed are hence likely to have beneficial effects both in the short and in the medium-long term.

Tables and Figures

Figure 1: Unemployment Rate in Great Britain, males only, 1992-2011



Source: ONS

Figure 2: Unemployment Rate and True State dependence, 1992-2011

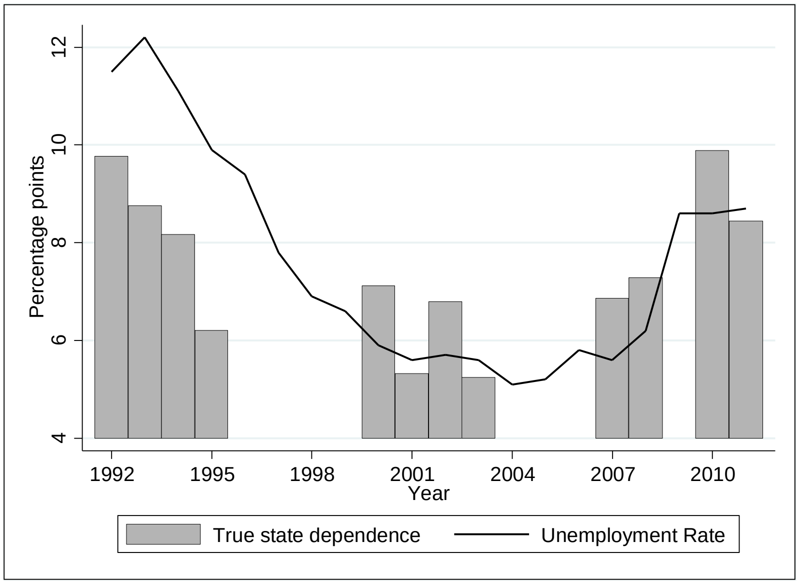


Figure 3: Unemployment Rate and True State dependence, scatterplot

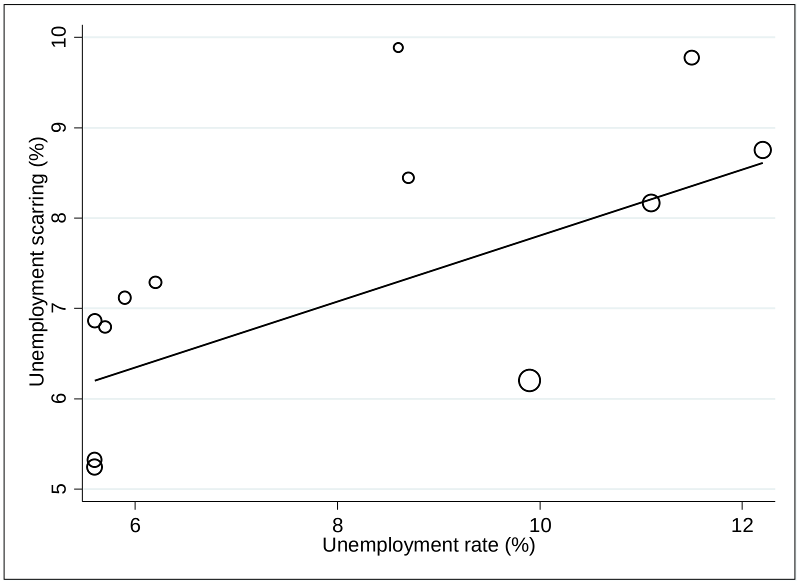


Table 1: Descriptive Statistics, wave 1-5

	1	2	3	4	5	Total
Unemployed	0.096	0.079	0.066	0.058	0.038	0.071
Unemployed (t-1)	.	0.077	0.066	0.058	0.048	0.064
Unemployed | Unemployed t-1	.	0.556	0.587	0.600	0.507	0.566
Unemployed | Employed t-1	.	0.039	0.029	0.025	0.014	0.028
Age 16-25	0.235	0.175	0.145	0.113	0.090	0.162
Age 26-35	0.338	0.349	0.345	0.330	0.313	0.337
Age 36-45	0.298	0.323	0.311	0.319	0.328	0.314
Age 46-55	0.128	0.153	0.199	0.237	0.269	0.188
Claimant proportion	6.360	7.332	7.271	6.331	5.624	6.622
Degree or higher	0.116	0.121	0.131	0.137	0.137	0.127
Other high	0.067	0.069	0.072	0.074	0.075	0.071
A level	0.223	0.229	0.226	0.227	0.230	0.227
O level	0.273	0.269	0.268	0.267	0.269	0.269
CSE level	0.077	0.077	0.080	0.078	0.077	0.078
None of these	0.244	0.235	0.224	0.217	0.211	0.228
Home owner	0.753	0.787	0.791	0.812	0.831	0.790
Social renter	0.144	0.131	0.125	0.107	0.089	0.123
Private renter	0.104	0.081	0.085	0.081	0.080	0.088
Married	0.588	0.640	0.666	0.677	0.694	0.646
Number of kids in HH	0.855	0.888	0.889	0.886	0.876	0.877
Poor health	0.033	0.037	0.035	0.034	0.030	0.034
Non white	0.041	0.031	0.031	0.031	0.027	0.033
London and SE	0.242	0.231	0.235	0.233	0.232	0.235
South West	0.089	0.093	0.094	0.093	0.092	0.092
East of England	0.084	0.087	0.089	0.090	0.092	0.088
Midlands	0.177	0.182	0.182	0.185	0.188	0.182
North, Yorkshire and the Humber	0.272	0.271	0.262	0.263	0.267	0.267
Wales	0.050	0.051	0.051	0.053	0.050	0.051
Scotland	0.087	0.085	0.087	0.083	0.080	0.085
N	2705	2186	1895	1727	1571	10084

Table 2: Descriptive Statistics, wave 9-13

	9	10	11	12	13	Total
Unemployed	0.057	0.038	0.024	0.027	0.019	0.035
Unemployed (t-1)	.	0.041	0.028	0.017	0.022	0.028
Unemployed | Unemployed t-1	.	0.496	0.429	0.538	0.304	0.452
Unemployed | Employed t-1	.	0.019	0.013	0.018	0.012	0.016
Age 16-25	0.212	0.159	0.111	0.091	0.063	0.136
Age 26-35	0.339	0.338	0.328	0.305	0.285	0.322
Age 36-45	0.332	0.351	0.373	0.378	0.379	0.360
Age 46-55	0.117	0.152	0.189	0.226	0.273	0.183
Claimant proportion	3.170	2.709	2.428	2.325	2.226	2.626
Degree or higher	0.171	0.175	0.180	0.186	0.192	0.180
Other high	0.086	0.091	0.093	0.093	0.093	0.091
A level	0.251	0.254	0.252	0.255	0.256	0.253
O level	0.269	0.271	0.270	0.270	0.269	0.270
CSE level	0.081	0.076	0.075	0.074	0.072	0.076
None of these	0.143	0.133	0.128	0.123	0.118	0.131
Home owner	0.760	0.794	0.816	0.836	0.852	0.806
Social renter	0.143	0.124	0.109	0.098	0.082	0.114
Private renter	0.098	0.081	0.076	0.066	0.065	0.079
Married	0.511	0.557	0.593	0.617	0.636	0.576
Number of kids in HH	0.835	0.886	0.898	0.901	0.890	0.879
Poor health	0.012	0.041	0.037	0.041	0.039	0.033
Non white	0.032	0.032	0.032	0.030	0.030	0.031
London and SE	0.161	0.162	0.165	0.160	0.160	0.162
South West	0.063	0.065	0.065	0.071	0.070	0.066
East of England	0.063	0.067	0.066	0.069	0.073	0.067
Midlands	0.124	0.129	0.131	0.136	0.138	0.131
North, Yorkshire and the Humber	0.181	0.188	0.192	0.193	0.192	0.188
Wales	0.190	0.175	0.174	0.167	0.160	0.175
Scotland	0.218	0.214	0.208	0.205	0.208	0.211
N	3287	2835	2540	2290	2081	13033

Table 3: Descriptive Statistics, wave 16-20

	16	17	18	19	20	Total
Unemployed	0.046	0.025	0.021	0.028	0.025	0.031
Unemployed t-1	.	0.035	0.020	0.017	0.026	0.025
Unemployed | Unemployed t-1	.	0.381	0.442	0.407	0.429	0.407
Unemployed | Employed t-1	.	0.012	0.013	0.022	0.014	0.015
Age 16-25	0.189	0.138	0.103	0.052	0.026	0.116
Age 26-35	0.311	0.299	0.289	0.252	0.222	0.282
Age 36-45	0.347	0.368	0.368	0.381	0.384	0.366
Age 46-55	0.153	0.195	0.241	0.315	0.368	0.235
Claimant proportion	2.259	1.896	2.327	3.503	3.569	2.557
Degree or higher	0.204	0.216	0.225	0.245	0.258	0.225
Other high	0.085	0.084	0.083	0.087	0.088	0.085
A level	0.261	0.256	0.257	0.262	0.253	0.258
O level	0.278	0.277	0.271	0.254	0.252	0.269
CSE level	0.080	0.077	0.077	0.071	0.076	0.077
None of these	0.092	0.089	0.087	0.079	0.073	0.086
Home owner	0.775	0.798	0.808	0.820	0.830	0.802
Social renter	0.117	0.108	0.094	0.089	0.076	0.100
Private renter	0.108	0.094	0.098	0.091	0.094	0.098
Married	0.480	0.528	0.564	0.608	0.645	0.551
Number of kids in HH	0.826	0.836	0.845	0.880	0.891	0.849
Poor health	0.034	0.034	0.037	0.011	0.012	0.028
Non white	0.033	0.032	0.031	0.034	0.035	0.033
London and SE	0.154	0.155	0.157	0.163	0.166	0.158
South West	0.067	0.068	0.068	0.070	0.076	0.069
East of England	0.066	0.068	0.069	0.071	0.072	0.069
Midlands	0.125	0.125	0.126	0.127	0.128	0.126
North, Yorkshire and the Humber	0.203	0.200	0.207	0.201	0.197	0.202
Wales	0.184	0.183	0.176	0.171	0.171	0.178
Scotland	0.202	0.200	0.198	0.196	0.190	0.198
N	2739	2375	2144	1581	1363	10202

Table 4: Model estimates, Waves 1-5

	(1) Pooled probit	(2) Wooldridge	(3) Unempl inter	(4) Age inter
Unemployed t-1	1.788***	0.909***	0.425	0.571**
	(25.05)	(5.93)	(1.11)	(2.55)
Claimant proportion	0.038***	0.167**	0.156**	0.175***
	(2.87)	(2.51)	(2.32)	(2.61)
Unemployed t-1 * Claimant proportion			0.067	
			(1.39)	
Age 26-35	-0.281***	-0.392***	-0.393***	-0.520***
	(-3.23)	(-2.91)	(-2.88)	(-3.48)
Age 35-45	-0.299***	-0.432***	-0.431***	-0.524***
	(-3.13)	(-2.82)	(-2.79)	(-3.22)
Age 46-55	-0.067	-0.087	-0.085	-0.248
	(-0.63)	(-0.51)	(-0.50)	(-1.37)
Unemployed t-1* Age 26-35				0.450*
				(1.89)
Unemployed t-1* Age 36-45				0.280
				(1.08)
Unemployed t-1* Age 46-55				0.762**
				(2.53)
Wave 2 (Ref.)				
Wave 3	-0.064	-0.101	-0.099	-0.086
	(-0.88)	(-1.12)	(-1.09)	(-0.95)
Wave 4	-0.070	0.007	0.006	0.015
	(-0.89)	(0.06)	(0.05)	(0.13)
Wave 5	-0.250***	-0.129	-0.120	-0.130
	(-2.72)	(-0.86)	(-0.79)	(-0.86)
Degree or higher (Ref)				
Other high	0.093	0.080	0.080	0.080
	(0.50)	(0.28)	(0.28)	(0.28)
A level	0.338***	0.522**	0.522**	0.503**
	(2.58)	(2.50)	(2.46)	(2.40)
O level	0.350***	0.462**	0.468**	0.441**
	(2.72)	(2.26)	(2.26)	(2.15)
CSE level	0.453***	0.624***	0.627**	0.616**
	(3.05)	(2.59)	(2.56)	(2.55)
None of these	0.509***	0.693***	0.698***	0.690***
	(3.98)	(3.33)	(3.31)	(3.31)
Private renters (Ref)				
Home owner	-0.218**	-0.313	-0.320	-0.335
	(-2.21)	(-1.12)	(-1.14)	(-1.21)
Social renter	0.273**	0.076	0.062	0.036
	(2.47)	(0.24)	(0.19)	(0.11)
Married	-0.292***	-0.248	-0.255	-0.229
	(-3.76)	(-0.87)	(-0.89)	(-0.81)
Number of children in HH	0.134***	-0.009	-0.011	-0.006
	(4.40)	(-0.09)	(-0.11)	(-0.06)
Poor-V poor health	0.180	0.012	0.011	0.014
	(1.25)	(0.05)	(0.04)	(0.05)
Non white	0.110	0.183	0.172	0.171
	(0.70)	(0.72)	(0.66)	(0.67)
Initial condition		1.309***	1.348***	1.333***
		(5.31)	(2.60)	(5.36)
Initial condition * Avg. Claimant prop			-0.006	
			(-0.09)	
_cons	-2.123***	-3.033***	-2.984***	-2.953***
	(-10.76)	(-8.00)	(-7.69)	(-7.76)
lnsig2u		-0.080	-0.038	-0.076
		(-0.27)	(-0.13)	(-0.26)
region dummies	Yes	Yes	Yes	Yes
Averages of time varying covariates	No	Yes	Yes	Yes
N	7379	7379	7379	7379

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: APEs on lagged unemployment, Waves 1-5

	(1)		(2)		(3)		(4)	
	APE	pvalue*	APE	pvalue**	APE	pvalue**	APE	pvalue**
Wave 2	0.425	0.000	0.098	0.001	0.101	0.000	0.100	0.001
Wave 3	0.401	0.000	0.088	0.000	0.090	0.000	0.095	0.001
Wave 4	0.383	0.000	0.082	0.001	0.077	0.001	0.091	0.001
Wave 5	0.314	0.000	0.062	0.001	0.055	0.002	0.071	0.001
Total	0.385	0.000	0.084	0.000	0.083	0.000	0.090	0.001

Note: *standard errors based on delta methods; **Bootstrapped standard errors, 500 replications

Table 6: APEs on lagged unemployment by claimant proportion, Waves 1-5

	(2)	
	APE	pvalue*
Claimant proportion %		
2-4	0.057	0.002
4-6	0.073	0.001
6-8	0.088	0.000
8-10	0.099	0.000
10-12	0.107	0.000
12-14	0.115	0.000
14+	0.124	0.001
Test 4-6 vs 2-4	0.016	0.004
Test 6-8 vs 2-4	0.031	0.001
Test 8-10 vs 2-4	0.041	0.001
Test 10-12 vs 2-4	0.051	0.001
Test 12-14 vs 2-4	0.058	0.003
Test 14+ vs 2-4	0.067	0.008

*Bootstrapped standard errors, 500 replications

Table 7: APEs on lagged unemployment by age, Waves 1-5

	(2)		(4)	
	APE	pvalue*	APE	pvalue*
Age 16-25	0.138	0.000	0.082	0.047
Age 26-35	0.079	0.001	0.091	0.001
Age 36-45	0.070	0.001	0.064	0.013
Age 46-55	0.078	0.002	0.134	0.010
Test 26-35 vs 16-25	-0.059	0.000	0.009	0.801
Test 36-45 vs 16-25	-0.068	0.000	-0.018	0.633
Test 46-55 vs 16-25	-0.060	0.000	0.052	0.329

* Bootstrapped standard errors, 500 replications

Table 8: Model estimates, Waves 9-13

	(1) Pooled probit	(2) Wooldridge	(3) Unempl inter	(4) Age inter
Unemployed t-1	1.712***	0.894***	0.843**	0.821***
	(19.12)	(4.79)	(2.17)	(3.34)
Claimant proportion	0.071**	-0.092	-0.095	-0.101
	(2.38)	(-0.77)	(-0.79)	(-0.86)
Unemployed t-1 * Claimant proportion			0.018	
			(0.15)	
Age 26-35	-0.285***	-0.361***	-0.362***	-0.367***
	(-3.10)	(-2.92)	(-2.91)	(-2.81)
Age 35-45	-0.273***	-0.305**	-0.306**	-0.303**
	(-2.79)	(-2.34)	(-2.34)	(-2.22)
Age 46-55	-0.233**	-0.239	-0.239	-0.306*
	(-2.06)	(-1.60)	(-1.60)	(-1.94)
Unemployed t-1* Age 26-35				0.052
				(0.19)
Unemployed t-1* Age 36-45				-0.037
				(-0.13)
Unemployed t-1* Age 46-55				0.535
				(1.61)
Wave 10 (Ref.)				
Wave 11	-0.124	-0.199*	-0.200*	-0.203*
	(-1.43)	(-1.92)	(-1.92)	(-1.96)
Wave 12	0.089	0.028	0.028	0.031
	(1.05)	(0.27)	(0.27)	(0.30)
Wave 13	-0.085	-0.152	-0.152	-0.163
	(-0.88)	(-1.25)	(-1.25)	(-1.34)
Degree or higher (Ref)				
Other high	0.124	0.173	0.173	0.165
	(0.94)	(1.00)	(1.00)	(0.96)
A level	-0.143	-0.136	-0.137	-0.133
	(-1.26)	(-0.92)	(-0.93)	(-0.92)
O level	0.021	0.039	0.038	0.041
	(0.20)	(0.28)	(0.27)	(0.30)
CSE level	0.061	0.075	0.075	0.074
	(0.43)	(0.40)	(0.40)	(0.40)
None of these	0.305***	0.366**	0.367**	0.356**
	(2.70)	(2.39)	(2.39)	(2.35)
Private renters (Ref)				
Home owner	-0.203*	0.058	0.061	0.047
	(-1.88)	(0.23)	(0.24)	(0.19)
Social renter	0.290**	-0.018	-0.016	-0.036
	(2.41)	(-0.06)	(-0.06)	(-0.12)
Married	-0.326***	-0.158	-0.156	-0.167
	(-4.11)	(-0.58)	(-0.58)	(-0.62)
Number of children in HH	-0.048	0.059	0.059	0.059
	(-1.33)	(0.51)	(0.51)	(0.52)
Poor-V poor health	0.180	0.191	0.190	0.195
	(1.31)	(0.79)	(0.79)	(0.82)
Non white	0.299*	0.370*	0.372*	0.364*
	(1.83)	(1.71)	(1.71)	(1.70)
Initial condition		1.146***	1.160***	1.126***
		(4.55)	(2.58)	(4.50)
Initial condition * Avg. Claimant prop			-0.003	
			(-0.03)	
_cons	-2.008***	-2.504***	-2.503***	-2.478***
	(-11.50)	(-8.57)	(-8.53)	(-8.55)
lnsig2u		-0.817*	-0.804*	-0.888*
		(-1.85)	(-1.80)	(-1.93)
region dummies	Yes	Yes	Yes	Yes
Averages of time varying covariates	No	Yes	Yes	Yes
N	9746	9746	9746	9746

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 9: APEs on lagged unemployment, Waves 9-13

	(1)		(2)		(3)		(4)	
	APE	pvalue*	APE	pvalue**	APE	pvalue**	APE	pvalue**
Wave 10	0.300	0.000	0.071	0.025	0.071	0.031	0.075	0.026
Wave 11	0.249	0.000	0.053	0.056	0.053	0.075	0.059	0.055
Wave 12	0.300	0.000	0.068	0.044	0.067	0.065	0.078	0.039
Wave 13	0.242	0.000	0.052	0.048	0.052	0.075	0.062	0.044
Total	0.274	0.000	0.062	0.037	0.061	0.052	0.069	0.035

Note: *standard errors based on delta methods; **Bootstrapped standard errors, 500 replications

Table 10: APEs on lagged unemployment by claimant proportion, Waves 9-13

	(2)	
	APE	pvalue*
Claimant proportion %		
0-2	0.047	0.056
2-4	0.067	0.034
4-6	0.089	0.023
6+	0.102	0.033
Test 2-4 vs 0-2	0.020	0.026
Test 4-6 vs 0-2	0.042	0.017
Test 6+ vs 0-2	0.054	0.079

*Bootstrapped standard errors, 500 replications

Table 11: APEs on lagged unemployment by age, Waves 9-13

	(2)		(4)	
	APE	pvalue*	APE	pvalue*
Age 16-25	0.122	0.015	0.112	0.045
Age 26-35	0.056	0.043	0.055	0.121
Age 36-45	0.051	0.059	0.042	0.130
Age 46-55	0.058	0.048	0.115	0.042
Test 26-35 vs 16-25	-0.066	0.009	-0.056	0.194
Test 36-45 vs 16-25	-0.072	0.005	-0.069	0.116
Test 46-55 vs 16-25	-0.065	0.009	0.003	0.949

* Bootstrapped standard errors, 500 replications

Table 12: Model estimates, Waves 16-20

	(1) Pooled probit	(2) Wooldridge	(3) Unempl inter	(4) Age inter
Unemployed t-1	1.506*** (13.64)	1.016*** (4.92)	1.111*** (2.98)	0.944*** (3.67)
Claimant proportion	0.054 (1.42)	0.020 (0.21)	0.031 (0.32)	0.021 (0.22)
Unemployed t-1 * Claimant proportion			-0.035 (-0.31)	
Age 26-35	-0.231** (-2.03)	-0.242* (-1.85)	-0.244* (-1.85)	-0.275* (-1.91)
Age 35-45	-0.384*** (-3.20)	-0.409*** (-2.86)	-0.417*** (-2.90)	-0.431*** (-2.84)
Age 46-55	-0.373*** (-2.74)	-0.386** (-2.42)	-0.395** (-2.46)	-0.410** (-2.45)
Unemployed t-1* Age 26-35				0.159 (0.52)
Unemployed t-1* Age 36-45				0.096 (0.29)
Unemployed t-1* Age 46-55				0.108 (0.27)
Wave 17 (Ref.)				
Wave 18	0.075 (0.72)	0.096 (0.80)	0.093 (0.77)	0.096 (0.80)
Wave 19	0.285** (2.28)	0.381** (2.02)	0.373** (1.98)	0.380** (2.03)
Wave 20	0.190 (1.39)	0.305 (1.51)	0.304 (1.50)	0.304 (1.51)
Degree or higher (Ref)				
Other high	0.049 (0.26)	0.079 (0.37)	0.087 (0.41)	0.076 (0.36)
A level	0.089 (0.69)	0.071 (0.48)	0.076 (0.51)	0.069 (0.47)
O level	0.110 (0.87)	0.106 (0.74)	0.114 (0.79)	0.102 (0.72)
CSE level	-0.013 (-0.07)	-0.019 (-0.09)	-0.018 (-0.09)	-0.023 (-0.11)
None of these	0.464*** (3.24)	0.494*** (2.93)	0.509*** (3.00)	0.487*** (2.90)
Private renters (Ref)				
Home owner	-0.193* (-1.66)	0.084 (0.34)	0.083 (0.34)	0.082 (0.33)
Social renter	0.419*** (3.26)	0.135 (0.42)	0.145 (0.45)	0.144 (0.45)
Married	-0.462*** (-4.74)	-0.395 (-1.24)	-0.409 (-1.28)	-0.393 (-1.24)
Number of children in HH	0.103*** (2.66)	0.041 (0.39)	0.044 (0.41)	0.045 (0.42)
Poor-V poor health	0.395** (2.20)	0.151 (0.55)	0.153 (0.55)	0.146 (0.53)
Non white	0.217 (1.09)	0.220 (0.96)	0.231 (1.00)	0.219 (0.96)
Initial condition		0.710*** (2.92)	0.046 (0.09)	0.698*** (2.89)
Initial condition * Avg. Claimant prop			0.233 (1.47)	
_cons	-2.267*** (-10.85)	-2.516*** (-8.07)	-2.453*** (-7.78)	-2.477*** (-7.78)
lnsig2u		-1.567** (-2.07)	-1.539** (-2.05)	-1.652** (-2.00)
region dummies	Yes	Yes	Yes	Yes
Averages of time varying covariates	No	Yes	Yes	Yes
N	7463	7463	7463	7463

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 13: APEs on lagged unemployment, Waves 16-20

	(1)		(2)		(3)		(4)	
	APE	pvalue*	APE	pvalue**	APE	pvalue**	APE	pvalue**
Wave 17	0.175	0.000	0.069	0.020	0.071	0.031	0.072	0.023
Wave 18	0.187	0.000	0.073	0.034	0.074	0.038	0.077	0.043
Wave 19	0.237	0.000	0.099	0.023	0.094	0.026	0.106	0.033
Wave 20	0.205	0.000	0.084	0.022	0.080	0.029	0.091	0.040
Total	0.197	0.000	0.079	0.021	0.078	0.022	0.084	0.029

Note: *standard errors based on delta methods; **Bootstrapped standard errors, 500 replications

Table 14: APEs on lagged unemployment by claimant proportion, Waves 16-20

	(2)	
	APE	pvalue*
Claimant proportion %		
0-2	0.063	0.034
2-4	0.082	0.020
4-6	0.102	0.016
6+	0.114	0.020
Test 2-4 vs 0-2	0.019	0.021
Test 4-6 vs 0-2	0.039	0.026
Test 6+ vs 0-2	0.051	0.056

*Bootstrapped standard errors, 500 replications

Table 15: APEs on lagged unemployment by age, Waves 16-20

	(2)		(4)	
	APE	pvalue*	APE	pvalue*
Age 16-25	0.159	0.008	0.147	0.021
Age 26-35	0.092	0.018	0.106	0.066
Age 36-45	0.064	0.036	0.068	0.123
Age 46-55	0.060	0.046	0.065	0.273
Test 26-35 vs 16-25	-0.067	0.015	-0.041	0.503
Test 36-45 vs 16-25	-0.095	0.004	-0.079	0.213
Test 46-55 vs 16-25	-0.099	0.005	-0.082	0.255

* Bootstrapped standard errors, 500 replications

Table 16: APEs at fixed values of covariates after model 2, Waves 1-5

	State Dependence	Pvalue
Wave 2	0.117	0.007
Wave 3	0.106	0.009
Wave 4	0.101	0.011
Wave 5	0.079	0.019

Note: Bootstrapped standard errors, 500 replications. Covariates are fixed at the following values: age between 16 and 25; O-level education; home owners; non married and with no children; not in poor health; from a white ethnic background and living in the Midlands. Claimant proportion is fixed at the wave specific average faced by people living in the Midlands.

Table 17: APEs at fixed values of covariates after model 2, Waves 9-13

	State Dependence	Pvalue
Wave 10	0.080	0.092
Wave 11	0.065	0.137
Wave 12	0.087	0.103
Wave 13	0.071	0.116

Note: Bootstrapped standard errors, 500 replications. Covariates are fixed at the following values: age between 16 and 25; O-level education; home owners; non married and with no children; not in poor health; from a white ethnic background and living in the Midlands. Claimant proportion is fixed at the wave specific average faced by people living in the Midlands.

Table 18: APEs at fixed values of covariates after model 2, Waves 16-20

	State Dependence	Pvalue
Wave 17	0.111	0.068
Wave 18	0.126	0.076
Wave 19	0.176	0.035
Wave 20	0.163	0.037

Note: Bootstrapped standard errors, 500 replications. Covariates are fixed at the following values: age between 16 and 25; O-level education; home owners; non married and with no children; not in poor health; from a white ethnic background and living in the Midlands. Claimant proportion is fixed at the wave specific average faced by people living in the Midlands.

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Appendix

Table A1: Robustness checks, model 2, Waves 1-5

	(1) Alternative active definition	(2) Balanced panel	(3) Essex sample	(4) No long spell
Unemployed t-1	0.982***	0.853***	0.909***	0.422**
	(7.24)	(5.02)	(5.93)	(2.18)
Claimant proportion	0.148**	0.206***	0.167**	0.077
	(2.46)	(2.68)	(2.51)	(1.09)
Age 26-35	-0.276**	-0.315*	-0.392***	-0.442***
	(-2.23)	(-1.93)	(-2.91)	(-3.30)
Age 35-45	-0.252*	-0.570***	-0.432***	-0.469***
	(-1.82)	(-2.92)	(-2.82)	(-3.17)
Age 46-55	0.068	-0.113	-0.087	-0.158
	(0.43)	(-0.55)	(-0.51)	(-0.98)
Wave 2 (Ref.)				
Wave 3	-0.071	-0.058	-0.101	-0.068
	(-0.85)	(-0.50)	(-1.12)	(-0.75)
Wave 4	-0.012	0.212	0.007	-0.107
	(-0.12)	(1.56)	(0.06)	(-0.89)
Wave 5	-0.117	0.113	-0.129	-0.339**
	(-0.87)	(0.66)	(-0.86)	(-2.10)
Degree or higher (Ref)				
Other high	0.068	0.029	0.080	0.056
	(0.27)	(0.08)	(0.28)	(0.22)
A level	0.399**	0.766***	0.522**	0.407**
	(2.16)	(2.93)	(2.50)	(2.19)
O level	0.362**	0.572**	0.462**	0.350*
	(2.00)	(2.24)	(2.26)	(1.93)
CSE level	0.495**	0.702**	0.624***	0.401*
	(2.26)	(2.37)	(2.59)	(1.80)
None of these	0.621***	0.950***	0.693***	0.461**
	(3.37)	(3.59)	(3.33)	(2.46)
Private renters (Ref)				
Home owner	-0.402	-0.507*	-0.313	-0.344
	(-1.55)	(-1.66)	(-1.12)	(-1.19)
Social renter	0.009	-0.031	0.076	-0.069
	(0.03)	(-0.08)	(0.24)	(-0.20)
Married	-0.158	-0.334	-0.248	-0.287
	(-0.65)	(-1.05)	(-0.87)	(-0.99)
Number of children in HH	0.028	0.141	-0.009	-0.044
	(0.30)	(1.17)	(-0.09)	(-0.41)
Poor-V poor health	0.258	-0.044	0.012	0.079
	(1.17)	(-0.14)	(0.05)	(0.29)
Non white	0.277	-0.151	0.183	0.151
	(1.26)	(-0.41)	(0.72)	(0.62)
unempl0	1.321***	1.194***	1.309***	0.716***
	(5.97)	(4.79)	(5.31)	(3.17)
_cons	-2.792***	-3.297***	-3.033***	-2.735***
	(-8.57)	(-7.38)	(-8.00)	(-7.45)
lnsig2u	-0.119	-0.147	-0.080	-0.529
	(-0.46)	(-0.48)	(-0.27)	(-1.28)
Initial condition				
region dummies	Yes	Yes	Yes	Yes
Averages of time varying covariates	Yes	Yes	Yes	Yes
N	7585	6284	7379	7110

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A2: APEs after robustness checks, Waves 1-5

	(1) APE	(2) APE	(3) APE	(4) APE
Wave 2	0.121	0.069	0.098	0.037
Wave 3	0.113	0.064	0.088	0.033
Wave 4	0.104	0.069	0.082	0.028
Wave 5	0.085	0.054	0.062	0.018
Total	0.107	0.064	0.084	0.030

Table A3: Robustness checks, model 2, Waves 9-13

	(1)	(2)	(3)	(4)
	Alternative active definition	Balanced panel	Essex sample	No long spell
Unemployed t-1	0.881***	0.919***	0.920***	0.444**
	(5.56)	(4.22)	(3.89)	(2.04)
Claimant proportion	0.001	0.084	-0.092	-0.189
	(0.01)	(0.56)	(-0.66)	(-1.52)
Age 26-35	-0.290**	-0.344**	-0.198	-0.415***
	(-2.34)	(-2.22)	(-1.30)	(-3.16)
Age 35-45	-0.259*	-0.266	-0.285*	-0.342**
	(-1.93)	(-1.63)	(-1.67)	(-2.48)
Age 46-55	-0.153	-0.154	-0.137	-0.323**
	(-0.99)	(-0.85)	(-0.74)	(-2.01)
Wave 10 (Ref.)				
Wave 11	-0.094	-0.309**	0.007	-0.224**
	(-0.96)	(-2.01)	(0.05)	(-2.03)
Wave 12	0.078	0.239*	0.132	0.018
	(0.76)	(1.79)	(0.99)	(0.16)
Wave 13	-0.033	0.084	-0.009	-0.167
	(-0.29)	(0.57)	(-0.06)	(-1.30)
Degree or higher (Ref)				
Other high	0.159	0.209	0.351	0.152
	(0.85)	(1.08)	(1.64)	(0.83)
A level	-0.033	-0.117	-0.154	-0.107
	(-0.21)	(-0.70)	(-0.82)	(-0.70)
O level	0.070	-0.103	0.032	0.034
	(0.47)	(-0.63)	(0.19)	(0.23)
CSE level	0.189	-0.099	0.194	0.105
	(0.97)	(-0.42)	(0.89)	(0.54)
None of these	0.445***	0.206	0.427**	0.338**
	(2.75)	(1.12)	(2.17)	(2.08)
Private renters (Ref)				
Home owner	0.088	0.179	0.163	-0.030
	(0.36)	(0.60)	(0.53)	(-0.11)
Social renter	-0.149	0.668*	0.344	-0.057
	(-0.54)	(1.76)	(0.94)	(-0.17)
Married	0.227	-0.130	0.023	-0.213
	(0.95)	(-0.42)	(0.07)	(-0.76)
Number of children in HH	0.017	-0.248*	0.137	0.045
	(0.17)	(-1.75)	(0.96)	(0.37)
Poor-V poor health	0.226	0.275	0.344	0.097
	(1.08)	(0.90)	(1.15)	(0.38)
Non white	0.451**	-0.017	0.205	0.407*
	(2.07)	(-0.05)	(0.82)	(1.82)
unempl0	1.461***	1.124***	1.090***	0.982***
	(6.09)	(4.26)	(3.51)	(3.77)
_cons	-2.901***	-2.435***	-2.753***	-2.685***
	(-9.45)	(-7.47)	(-7.42)	(-8.17)
lnsig2u	-0.357	-0.912*	-0.844	-0.725
	(-1.16)	(-1.89)	(-1.48)	(-1.56)
Initial condition				
region dummies	Yes	Yes	Yes	Yes
Averages of time varying covariates	Yes	Yes	Yes	Yes
N	9948	8324	7002	9640

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A4: APEs after robustness checks, Waves 9-13

	(1) APE	(2) APE	(3) APE	(4) APE
Wave 10	0.068	0.051	0.057	0.024
Wave 11	0.059	0.031	0.056	0.017
Wave 12	0.067	0.066	0.065	0.023
Wave 13	0.058	0.053	0.052	0.018
Total	0.063	0.050	0.058	0.021

Table A5: Robustness checks, model 2, Waves 16-20

	(1)	(2)	(3)	(4)
	Alternative active definition	Balanced panel	Essex sample	No long spell
Unemployed t-1	0.858***	1.029***	1.248***	0.550**
	(4.83)	(3.95)	(4.83)	(2.38)
Claimant proportion	0.010	-0.080	0.095	0.106
	(0.10)	(-0.59)	(0.81)	(1.14)
Age 26-35	-0.173	-0.195	-0.183	-0.334***
	(-1.29)	(-1.02)	(-1.14)	(-2.65)
Age 35-45	-0.276*	-0.308	-0.238	-0.482***
	(-1.93)	(-1.57)	(-1.42)	(-3.55)
Age 46-55	-0.355**	-0.320	-0.282	-0.511***
	(-2.16)	(-1.52)	(-1.48)	(-3.32)
Wave 17 (Ref.)				
Wave 18	0.121	0.234	0.152	-0.001
	(1.08)	(1.34)	(1.07)	(-0.01)
Wave 19	0.416**	0.599**	0.274	0.222
	(2.29)	(2.15)	(1.26)	(1.23)
Wave 20	0.341*	0.550*	0.027	0.125
	(1.75)	(1.88)	(0.11)	(0.64)
Degree or higher (Ref)				
Other high	0.125	0.269	0.386*	0.035
	(0.58)	(1.18)	(1.68)	(0.18)
A level	0.107	0.068	0.178	0.016
	(0.70)	(0.38)	(0.98)	(0.12)
O level	0.135	0.222	0.268	0.070
	(0.91)	(1.30)	(1.55)	(0.53)
CSE level	0.041	0.125	-0.051	-0.107
	(0.20)	(0.52)	(-0.20)	(-0.55)
None of these	0.542***	0.482**	0.474**	0.446***
	(3.07)	(2.27)	(2.26)	(2.85)
Private renters (Ref)				
Home owner	-0.020	0.143	0.096	0.032
	(-0.08)	(0.50)	(0.34)	(0.14)
Social renter	-0.054	0.129	0.327	0.171
	(-0.20)	(0.31)	(0.88)	(0.52)
Married	-0.376	-0.172	-0.482	-0.543*
	(-1.23)	(-0.50)	(-1.27)	(-1.74)
Number of children in HH	0.013	-0.066	0.110	-0.007
	(0.13)	(-0.51)	(0.83)	(-0.07)
Poor-V poor health	-0.058	-0.310	0.218	0.128
	(-0.24)	(-0.83)	(0.61)	(0.44)
Non white	0.401*	0.342	0.079	0.234
	(1.79)	(1.32)	(0.31)	(1.09)
unempl0	1.281***	0.773***	0.562*	0.427*
	(5.23)	(2.70)	(1.91)	(1.87)
_cons	-2.781***	-2.715***	-2.278***	-2.081***
	(-8.59)	(-6.40)	(-6.63)	(-7.37)
lnsig2u	-0.702*	-1.686*	-2.433	-2.811
	(-1.77)	(-1.78)	(-1.29)	(-1.34)
Initial condition				
region dummies	Yes	Yes	Yes	Yes
Averages of time varying covariates	Yes	Yes	Yes	Yes
N	7637	5452	5256	7397

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A6: APEs after robustness checks, Waves 16-20

	(1) APE	(2) APE	(3) APE	(4) APE
Wave 17	0.056	0.052	0.099	0.028
Wave 18	0.060	0.068	0.121	0.027
Wave 19	0.078	0.096	0.149	0.041
Wave 20	0.068	0.088	0.103	0.032
Total	0.064	0.076	0.117	0.031