The Wounds That Do Not Heal.

The Life-time Scar of Youth Unemployment.

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Abstract: This paper uses a UK administrative dataset to study the long term effects of unemployment on earnings. We find that unemployment shocks affect young workers for the rest of their lives. This scar of youth unemployment is concentrated in the first few years after entry into the labour market: each month of unemployment between the ages of 18 and 20 causes a permanent income loss of 2%. However, unemployment after that age has limited term effect. The result is robust to different specifications, and it affects most the individuals at the lower end of the ability distribution.

Keywords: Youth unemployment, Lifetime earnings, Scarring effect.

JEL-Codes: J64, J31

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Introduction

Following the 2008 financial crisis, the number of young people out of work reached unprecedented levels in many OECD countries and has remained stubbornly high since. Substantial economic and social losses are created by the idleness of so many otherwise productive workers. Concerns about such losses are compounded by fears about the associated long-term consequences. These fears stem from the well established regularity that a person's past unemployment is a good predictor of their future labour market success. A seminal contribution is Ruhm's (1991) analysis of the long term effects of *past* displacement in the US, confirmed by subsequent research, as summarised in Couch and Placzeck (2010). A parallel literature has concentrated on the long term effects of *youth* unemployment (see, for example, Lynch 1989 for the US , and Lynch 1985, Nickell et al 2002, and Gregg and Tominey 2005 for the UK).[1]

For an adult, of course, youth is in the past, and yet the qualifiers "youth" and "past" carry distinct connotations. This is not just a matter of semantics, but hints, instead, at an important lacuna in our understanding of the causal link between individuals' labour market history and their current outcomes. The term "past" emphasises *how distant* in time the shock was, whereas "youth" highlights that the shocks occur in a *specific period* of a person's life, regardless of how long ago that was. This distinction, thus, begs the question: What matters more for today's labour market outcomes, the timing of an unemployment shock or how far back in time it occurred? It is by now firmly established that different periods in a person's formative years have different impacts on their future cognitive and non-cognitive abilities. Heckman and his co-authors have convincingly demonstrated that people's early environment is substantially more important than their later environment in determining these abilities (Cunha et al 2010). Thus, in this paper, we investigate whether the acquisition of labour market skills obeys a similar temporal pattern.

The aim of this paper is therefore to separate the effects of youth unemployment, qua youth unemployment, from its effects as past unemployment. Our main finding is that unemployment shocks at the time of a person's entry into the labour market are the most

[1]Bell and Blanchflower (2011) analyse the effect of the Great Recession on young people in the US and in the UK, while Cahuc et al (2013) consider the effect on those living in France and Germany, Genda et al (2010) in Japan, and Eliason and Storrie (2006) for Sweden. See Scarpetta et al (2010) for a policy oriented perspective, and oecd.org/youth.htm for data.

damaging. The punchline of our paper is, thus, that *wounds from youth unemployment permanently scar, while wounds from past unemployment heal*. To be precise: *ceteris paribus*, for men, an additional month of unemployment between ages 18 and 20, that is in the first three years after entry into the labour market, permanently lowers earnings by around 2% per year. This *scar* effect is very large, with the same order of magnitude as the estimated decrease in earnings attributable to a reduction of one year in formal education (Harmon et al 2001). Furthermore, this effect shows no sign of abating by the time individuals reach age 40 (see Figure 3 below). We also find that the age interval 18 to 20 is crucial: a similar negative shock during the following six years, namely between ages 21 and 26, has no long-term effects, as shown again in Figure 3.

There is, therefore, a substantial difference in the impact of unemployment in different sub-periods of youth and the damaging, permanent effect is entirely concentrated in early youth. This qualitative difference across years is blurred, to the point of not being recognisable, when youth is treated as a homogeneous period of nine years, i.e. from 18 to 26. This is also clearly illustrated in Figure 3, where the scar effect of the aggregate period is shown alongside those of the three separate subperiods. Averaging the effects across youth, therefore, misses the sharp difference between sub-periods within youth: in later youth (ages 24 to 26), the impact of a shock is determined by *distance* and its effect fades as time passes.

The difference in the impact of the sub-periods of youth, theoretical interest aside, has obvious implications for the design of policies aimed at lessening the long term effects of youth unemployment, such as the European Youth Guarantee (ILO 2012). Our analysis suggests that measures intended to assuage youth unemployment are likely to be more effective in the long term when they are specifically targeted at new entrants into the labour market. It certainly casts doubts on the wisdom of institutional rules whose effect is to favour older workers to the detriment of younger workers.

A similar inference on the relative importance of different periods of unemployment can be drawn when the overall effect is separated into its direct and indirect components. In addition to its long term effect on earnings, a period of unemployment in youth may also have a short term effect on employment, which, in turn, may have long term effects on earnings. That is, being unemployed at age 18 may increase the chance of being unemployed at age 22, and being unemployed at age 22 may reduce a person's future earnings. When we separate these effects, we find that unemployment at entry has the strongest indirect effect.

One further, crucial dimension of variation we uncover is that individuals of different abilities are affected differently by the scar effect (Figure 6). Importantly, the severity of the scar effect increases as we move down the ability scale. An unemployment shock hitting a given cohort of young workers will be weathered more effectively, in the long term, by high ability individuals. It follows that this shock would exacerbate the long term inequality in earnings among individuals of that cohort over and above any pre-existing pre-shock inequality. Given the high level of youth unemployment in many advanced economies, this generates an upward tendency for the long term.

For women, the negative effect of unemployment at entry into the labour market appears to be similar (compare columns (3) and (4) in Table 1). However, in comparison to men, the effect extends, albeit weakened, into the next three years. It also appears to be reversed between ages 24 to 26. This might be because other intervening variables are at play, information about which is not available in our dataset, and so we cannot control for in our empirical model. Among these omitted variables are fertility choices and hours worked per week. Both are plausibly endogenous and likely to be more important determinant of earnings for women than for men (see Blundell et al 2013, among others). The number of hours worked per week has also been shown to have a non-linear effect on earnings (Goldin 2014). As a result, it is harder to disentangle the effect of youth unemployment from the effect of other factors on earnings for females in our dataset. Thus, we follow most of the literature and focus our analysis on men.

We use the UK Lifetime Labour Market Database. This is sizeable and long, and it combines anonymised administrative tax and social security records into a dataset that tracks a random sample of almost 650,000 individuals, corresponding to 1% of the holders of the social security identifier, between 1978 and 2006. We restrict our sample to those born between 1960 and 1967 and we observe their periods of unemployment, along with their periods of employment and earnings, between the ages of 18 and 40 (or 46 for older individuals). This allows us to follow individuals for an extensive period of 23 (29) years after their entry into the labour market. Observing unemployment periods, measured as the number of weeks unemployed within the year, constitutes a more precise and informative measure of unemployment shocks than most measures in the recent US literature, which are based on a binary variable measuring "displacement" (see, for example, Jacobson et al 1993 and 2005, who study long term "scar" unemployment effects in Pennsylvania and Washington).

Our dataset is also rich in geographical detail, since it records change of address within the year. This makes it particularly well suited to controlling for specific characteristics of the local labour market, which affect both youth unemployment and later earnings. Crucially, we are able to allow returns to unobserved ability to vary across local labour markets. This is important since individuals might move to labour markets where their individual skills are more valuable. Thus, an important feature of our model is that we are able to use of detailed geographical information to control for endogenous geographical mobility, following Moretti's (2004) seminal contribution. Separating the effect of unemployment shocks from the effect of unobserved individual ability, and from the effect of local labour market characteristics, and, crucially, from the effect of the interaction of the two, is vital to ensure identification of the causal effect on earnings of early unemployment, and its associated permanent effects. Another important feature of our model is that we are able to allow the effect of youth unemployment to vary with the time of entry in the labour market (Figure 5). To allow for this, we follow Oreopoulos et al (2012), who found that the regional conditions at the time of entry into the labour market for Canadian graduates matter more for earnings than contemporaneous regional unemployment.

Knowing that there is a marked difference between the effect of unemployment at the time of entry and the effect of later unemployment on earnings is different from knowing why this should be so. So a key question is why are younger people more vulnerable in the long term. The literature has suggested several possible causes of a permanent effect of unemployment, ranging from the decay of human capital (Pissarides 1992), to psychological discouragement or habituation effects (Clark et al 2001), to stigma effects (Vishwanath 1989, Lockwood 1991, Kübler and von Weizsäcker 2003, Biewen and Steffes 2010), to the nature of the search technology (Tatsiramos 2009). Neal (1995) studies the scar effect for workers who subsequently find a new job in the same sector to identify the extent to which the loss of earnings is due to sector specific loss of human capital.

Understanding the causes of these differences would assist the design of policies specifically directed at relieving youth unemployment. It would also have implications for macroeconomic policy more generally, given the potentially large difference in the long term costs and benefits of tackling unemployment for individuals at different ages. A promising explanation is the importance of experimentation and learning (Papageorgiou 2014). Wee (2016) argues that those entering the labour market during a recession may suffer a wage scar: this is because reduced early career mobility limits learning and the accumulation of human capital. This would be in line with our results, which show that these effects are particularly pronounced for those at the very beginning of their careers.

The paper is organised as follows. Section 2 summarises the established theoretical background on the long term effects of unemployment, and motivates the econometric specification discussed in Section 3. Section 4 presents the data. Our main results and some robustness tests are presented in Section 5 and Section 6 concludes in the light of the existing literature.

2 The model

The theoretical model is a straightforward Mincerian equation. In its most general form, we can write:

$$w_i^t = f\left(Z_i, \lambda^t, \boldsymbol{e}_i^t, \varepsilon_i^t\right), \tag{1}$$

where w_i^t are person i's earnings in period t; Z_i is a vector of personal characteristics such as years of education, innate ability, family background, and so on; λ^t measures the labour market conditions in period t, given, for example, by local unemployment rates and other labour demand side variables; $\boldsymbol{e}_i^t$ is person i's "experience" at time t; and ε_i^t is a random shock affecting earnings.

Early theoretical models, such as Ben-Porath's (1967), captured experience $\boldsymbol{e}_i^t$ as a single figure, typically, as the total number of years individual i had spent in work at date t. This reflects the idea that, when employed, a person receives both formal training and "on-the-job" training.[2] If information on experience is not available, "potential

[2]Whether generic or job specific, training enhances a person's productivity, and, thus, future earnings. When formal training is unpaid, a further trade-off arises, as workers must choose between formal training

experience", given by the number of years not spent in formal education, is often used as a proxy, as in Mincer's landmark studies (1958 and 1974) among others.

The long term importance of labour market experience is, of course, well established, and the focus of our paper is on the description of the role of experience in more detail. Towards this end, one can think, as we argued above, of at least two conceptual reasons why the importance of past events for present day outcomes depends on the timing of when these events were experienced. Firstly, it is possible that recent occurrences may matter more than distant ones: negative events fade in importance, and, conversely, work skills acquired in the distant past become less relevant. Secondly, time may matter because some periods in life are more important than others.

To formalise these ideas, we replace e_i^t in (1) with a vector $\left(e_i^t, e_i^{t-1}, \ldots, e_i^2, e_i^1\right)$, which measures the experience in each of the years since the time of potential entry into the labour market, year 1. By convention, events which occurred before year 1 are captured by the time invariant individual characteristics term, Z_i. Experience in each period is influenced by a variety of factors, but to highlight the link between periods, we explicitly state it as a function of past experience and the period specific random component by writing $e_i^2 = e^2\left(e_i^1, \varepsilon_i^2\right)$, $e_i^3 = e^3\left(e_i^2, e_i^1, \varepsilon_i^3\right)$, and so on. For example, the lack of experience of "entry level" jobs caused by an early unemployment shock hinders access to jobs higher up the jobs ladder, and, hence, reduces experience at this level. Thus, (1) is replaced by:

$$w_i^t = f^t\Big(Z_i, \lambda^t, e^t\Big(e^{t-1}\left(\ldots\right), \ldots, e^2\left(e_i^1, \varepsilon_i^2\right), e_i^1, \varepsilon_i^t\Big), \ldots, e^2\left(e_i^1, \varepsilon_i^2\right), e_i^1, \varepsilon_i^t\Big). \tag{2}$$

Naturally, (2) includes e_i^t as an argument to account for the obvious direct effect of contemporaneous events on earnings. Since experience is a "good thing", in the sense that it enhances earnings, we measure it in such a way that the sign of the derivative of w_i^t with respect to past experience $e_i^{t-\tau}$ is non-negative. The partial derivative, $\partial w_i^t / \partial e_i^{t-\tau}$, is the direct effect of date $t-\tau$ experience on date t earnings, whereas the total derivative, $\mathrm{d}w_i^t / \mathrm{d}e_i^{t-\tau}$, is its overall effect. From the latter, we can conceptually separate a direct and an indirect effect. Taking the case $t = 3$ as an illustrative example, we can write:

$$\frac{\mathrm{d}f_i^2}{\mathrm{d}e_i^1} = \frac{\partial f_i^3}{\partial e^2}\frac{\partial e^2}{\partial e_i^1} + \frac{\partial f_i^3}{\partial e_i^1} \tag{3}$$

and human capital accumulation while employed (Mroz and Savage 2006).

where the total effect, $\mathrm{d}f_i^3/\mathrm{d}e_i^1$ on the RHS of (3), is decomposed into the direct effect of period 1 experience, $\frac{\partial f_i^3}{\partial e_i^1}$, and the indirect effect of period 1 experience, given by its effect on period 2 experience, $\frac{\partial e^2}{\partial e_i^1}$ multiplied by the direct effect of period 2 experience on period 3 earnings, $\frac{\partial f_i^3}{\partial e^2}$. In Table 2 in Section 5.2, we illustrate how our econometric strategy allows us to separate the direct from the indirect effects. To do so is important, as the direct effect sheds light on relative importance of the different links of the causal chain of transmission turning past shocks into present outcomes, while the total effect measures the relative importance of shocks occurring at different times.

If

$$\frac{\partial w_i^t}{\partial e_i^{t-\tau}} > 0$$

for some values of $\tau > 0$ and t, then the effects of past experience are persistent: events which occurred at time $t - \tau$ positively influence earnings at time t.

Some events have only temporary effects and fade away with time. To express this hypothesis formally, we can write

$$\left|\frac{\partial w_i^t}{\partial e_i^s}\right| < \delta, \qquad \text{for } t > t^* \text{ and } s = 1, \ldots, s^*, \tag{4}$$

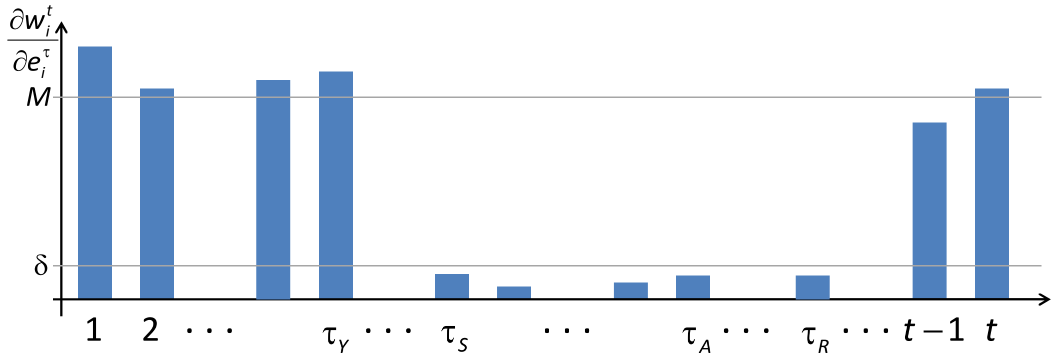
for some t^* and s^* with $t^* > s^*$ and for a suitably small value of δ. In other words, (4) asserts that if an individual is old enough (has entered the labour market at least t^* years ago), then early events (those that occurred in the first s^* years after entry into the labour market) have a "small" (less than δ) direct effect on earnings in the years more recent than t^*. More succinctly, the effect of events experienced $t - s^*$ or more years ago *fades with time*.

If, instead, experience gained in some years had a permanent effect on earnings, in the way that formal education has, then (4) is replaced by the hypothesis that, for some s^* and t^* with $t^* > s^*$ and $M > 0$,

$$0 < M < \frac{\partial w_i^t}{\partial e_i^s}, \qquad \text{for } t > t^* \text{ and } s = 1, \ldots, s^*. \tag{5}$$

That is, experience acquired early (before year s^*) has a "large" effect (larger than M) on recent earnings (later than time t^*), irrespective of the length of the period $t - s^*$: shocks

Figure 1:
The partial derivatives of the earnings at time t implied by Assumption 1.



occurring before date s^* *leave a permanent scar*.

We measure experience in year t as the negative of the weeks of unemployment in year t. This is available in our data for each person in each year. The idea that youth unemployment leaves permanent "scars" but the effect of later unemployment "heals" can be cast formally in the following hypothesis.

Assumption 1 *There exists τ_Y, τ_S, τ_A and τ_R, with $\tau_Y \leq \tau_A \leq \tau_S \leq \tau_R$, and positive constants M and δ, such that for $t \geqslant \tau_R$*

$$\textit{Scar effect:} \qquad \frac{\partial w_i^t}{\partial e_i^\tau} > M, \qquad \tau = 1, \ldots, \tau_Y, \tag{6}$$

$$\textit{Healing effect:} \qquad 0 \leqslant \left| \frac{\partial w_i^t}{\partial e_i^\tau} \right| < \delta, \qquad \tau = \tau_S, \ldots, \tau_A. \tag{7}$$

Where $e_i^\tau < 0$ is the negative of the unemployment suffered in period τ by individual i. In other words, (6) states that a shock suffered in the first τ_Y periods has a permanent effect on earnings, whereas according to (7), a shock suffered in periods τ_S to τ_A has a small effect on earnings, even though periods after τ_S are more recent. Figure 1 sketches this: recent events, those happening later than τ_R, may again have a large impact, due to the very fact that they are recent. Testing the hypothesis stated in Assumption 1 is the aim of our empirical analysis

3 The econometric specification

If we assume equation (2) to be log-linear and consider earnings up to the age of 40, then its empirical counterpart may be written as follows:[3]

$$\log w_i^t = Z_i^t \alpha^t + \underbrace{\gamma^t e_i^t}_{\substack{\text{Current}\\ \text{Unemployment}}} + \underbrace{\beta_{t-1}^t e_i^{t-1} + \beta_{t-2}^t e_i^{t-2} + \ldots + \beta_{s+1}^t e_i^{s+1} + \beta_s^t e_i^s}_{\text{Past Unemployment Scar Effects}}, \tag{8}$$

$$t = 19, \ldots, 40, \qquad s = 18, \ldots, t-1.$$

Where, as in (1) and in (2), w_i^t are the earnings of individual i in period t; Z_i^t is a vector of potentially time-varying individual characteristics; and $-e_i^t$ is the negative of the number of weeks that individual i was unemployed in year t. In most papers in the literature, for example in Jacobson et al (1993) and Couch and Placzek (2010), only job losses, "displacement events", are observed. Our data is richer and more nuanced, allowing us to measure experience as the number of weeks of unemployment in each year. This enables us to account for the fact that the loss of a job may affect future earnings differently when it is followed by a long spell of unemployment than when a new job is found after a short period.

The vector of individual specific characteristics in (8), Z_i^t, may be decomposed into an observable component X_i^t, and an unobservable component V_i^t. As individual characteristics influence both earnings and early unemployment, unobserved heterogeneity is a common problem with this type of model. This makes it hard to disentangle the permanent negative effect of random unemployment shocks from the influence of an unobserved variable, such as "ability" or "earning potential", on both youth employment and future earnings. Intuitively, to the extent that employers recognise a relatively unproductive worker, they are less likely to employ him, and, because he is relatively unproductive, he also experiences lower earnings later in life. In his early contribution, Ellwood (1982 p 346) remarks that this is likely to mar cross sectional studies. In some cases, the problem is alleviated by the inclusion of a rich set of observable individual

[3]The main regression sets 40 as the oldest age. This cut-off age constitutes the best compromise between the number of observations and the number of coefficients. As Figure 4 below illustrates, the results are robust to the cut-off age of 46, when only one cohort is included in the regression sample.

characteristics (Gregg 2001), or by using local unemployment levels at the time of entry as an instrument (Gregg and Tominey 2005). In this paper, our strategy to identify the coefficients in vector β is to define a rich set of fixed effects to capture heterogeneity across individuals, labour markets, time, and cohorts. This strategy is possible because we observe a large number of individuals for well over 20 years with detailed geographical information for each year. The vector of fixed effects we create allows us to effectively filter out individual, area, time and cohort characteristics and their interactions.

We formally present our treatment of the fixed effects by writing unobserved individual characteristics as follows:

$$V_i^t = \theta_i \mu_a + \eta_{ac}^t + \varepsilon_i^t. \tag{9}$$

The error term (9) has three components. Let time-invariant individual unobserved determinants of earnings, such as innate ability or education, be denoted by θ_i. The return to these unobserved characteristics may well vary across different labour markets. These differences might motivate individuals to move to areas where their specific skills are more valued, which makes location decisions endogenous. This potential problem is analogous to that convincingly addressed by Moretti's (2004) study of externalities of higher education. We follow his approach by including the interaction of individual fixed effects θ_i and area fixed effects μ_a. This captures the differences in how particular individual characteristics, including education, are rewarded in different labour markets.[4] The first term in (9), thus, allows the returns to individuals' characteristics to vary in an unrestricted way across labour markets.

The timing of entry into the labour market is also potentially important, as shown by Oreopoulos et al (2012) for Canadian graduates. In the second term in (9), therefore, we include cohort fixed effects. These can vary across local labour markets and across time, and so we interact cohort fixed effects with time and area fixed effects. Formally, η_{ac}^t, captures the shocks affecting cohort c in the local labour market in area a in period t.

The third term in (9), ε_i^t, is the individual specific transitory component of log wages,

[4] In the UK, in the period we consider, formal education was virtually always completed by age 23. Since this is the earliest that individual earnings are used in our regressions, education is a time invariant variable in our models, and, therefore, the effects of education (which we do not observe in our data) on earnings are adequately captured by individual fixed effects θ_i.

which is allowed to be correlated with other individuals in the same cohort c, entering a given local labour market a in a given year, and is otherwise independent across individuals. That is, we cluster by cohort and initial local labour market. Note that the inclusion of interaction fixed effects encompasses single fixed effects: formally, $\theta_i \mu_a$ comprises θ_i, and the triple interaction term η^t_{ac} comprises area fixed effects, cohort fixed effects and time fixed effects, as well as all the "double" interaction fixed effect terms.

To sum up, our identification strategy is as follows: for those who do not move, we control for any systematic variation in labour market opportunities, with time and cohort varying regional effects, η^t_{ac}. For those who do move, perhaps in search of local labour markets better suited to their specific skills, this is extended with the inclusion of a "Moretti" (2004) term, $\mu_a \theta_i$, which allows the returns to individual unobservable characteristics to vary across local labour markets. Formally, our identification assumption is

$$E[\varepsilon^t_i e^t_i | \theta_i \mu_a, \eta^t_{ac}, X_{it}] = E[\varepsilon^t_i e^{t-1}_i | \theta_i \mu_a, \eta^t_{ac}, X_{it}] = \cdots = E[\varepsilon^t_i e^{18}_i | \theta_i \mu_a, \eta^t_{ac}, X_{it}] = 0. \tag{10}$$

If we re-write (8) long-hand, to focus on the effects of the previous labour market experience for individual i up to the age of 40, we obtain:

$$\begin{aligned}
\log w^{40}_i &= X^{40}_i \alpha^{40} + \underbrace{\gamma^{40} e^{40}_i} + \underbrace{\beta^{40}_{39} e^{39}_i + \beta^{40}_{38} e^{38}_i + \ldots + \beta^{40}_{19} e^{19}_i + \beta^{40}_{18} e^{18}_i} + V^{40}_i, \\
\log w^{39}_i &= X^{39}_i \alpha^{39} + \underbrace{\gamma^{39} e^{39}_i} + \underbrace{\beta^{39}_{38} e^{38}_i + \ldots + \beta^{39}_{19} e^{19}_i + \beta^{39}_{18} e^{18}_i} + V^{39}_i, \\
&\vdots \\
\log w^{20}_i &= X^{20}_i \alpha^{20} + \underbrace{\gamma^{20} e^{20}_i} + \underbrace{\beta^{20}_{19} e^{19}_i + \beta^{20}_{18} e^{18}_i} + V^{20}_i, \\
\log w^{19}_i &= X^{19}_i \alpha^{19} + \underbrace{\gamma^{19} e^{19}_i} + \underbrace{\beta^{19}_{18} e^{18}_i} + V^{19}_i,
\end{aligned} \tag{11}$$

where, as in (8), in each equation, the first brace is the effect of current unemployment and the second brace is the effect of past unemployment spells. We can write the above system compactly in matrix form:

$$\log \boldsymbol{w}_i = \boldsymbol{\alpha} \boldsymbol{X}_i + \boldsymbol{\gamma} \boldsymbol{E}_i + \boldsymbol{\beta} \boldsymbol{E}^L_i + \boldsymbol{V}_i, \tag{12}$$

where $\boldsymbol{w}_i = \left(w_i^{40}, \ldots, w_i^{19}\right)$, $\boldsymbol{X}_i = \left(X_i^{40}, \ldots, X_i^{19}\right)$, $\boldsymbol{E}_i = \left(e_i^{40}, \ldots, e_i^{19}\right)$, $\boldsymbol{E}_i^L = \left(e_i^{39}, \ldots, e_i^{18}\right)$ and $\boldsymbol{V}_i = \left(V_i^{40}, \ldots, V_i^{19}\right)$ are 22-dimensional vectors, $\boldsymbol{\alpha}$ and γ are 22 by 22 diagonal matrices, with $\left(\alpha_i^{40}, \ldots, \alpha_i^{19}\right)$ and $\left(\gamma^{40}, \ldots, \gamma^{19}\right)$ along the diagonal, and $\boldsymbol{\beta}$ is the following upper triangular matrix:

$$\begin{bmatrix} \beta_{39}^{40} & \beta_{38}^{40} & \beta_{37}^{40} & \cdots & \beta_{19}^{40} & \beta_{18}^{40} \\ & \beta_{38}^{39} & \beta_{37}^{39} & \cdots & \beta_{19}^{39} & \beta_{18}^{39} \\ & & \beta_{37}^{38} & \cdots & \beta_{19}^{38} & \beta_{18}^{38} \\ & & & \ddots & \vdots & \vdots \\ & & & & \beta_{19}^{20} & \beta_{18}^{20} \\ & & & & & \beta_{18}^{19} \end{bmatrix}. \tag{13}$$

Writing (8) as (12) makes it clear that (8) is not identified: each equation has the same number of coefficients and observations per individual. To achieve identification, we impose restrictions on the matrix $\boldsymbol{\beta}$. As a first step, we consider a two year interval for the effect of past unemployment on earnings. Formally, we set:

$$\beta_s^t = \beta_s^{t+1}, \qquad t = 23, 25, 27, \ldots, 39. \tag{14}$$

This parallels the restriction imposed by Oreopoulos et al (2012) and reduces multicollinearity. Effectively, we study the effect of unemployment on earnings measured over two years, rather than one.

With the next set of restrictions, we concentrate on isolating the effects of unemployment for entrants into the labour market. We split the period from age 18 to 26 into three three-year intervals. *Entry* into the labour market, indexed by the letter E, age 18 to 20 inclusive; *Youth*, letter Y, age 21 to 23; and *early Adulthood*, letter A, age 24 to 26. We begin by imposing:

$$\beta_s^t = \beta_E^t, \quad \text{if} \quad s = 18, 19, 20 \quad \text{and} \quad t > 22; \tag{15}$$

$$\beta_s^t = 0, \qquad \text{otherwise.} \tag{16}$$

Restriction (15) posits that a spell of unemployment at age 18 is equivalent to a spell of the same duration at age 20. The coefficients β_E^t measure the effect of a labour market entrant's unemployment on their earnings from age 23 onwards. Unemployment at ages greater than 20 is restricted in (16) not to have any long term direct effect.

The results obtained with restrictions (15)-(16) are reported in the first column of Table 1. When we impose these restrictions, the estimated coefficients measure the *total* impact of being unemployed between ages 18 and 20. As noted earlier, however, if labour market outcomes at a given time are influenced by past experience, then unemployment between ages 18 and 20 harms labour market prospects at later ages. That is, if someone is unemployed at 19, and if experience matters for labour market prospects at 25, they are also more likely to be unemployed at 25. As long as there is an independent effect of unemployment at 25 on labour market outcomes at 40, this exacerbates the direct negative effects of an entrant's unemployment on his or her labour market outcomes at 40.

To disentangle the direct and indirect effects of being unemployed when young, that is, to evaluate the relative magnitude of the two terms on the RHS of (3), we modify (16) to include additional unemployment shocks as explanatory variables. We do so in two stages. Firstly, we add the coefficients that estimate the effects of "youth" unemployment, defined as the years between ages 21 and 23 inclusive. Thus, we replace (16) with:

$$\beta_s^t = \beta_Y^t, \qquad \text{if} \qquad s = 21, 22, 23 \qquad \text{and} \qquad t > 24; \tag{17}$$

$$\beta_s^t = 0, \qquad \text{otherwise.} \tag{18}$$

The results obtained with restrictions (15), (17), and (18) are reported in the second column in Table 1. Finally, we add a third possible effect, "early adulthood" unemployment, replacing (18) with:

$$\beta_s^t = \beta_A^t, \qquad \text{if} \qquad s = 24, 25, 26 \qquad \text{and} \qquad t > 28; \tag{19}$$

$$\beta_s^t = 0, \qquad \text{otherwise.} \tag{20}$$

Note that we follow Oreopoulos et al (2012) and, in (16), (18) and (20), we require that the coefficients capturing the effects of unemployment after a certain age are 0. Thus, we disregard potential effects that are close in time to the current unemployment: time t unemployment affects earnings at time t, whereas unemployment at time $t-1$ does not. The estimated coefficients, therefore, reflect any persistence in the unemployment process.

To sum up, with the assumptions on the fixed effects in (9) and the restrictions on the βs given in (15), (17) and (19)-(20), the regression specification (8) becomes:

$$\ln w_{iac}^t = X_i^t \alpha^t + \gamma^t e_i^t + \underbrace{\beta_E^t \sum_{s=18}^{20} e_i^s}_{\substack{\text{Scar effects of}\\ \text{unemployment}\\ \text{for Entrants}}} + \underbrace{\beta_Y^t \sum_{s=21}^{23} e_i^s}_{\substack{\text{Scar effects of}\\ \text{unemployment}\\ \text{for Youths}}} + \underbrace{\beta_A^t \sum_{s=24}^{26} e_i^s}_{\substack{\text{Scar effects of}\\ \text{unemployment}\\ \text{for early Adults}}} + \mu_a \theta_i + \eta_{ac}^t + \varepsilon_i^t,$$

$$t = 23\text{-}24, 25\text{-}26, \ldots, 39\text{-}40. \tag{21}$$

The coefficients β_E^t, β_Y^t and β_A^t measure the effects of unemployment for "Entrant" (age 18-20), "Youth" (age 21-23) or "Early Adult" (age 24-26). The last three terms are the error term, which are described in detail in (9).

4 The data

We use data from the Lifetime Labour Market Database (LLMDB). The LLMDB combines tax and social security records into a dataset that follows a 1% random sample of the universe of those with the UK social security number, amounting to 647,068 individuals between 1978 and 2006.[5] The LLMDB is, therefore, a rich, accurate, long and broad longitudinal dataset, which contains information on sex, date and country of birth. For each year, it contains information on the address of residence, earnings, nature of employment (employee or self-employed), number of weeks of employment and unemployment in the year and benefits received. Similarly to most administrative datasets, the LLMDB does not contain information on education or family background. As these are time-invariant individual characteristics, they are controlled for with the inclusion of individual fixed effects, as explained above. Unlike Orepopolous et al (2012), we can measure employment and unemployment at the beginning of individuals' careers, rather than having to proxy it with local labour averages. Given the importance to this literature of the time of entry into the labour market, our dataset also improves on other

[5] A fresh cohort of individuals enters the data every year and is followed from then on. This administrative data is derived from a number of datasets linked by the unique individual identifier NINo, which is allocated to British nationals automatically just before they turn 16 years old, but to foreign nationals only if they are eligible and apply to work and/or claim benefits in the UK.

studies, such as Gregg and Tominey (2005), Jacobson et al (1993 and 2005) and Couch and Placzeck (2010), which observe one cohort of individuals only.[6]

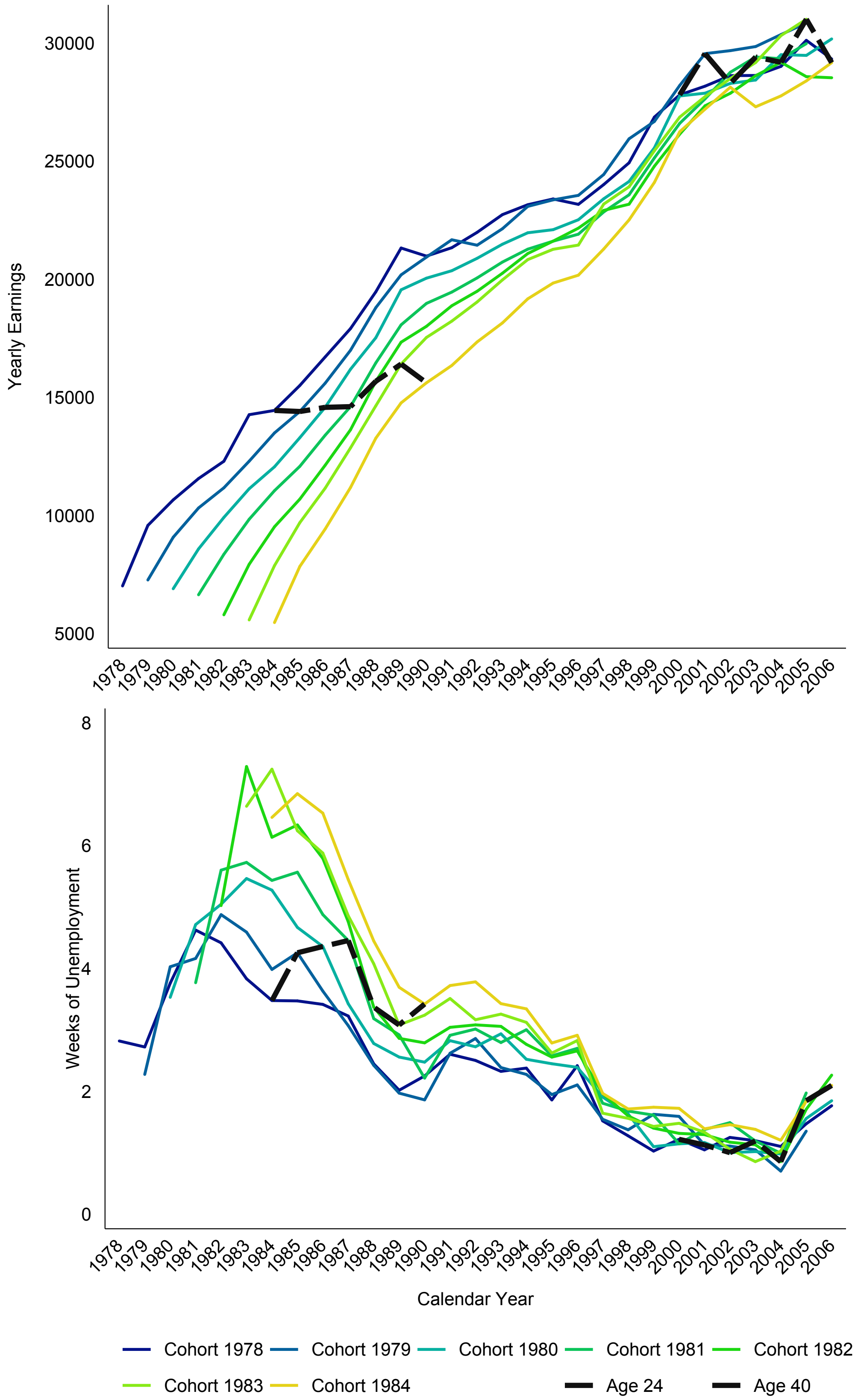
We restrict our sample to UK nationals, for whom we observe earnings, benefits, employment and unemployment continuously between ages 18 and 40. The first cohort in our dataset comprises individuals born in 1960, who therefore entered the labour market in 1978. The last cohort are those born in 1966, who entered in 1984. We exclude individuals who are recorded as ever being self-employed; these constitute 12.1% of the sample. We do so for several reasons. Firstly, income from self-employment may not be recorded accurately. Secondly, the self-employed might have more opportunity to understate their employment and earnings to reduce their tax liability. Thirdly, in the absence of information on balance sheets, we are unable to distinguish an individual's earnings from the return on the capital that the self-employed often own (Gollin 2002). Each of these reasons exacerbates measurement error in earnings, and in a way that is unlikely to be orthogonal to unemployment during the individual's youth. As a robustness check, we anyway run the model including individuals who report to be self-employed in some years, though we still exclude the years in which they reported to be self-employed. This increases the sample and makes the panel unbalanced. The results for this case are reported in column (5) of Table 1.

The two main quantitative variables in our model are earnings and the number of weeks of unemployment in each year. Data on earnings for those employed is constructed using tax records, and as such is very reliable and accurate. Unemployment data in the LLMDB is derived from benefit records.[7] Because the information on the number of weeks in unemployment forms the basis on which benefits are paid to claimants, it is recorded precisely and accurately for those who receive benefits. The LLMDB also records the "number of employed weeks". For just over half of the observations in our sample, the numbers of employed and unemployed weeks in the year add up to 52. When they do not, we determine unemployment for individual i in year t as the number of

[6]The LLMDB has been used to study income mobility and changes in inequality (Gardiner and Hills 1999, Dickens and McKnight 2008a), the intensity of job search (Petrongolo 2009), the assimilation of immigrant workers into the UK labour market (Lemos 2013 and 2014, Dickens and McKnight 2008b), and the link between unemployment and low pay (Gosling et al 1997).

[7]These records are maintained by two separate government departments, the Inland Revenue, now renamed HMRC, and the Department for Work and Pensions, and for different purposes, income tax and social security, respectively.

Figure 2:
Yearly Earnings and Weeks of Unemployment per Year by Cohort - Men



Note: Average year earnings, measured in 2004 pounds (top panel), and average number of weeks unemployed per year (bottom panel), for men born in the various years (dark lines for individuals born earlier), in the calendar year measured along the horizontal axis. The thick dashed lines joint the age 24 points and age 40 points for each cohort.

weeks individual i is recorded as unemployed. When this figure is missing, it is not necessarily the case that the individual was never unemployed in the year, but rather that they were not in receipt of benefits, either because they were not entitled to benefits or, if entitled, were not claiming them. When "unemployed weeks" is missing, individual i's unemployment in the year is defined as 52 minus the number of weeks individual i is recorded as employed. This natural imputation populates the unemployment variable for over 97% of the observations in our dataset. For the remaining 3% of observations, "employed weeks" and "unemployed weeks" do not add up to 52. In these cases, we calculate the number of week in unemployment using information from the ratio of reported "unemployed weeks" and reported "employed weeks" in the three year window centred in the year considered.

The final sample for our main results comprises $14,348$ men and $13,602$ women observed for 23 years (ages 18 to 40 inclusive), a total of $645,656$ observations. Summary statistics for our dataset are presented in Figure 2 and in Table A1 in the Appendix. The plots in the figure report the cohort average rate of unemployment for each year for men entering the labour market between 1978 and 1984, and their average gross yearly real earnings, adjusted by the Retail Price Index and measured in 2006 pounds. The colour of the various lines move from blue to yellow for later cohorts. We have also plotted, in dashed black, the line that joins the values for each cohort at age 24 and at age 40.[8]

The vector X_i^t in (21) includes an indicator variable that takes a value of 1 if the individual is in receipt of a benefit in the year. It also includes four indicator variables to identify those who are structurally or long-term unemployed: the first is 1 in year t if individual i is unemployed for all the 52 weeks of year t; the second is 1 if an individual is unemployed for two whole years, that is, for all the 104 weeks of two consecutive years. And similarly, for three and five years. These indicator variables capture the non-linear effects of protracted periods of structural unemployment on long-run wages.

The last terms in (21) are fixed effects interacted with one another, as explained in (9). These are essential features of our econometric specification and allow us to separate the effects of unemployment shocks from the influence of individual characteristics,

[8]The summary statistics reported in Figure 2 and Table A1 are adjusted to make them comparable over time, given changes in the underlying administrative processes generating the data. In our regressions, we use the unadjusted data and control for these changes in processes using fixed effects.

the conditions of the local labour market where individuals find themselves or move to, and the effects of the business cycle on different areas of the country. We use the administrative division of the country into 409 "local authority districts" to define area fixed effects, indexed by a.[9]

The information on individual addresses is complete from 1997 onwards. Prior to this, it is missing for 36% of the observations. Given that our identification strategy is based on the local authority district where each individual resides, care must be taken in dealing with missing addresses. While most moves in the UK are of a short distance and, therefore, subsequent local areas of residence are good predictors of previous ones, some people will have moved further and these individuals may be those whose labour market skills are more specialised, and so they may be systematically different from the rest. To account for this difference, we introduce an artificial second set of area fixed effects: the *inferred* area fixed effects, denoted by $a^0 \in \{1, \ldots, 409\}$. Individual i's location in year t is given by a if he is recorded as living in area a in year t; it is given by a^0 if his address is missing and his next recorded address is a, $t = 23, \ldots, 40$. This assumption is a mid-point between two "naïve" alternatives. In the first of these alternatives, we assume that all locations in the country are equivalent, implicitly assuming that the labour market consequences of individuals' moves are on average zero; in practice, we impute a single "notional-national" address to observations where the information on location is missing.[10] The results for this treatment of missing observations are reported in Column (6) of Table 1. In the second alternative, the assumption is that the current address has perfect predictive power for previous addresses, that is we do not distinguish between a and a^0. The results for this case are reported in Column (7) of Table 1. These extremes can be seen as upper and lower bounds containing the true estimate, and comparisons between columns (3), (6) and (7) in Table 1 suggest that our results are not sensitive to alternative treatments of missing address.

[9]A full list of local authority districts is available at data.gov.uk/dataset/local-authority- districts-uk-2012-names-and-codes. We use these, instead of "travel to work areas" (TTWA), as the latter are not defined consistently for our entire sample period and have been identified as problematic, especially prior to recent revisions (Coombes and Openshaw 1982). They are also larger and hence identify location less accurately.

[10]We could also drop all observation with a missing address: this is an inferior alternative, though, as it would reduce the sample size, make the panel unbalanced, and omit individuals' observations in a way likely to be correlated to their employment record.

5 Results

5.1 Baseline specification

The results from our preferred specification are reported in Table 1. As we explain above, the regression in (21) is estimated for the subset of individuals who are in the sample continuously from age 18 to 40, pooled across cohorts. All coefficients are multiplied by -100, to measure the "scar" effect in percentage terms.

The first coefficient in each column of Table 1 shows the effect of current unemployment on current earnings: being unemployed for an additional week at age 40, other things equal, brings about a reduction in earnings at age 40 of approximately 2.3% for men and 2% for women. These figures are very close to $\frac{1}{52}$, the proportionate earnings loss of a week of employment. We take this correspondence as a strong suggestion that our specification does capture other individual characteristics that may be determining earnings.

The rest of the table presents the long term effect of unemployment on current earnings. In the first column, we report, for men, the effect of "unemployment as Entrant" only. That is, we impose restrictions (15)-(16), namely $\beta^t_Y = \beta^t_A = 0$, in (21). If a man is unemployed for an additional week between ages 18 and 20, his earnings during two year intervals between ages 23 and 40 are lowered by the percentage amount in the corresponding row of the table. Thus, for example, the coefficient "On earnings aged 35-36" means that one additional week of unemployment suffered between ages 18 and 20 (inclusive) decreases annual earnings received between ages 35 and 36 (inclusive) by 0.54%. Similarly, the rows in the second column, labelled "Youth", report coefficients measuring the effect of an additional week of unemployment between ages 21 and 23: (17)-(18) replace (16), that is. β^t_Y is unrestricted in (21). The third column adds the period of "Early adulthood", ages between 24 and 26: in this column, the restrictions on the coefficient βs are (15), (17), (19), and (20). The fourth column is the specification of column (3) for women in the sample.

We see a strong direct effect of unemployment at entry (age 18-20) on lifetime earnings, up to the age of 40, and, although in a necessarily smaller sample, there is no indication that this effect is dampened when we consider a longer time frame (Figure 4).

Table 1:
Long term effects of early unemployment

	Entrant	Entrant & Youth	Whole Period	Women	Self-Employed	National Address	First Address
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Current Unemployment	2.312***	2.321***	2.318***	1.949***	2.262***	2.423***	2.291***
	(0.051)	(0.051)	(0.051)	(0.035)	(0.046)	(0.047)	(0.044)
Entrant Unemployment (18-20)							
On Earnings Aged 23-24	0.320***	0.321***	0.321***	0.562***	0.334***	0.383***	0.340***
	(0.040)	(0.040)	(0.040)	(0.041)	(0.038)	(0.031)	(0.031)
On Earnings Aged 25-26	0.439***	0.447***	0.447***	0.621***	0.442***	0.534***	0.468***
	(0.041)	(0.051)	(0.051)	(0.051)	(0.046)	(0.039)	(0.042)
On Earnings Aged 27-28	0.511***	0.537***	0.537***	0.662***	0.510***	0.607***	0.537***
	(0.042)	(0.052)	(0.052)	(0.051)	(0.048)	(0.039)	(0.044)
On Earnings Aged 29-30	0.607***	0.570***	0.566***	0.633***	0.546***	0.641***	0.582***
	(0.045)	(0.054)	(0.054)	(0.055)	(0.050)	(0.040)	(0.046)
On Earnings Aged 31-32	0.602***	0.553***	0.552***	0.607***	0.525***	0.634***	0.548***
	(0.044)	(0.053)	(0.053)	(0.059)	(0.050)	(0.041)	(0.047)
On Earnings Aged 33-34	0.550***	0.498***	0.498***	0.604***	0.499***	0.602***	0.496***
	(0.044)	(0.053)	(0.053)	(0.059)	(0.050)	(0.041)	(0.046)
On Earnings Aged 35-36	0.542***	0.491***	0.492***	0.541***	0.502***	0.580***	0.494***
	(0.046)	(0.055)	(0.055)	(0.063)	(0.052)	(0.042)	(0.048)
On Earnings Aged 37-38	0.526***	0.487***	0.492***	0.512***	0.500***	0.568***	0.494***
	(0.047)	(0.056)	(0.056)	(0.062)	(0.052)	(0.041)	(0.049)
On Earnings Aged 39-40	0.510***	0.500***	0.506***	0.488***	0.518***	0.587***	0.509***
	(0.046)	(0.057)	(0.056)	(0.062)	(0.052)	(0.043)	(0.050)
Youth Unemployment (21-23)							
On Earnings Aged 25-26		−0.013	−0.013	0.056	−0.010	−0.029	−0.046
		(0.045)	(0.045)	(0.048)	(0.041)	(0.033)	(0.037)
On Earnings Aged 27-28		−0.047	−0.047	0.061	−0.033	−0.015	−0.064
		(0.046)	(0.046)	(0.052)	(0.044)	(0.034)	(0.040)
On Earnings Aged 29-30		0.073	0.042	0.179***	0.033	0.081*	0.003
		(0.048)	(0.053)	(0.053)	(0.050)	(0.039)	(0.047)
On Earnings Aged 31-32		0.096	0.091	0.151**	0.086	0.116**	0.084
		(0.050)	(0.055)	(0.058)	(0.051)	(0.040)	(0.049)
On Earnings Aged 33-34		0.100*	0.091	0.121*	0.076	0.099*	0.069
		(0.051)	(0.055)	(0.060)	(0.051)	(0.040)	(0.049)
On Earnings Aged 35-36		0.100	0.098	0.143*	0.082	0.115**	0.075
		(0.052)	(0.056)	(0.062)	(0.052)	(0.041)	(0.050)
On Earnings Aged 37-38		0.077	0.110	0.178**	0.078	0.145***	0.089
		(0.052)	(0.056)	(0.064)	(0.053)	(0.040)	(0.051)
On Earnings Aged 39-40		0.024	0.067	0.200**	0.040	0.104*	0.045
		(0.053)	(0.057)	(0.064)	(0.054)	(0.041)	(0.052)
Early Adulthood Unempl. (24-26)							
On Earnings Aged 29-30			0.060	−0.137**	0.051	0.043	0.057
			(0.047)	(0.042)	(0.043)	(0.037)	(0.043)
On Earnings Aged 31-32			0.007	−0.141**	0.005	−0.001	0.011
			(0.046)	(0.046)	(0.044)	(0.035)	(0.042)
On Earnings Aged 33-34			0.016	−0.158***	0.009	0.013	0.019
			(0.049)	(0.047)	(0.046)	(0.038)	(0.046)
On Earnings Aged 35-36			0.000	−0.206***	−0.020	0.023	0.005
			(0.050)	(0.050)	(0.046)	(0.037)	(0.046)
On Earnings Aged 37-38			−0.070	−0.259***	−0.089	−0.057	−0.069
			(0.051)	(0.050)	(0.048)	(0.037)	(0.047)
On Earnings Aged 39-40			−0.092	−0.275***	−0.114*	−0.073*	−0.092
			(0.051)	(0.051)	(0.048)	(0.037)	(0.048)
N	319481	319481	319481	302328	358864	319481	319481
Number of Individuals	14348	14348	14348	13602	16082	14348	14348

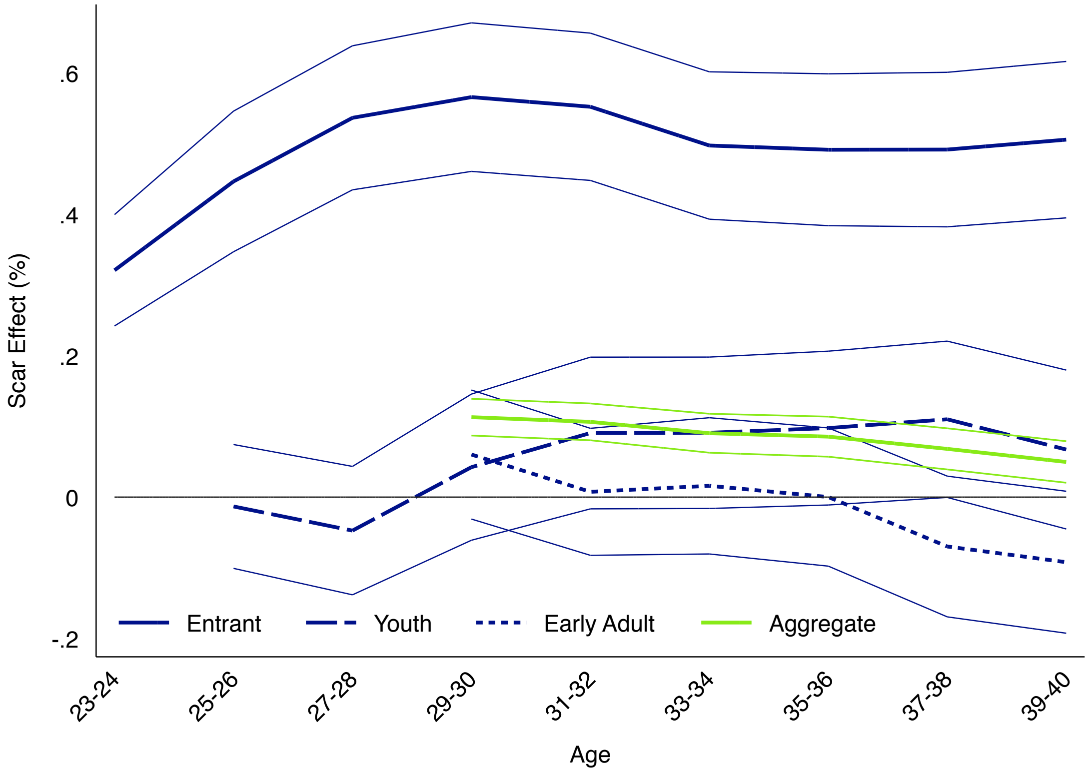
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. The dependent variable is the (log of) total annual earnings. The estimation uses felsdvreg (Cornelissen 2008). Standard errors are clustered by η_{ac}, i.e. cohorts defined by initial local area and are below the associated coefficients. Reported coefficients are obtained using the estimator described in (21) and measure the percentage effect of an increased week of unemployment in the three age brackets, 18-20, 21-23, and 24-26, on earnings in different subsequent periods. All specifications also include dummy variables recording the receipt of benefits and long-term unemployment in during a year, as well as individual, local labour market, cohort, and time fixed effects and their interactions as explained in the discussion of (9). Columns (1)-(3) report results for men from our prefered treatment of missing addresses and exclude those ever self-employed. Column (4) reports results for women. Columns (5)-(7) present robustness tests. In Column (5) individuals who were self-employed in some years between the ages of 18-40 are included, though not for those years when they were self-employed. In Column (6) missing addresses are allocated to a single address, the same for every observation; in Column (7) missing addresses are assumed to be identical to the earliest recorded address.

Columns (2) and (3) add first unemployment between ages 21 and 23, and then between ages 24 and 26. The coefficients in the first block in the first three columns are fairly similar. This suggests that the long term effects of unemployment for an entrant are fully captured by β_E, and that unemployment in Youth and Early Adulthood does not have a long term effect on earnings. This smoking gun strongly suggests that the long term "damage" of youth unemployment is concentrated in the earlier years. The possible channels through which this effect operates are explored further in Section 5.2.

Column (4) reports the results for women. They are similar to those for men: the effect of entrants' unemployment and the effect of current unemployment on earnings are similar in sign and size. Unlike for men, however, there are some significant coefficients in Youth (age 21 to 23). Counterintuitively, moreover, unemployment in early Adulthood (age 24 to 26) seems to have a positive effect on future earnings. As discussed in the introduction, we feel less confident about the results for women, because we lack information on two important determinants of earnings: the number of hours worked per week and childbearing choices. This might also explain the difference to Gregg's (2001) findings of a weaker persistence for women, since he can control for a large array of individual characteristics, including, of course, those related to childbearing.

The results reported in column (3) of Table 1 are illustrated in Figure 3. In the diagram, the horizontal axis gives two-year age windows, and the vertical axis the coefficients which measure the scar. These coefficients measure the effect of an additional week of unemployment, in the three age brackets we consider, on the yearly earnings at the age window marked on the horizontal axis. The three age brackets we consider are 18-20 ($-\beta_E^t$, shown as the solid line), 21-23 ($-\beta_Y^t$, shown as the dashed line), and 24-26 ($-\beta_A^t$, the dotted line). The thin lines are the 95% confidence intervals around the estimated coefficients. Figure 3 shows how the scar effect of unemployment for labour market entrants increases with time, settling around age 30 at around 0.5%. Conversely, the effect of an extra week's unemployment in Youth and Early Adulthood (age 21-26) is not significantly different from 0. To get a handle on the magnitude of the scar effect, the coefficients indicate that one year of unemployment between ages 18 and 20 determines a long term permanent earnings loss exceeding 22% per year. This is a large effect. It is in the upper end of US estimates of earnings losses due to displacement, which range

Figure 3:
The scar effect of youth unemployment



Estimated coefficients from equation (21) for the effect of Entrant, Youth, and early Adulthood unemployment, β^t_E (solid line), β^t_Y (dashed line), and β^t_A (dotted line); the dashed lines include the 95% confidence intervals.

from 7% (Stevens 1997) to over 20% (Jacobson et al 1993). It is also at the upper end of Gregg and Tominey's (2005) cross sectional IV estimates for the UK, which are between 13% and 21%.

The green solid line in Figure 3 depicts the estimated coefficients when the restrictions on the βs are given by:

$$\beta^t_Y = \beta^t_s, \qquad s = 18, \ldots, 26, \qquad t > 22; \tag{22}$$

$$\beta^t_s = 0, \qquad s \geqslant 27, \qquad t > s, \tag{23}$$

that is, when $\beta^t_V = \beta^t_Y = \beta^A_Y$ in (21), so that no distinction is made between the ages of 18 and 26, these βs give the overall effect of unemployment experienced between ages 18 and 26 on future earnings. The thin lines include the 95% confidence interval.

The coefficients for this case are reported in Column (5) of Table A2, and they indicate a much lower and slightly decreasing effect of unemployment in the first nine years after entry into the labour market. The strong suggestion emerging from the comparison of the three blue lines and the single green line is that lumping together all the spells of unemployment between 18 and 26 is misleading, as it misses the large difference between Entrant, Youth and Early Adulthood unemployment highlighted by our regressions and shown in Figure 3. Indeed, in our data, averaging large and statistically significant coefficients with those close to 0 for later years almost completely conceals the long run effect of youth unemployment.[11]

5.2 Decomposition of the effect of unemployment at entry

As argued above, in the discussion of equation (3), the overall effect of unemployment at entry on later earnings can be decomposed into the direct effect of unemployment at entry, and the indirect effect due to the fact that a spell of unemployment at age, say 19, reduces the opportunities to gain experience and so it increases the chances of unemployment at age 25. We now apply this idea to (21) and obtain the following expression (the derivation of the decomposition can be found in the Appendix):

$$\frac{dw_i^t}{duw_{1820}} = \overbrace{\beta_E^t}^{(1)} + \overbrace{\underbrace{\beta_Y^t}_{(3)} \underbrace{\frac{\partial uw_{2123}}{\partial uw_{1820}}}_{(4)}}^{(2)} + \overbrace{\underbrace{\beta_A^t}_{(6)} \left(\underbrace{\frac{\partial uw_{2426}}{\partial uw_{2123}}}_{(7)} \underbrace{\frac{\partial uw_{2123}}{\partial uw_{1820}}}_{(4)} + \underbrace{\frac{\partial uw_{2426}}{\partial uw_{1820}}}_{(8)} \right)}^{(5)}. \quad (24)$$

The braces which collect the terms refer to the column in Table 2 where the value of the contribution to the total effect is reported. The partial derivatives denote the impact of earlier periods of unemployment on unemployment in a subsequent period, and these along with the coefficients β are calculated using the results in Table 1. Table 2 reports the estimates of each term, and the columns correspond to the terms of (24) as indicated.

Column (1), which is the same as Column (1) in Table 1 is the direct effect of unemployment at age 18-20 on earnings at age t. In column (2) we report the effect of unemployment at age 18-20 on earnings at age t via the negative impact of being

[11] Column (6) of Table A2 in the Appendix reports the results of a robustness check using two alternative periods. We find, unsurprisingly, given our other main results, a precisely estimated, but smaller effect for the first period (ages 18 to 22) and no effect for the second (ages 23 to 27).

Table 2:
Decomposition of the Scar Effect

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
On Earnings Aged 29-30	0.566	−0.021	−0.042	0.507	0.062	0.060	1.917	0.067
On Earnings Aged 31-32	0.552	0.046	0.091	0.510	0.004	0.007	0.714	0.143
On Earnings Aged 33-34	0.498	0.047	0.091	0.520	0.005	0.016	0.563	0
On Earnings Aged 35-36	0.492	0.050	0.098	0.510	0.000	0.001	2	−1
On Earnings Aged 37-38	0.492	0.056	0.110	0.506	−0.022	−0.070	0.471	0.071
On Earnings Aged 39-40	0.506	0.028	0.067	0.417	−0.024	−0.092	0.467	0.065

Estimates report decomposition of scar effect into direct and indirect components. Columns(1)-(8) correspond to the terms of equation (A6). Column (1) is the direct effect of Entrant Unemployment, β_E^t. Column (3) is the effect of Youth Unemployment β_Y^t and Column (4) is the effect of Entrant Unemployment on Youth Unemployment $\frac{\partial uw_{2123}}{\partial uw_{1820}}$. Column (2) is the product of columns (3) and (4). Column (6) is β_A^t, the effect of early Adult unemployment on future wages. Column (7) is the effect of Youth unemployment on early Adult unemployment $\frac{\partial uw_{2426}}{\partial uw_{2123}}$. Column (8) is the effect on early Adult unemployment of Entrant unemployment $\frac{\partial uw_{2426}}{\partial uw_{1820}}$. Column (5) is given by the sum of Column (8) and the product of Column (7) and Column (4) all multiplied by Column (6). That is,$\beta_A^t * \left(\frac{\partial uw_{2426}}{\partial uw_{2123}}\frac{\partial uw_{2123}}{\partial uw_{1820}} + \frac{\partial uw_{2426}}{\partial uw_{1820}}\right)$

unemployed at age 21-23. This is calculated as the product of the direct effect of unemployment at age 21-23 on earnings at age t (β_2^t in the Appendix, reported in column (3)), times the effect of unemployment at age 18-20 on the unemployment at age 21-23, $\frac{\partial uw_{2123}}{\partial uw_{1820}}$, and this is reported in column (4). We can see that the indirect effect in (2) is small compared to the direct effect in (1) suggesting that the scar effect is not mediated via higher subsequent unemployment. Comparison of columns (3) and (4) suggests that this reflects not that Entrant unemployment does not increase Youth Unemployment, but rather that Youth Unemployment is not an important determinant of later earnings.

Column (5) shows the effect of unemployment at age 18-20 on earnings at age t via the negative impact of being unemployed at age 24-26. This is conceptually similar, but slightly more complex to the above. As shown in (24), it is the product of two terms: the direct effect of unemployment at age 24-26 on earnings at age t (γ_3^t in the Appendix, reported in column (6)) multiplied by the sum of the direct effect of unemployment at age 24-26 on the unemployment at age 18-20 ($\frac{\partial uw_{2426}}{\partial uw_{1820}}$ reported in column (7)) and the effect of unemployment at age 24-26 on the unemployment at age 18-20 via the unemployment at age 21-23. This in turn is the product of two terms, the effect of unemployment at age 18-20 on the unemployment at age 21-23 ($\frac{\partial uw_{2123}}{\partial uw_{1820}}$ reported in column (4)) times the effect of unemployment at age 21-23 on the unemployment at age 24-26 (reported in column (7), and given by the expression (A7) in the Appendix). Looking at column (5) we can see that the magnitude is similar to that of column (2) and again much smaller than (1). This in turn can be seen to reflect the limited importance of adult unemployment in column (6). The coefficients in Columns (7) and (8) are larger but vary considerably, this reflects that they are calculated as ratios with small denominators, and also the comparative lack of precision of the underlying estimates. Taken together, the results suggest that the scar effect associated with unemployment aged 18-20 is driven by its direct effect on subsequent earnings and while it is also associated with higher subsequent unemployment, this has little effect on future wages. One, non-exclusive, interpretation of this result is that it reflects unemployment at age 18-20 being particularly associated with reduced experimentation and learning as in Papageorgiou (2014) or Wee (2016), rather than stigma effects which might be expected to operate through subsequent periods of unemployment as in Lockwood (1991).

5.3 Robustness analysis

In addition to lumping together ages 18-26, as we do when drawing the green line in Figure 3, we consider another split of this period. Column (6) in Table A2 and Figure A.1 in the Appendix report the coefficients estimated in the case when this nine year period is split in two sub-periods. That is, when the set of restriction (15)-(18) is replaced by:

$$\beta_1^t = \beta_s^t, \qquad s = 18, \dots, 22, \qquad t > 24; \tag{25}$$

$$\beta_2^t = \beta_s^t, \qquad s = 23, \dots, 26, \qquad t > 27; \tag{26}$$

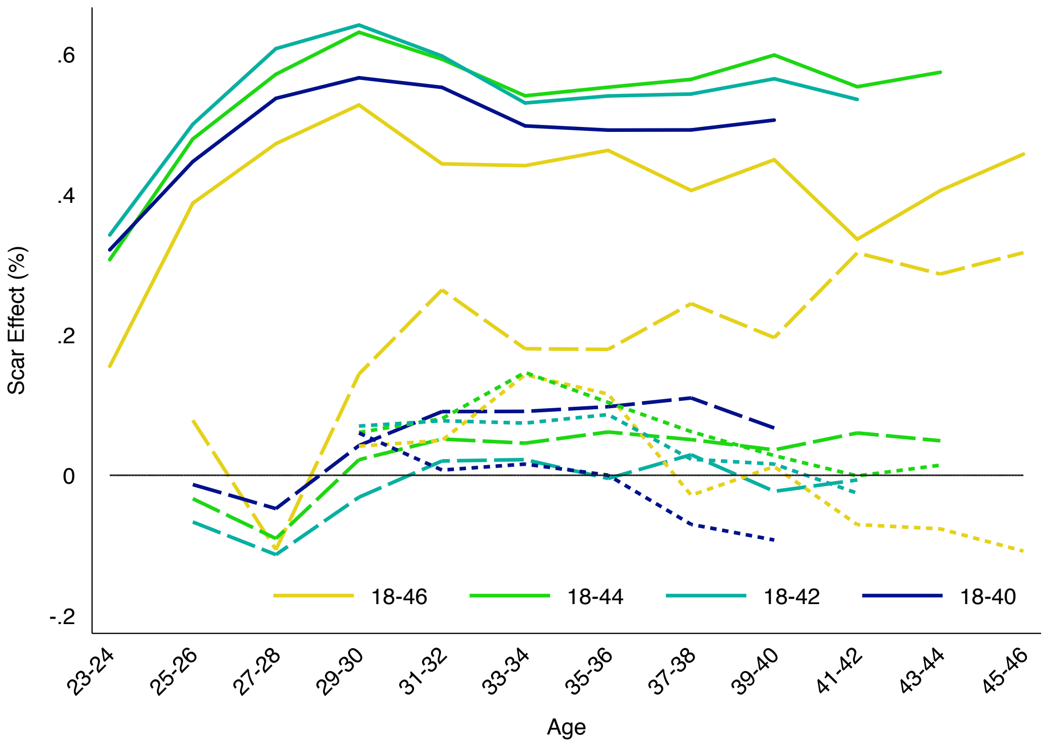
$$\beta_s^t = 0, \qquad s \geqslant 27, \qquad t > s. \tag{27}$$

Where the subscripts 1 and 2 label the first and the second part of the whole period. These are depicted by the aquamarine lines in Figure A.1in the Appendix. These confirm our main finding: early shocks scar, later ones do not.

Columns (5)-(7) of Table 1 confirm that our results are robust to changes in the empirical specification. Column (5) shows that our estimates change only marginally when, for individuals who report ever being self-employed, we include observations for years in which they are not self-employed.[12] In columns (6) and (7), we report estimates

[12] For example, if individual i from the cohort entering in 1978 is recorded as being self-employed in years 1994 and 1997, we drop only these observation from the estimations reported in column (5).

Figure 4:
Scar Effect of Youth Unemployment for Different Cut-off Ages

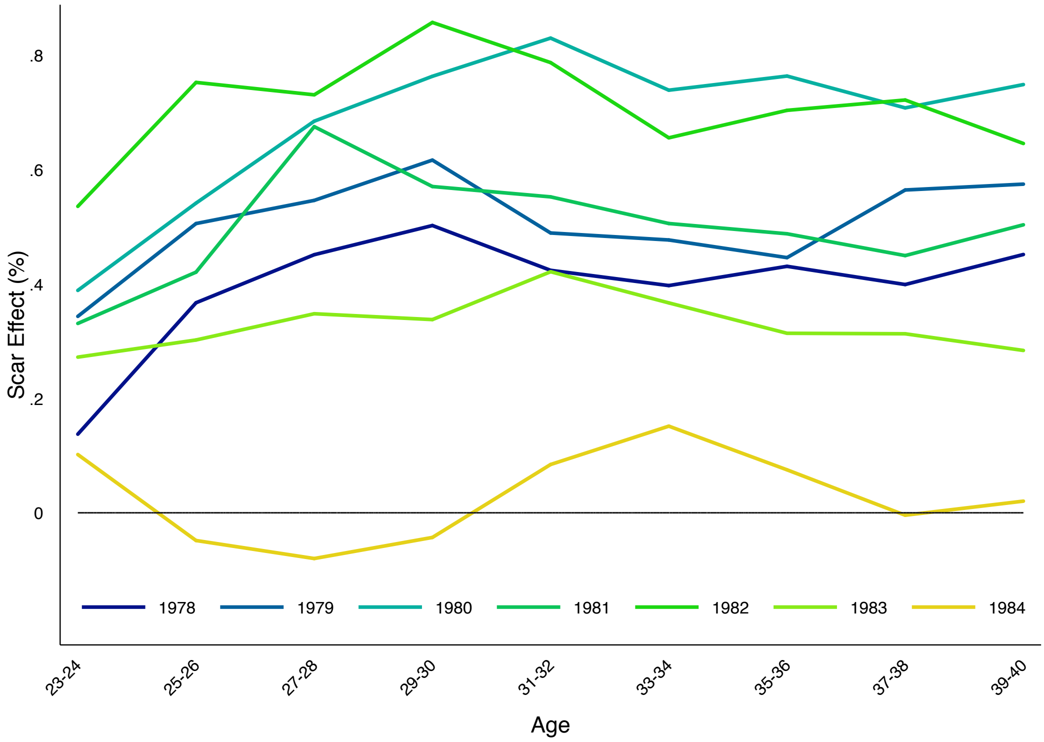


Note: Estimated coefficients for the long term effect of unemployment for different cut-off ages, estimated from the corresponding version of equation (21) for the effect of unemployment for Entrant, Youth, and early Adult. The dark blue curves are the same as in Figure 3, and, for each age group, solid, dashed, and dotted lines denote the coefficients for Entrant, Youth, and early Adult, respectively. The values of the coefficients used to draw the lines are in first four columns of Table A2. We have not included confidence intervals.

obtained when, as explained above at the end of Section 4, the missing address is inferred by replacing the missing information with a "fictitious" local area given by the earliest known address, controlling for the fact that the address is missing. Column (6) simply replaces all missing addresses with an amorphous "national" address, which captures the "average national labour market", with the implicit assumption that everyone had the same chance to have been at any given location. Column (7) replaces a missing address with the next recorded address, without accounting for the fact that the information is, in fact, missing. In both columns results are very similar to those in column (3), perhaps with some evidence of a small scar effect in the Youth period (21 to 23) in column (6) only. This suggests that the results are not sensitive to alternative treatments of missing addresses.

Figure 4 illustrates the results obtained when we allow the reach of negative shocks

Figure 5:
Scar Effect of Entry Unemployment for Different Cohorts



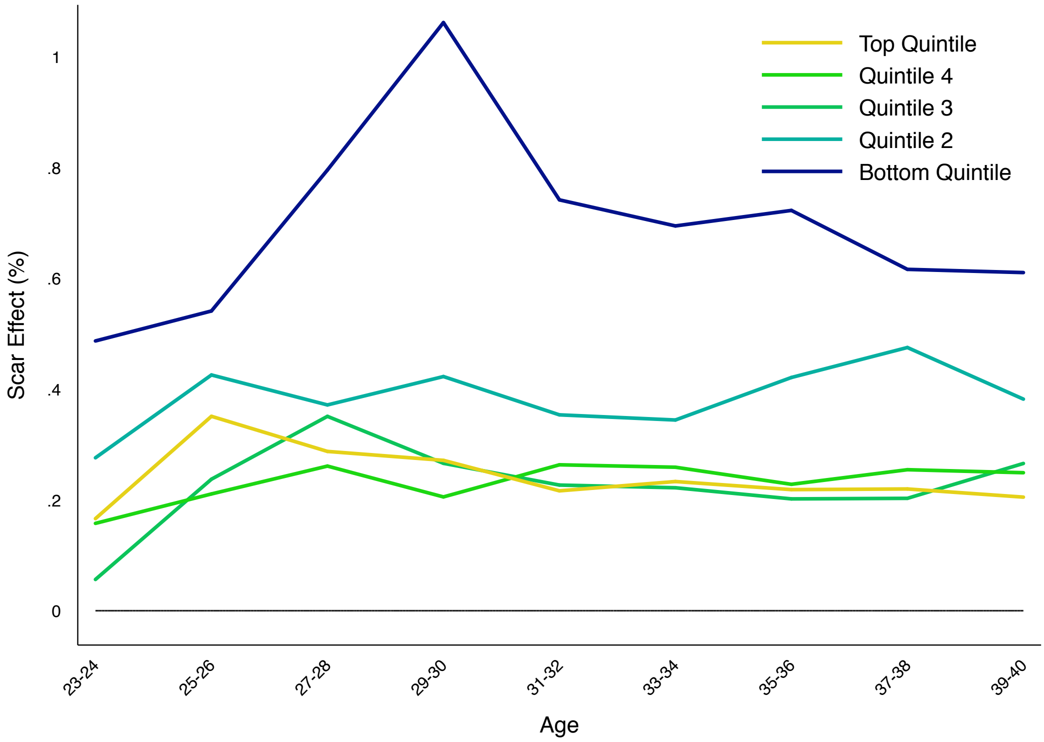
Note: Coefficients β_E^t, calculated from each subsample of individuals in the same cohort in the sample of the main regression, column (3) in Table 1. The values of the coefficients used to draw the lines are in Table A4. We have not included confidence intervals.

to extend beyond age 40. The results are once again robust. For those observed up to age 46, unemployment at age 21-23 now has some long term effect. The smaller sample size (only one cohort is observed up to age 46) reduces the precision of the estimates a little, but all Entrant coefficients remain significant at all conventional levels, as shown in Table A2 in the Appendix.

5.4 Unemployment shocks and income distribution

Oreopoulos et al (2012) study the effect of the business cycle on the importance of the scar effect for Canadian graduates. Similar analyses for American and Japanese men are carried out by Kahn (2010) and by Genda et al (2010). Our data allows us to ask the same question for different types of workers in a different country. Are there systematic differences in the effects for different cohorts which enter the labour market at different

Figure 6:
Scar Effect of Entry Unemployment on Individuals of Different Abilities.



Note: Coefficients β_E^t, calculated from the subsamples of individuals made from the quintile according to the rank determined by their earnings potential. The values of the coefficients used to draw the lines are in Table A4. We have not included confidence intervals.

stages in the business cycle? The results of this analysis are summarised in Figure 5, where, for Entrants only, we break down the pattern shown in Figure 3 by cohort. The coefficients for Youth and Early Adulthood are depicted in Figure A.2 in the Appendix. The estimates of β_E for the 1984 cohort are less precisely estimated. This cohort appears to be the only one to diverge from the overall pattern derived in the pooled regression. Apart from the possible effects of the recovery from the deep recession of the early 1980s, it is difficult to conceive other possible causes for the difference in this cohort.

To close the paper, we reprise one of the questions addressed by Oreopoulos et al (2012), namely, whether the scar effect is different for individuals with different abilities. Following their strategy, we split the sample into five "ability quintiles", and allocate individuals to quintiles according to their predicted permanent income estimated on the basis of the permanent incomes of women who lived in the same areas at the same time.[13] The results of this exercise for those in the 18-40 age range are presented in Figure 6, again only for the shocks in the Entry period. Individuals in the lowest ability group suffer the most severe scar. Furthermore, Table A3 in the Appendix shows that the scar effect is not significantly different from 0 for workers in the upper half of the ability distribution. The worsening of the scar effect for less able workers is a worrying aspect of our results: youth unemployment seems to reduce the income of the lowest paid workers the most. This exacerbates the inequality of lifetime incomes.

As we mentioned in Section 3, we do not observe whether an individual is a university student. While it would be interesting to separate the university students, we believe that, were we able to do so, our results on the importance of the scar effect would not change. This for a number of reasons. Firstly, we note that only approximately 10% of 18 year olds went to university in the late 1970s and early 1980s, and that those who did attend, typically finished their studies by the age of 21-22. Secondly, to the extent that students experience low unemployment when young and high earnings later in life, not being able to identify students would bias the scar effect downward: that is, concentrating the analysis on those who did not attend university would, if anything, strengthen the estimated scar effect. Finally, we have repeated the analysis excluding individuals who reported both low unemployment and low employment between the ages of 18 and 20, and the qualitative nature of the results is unchanged.

6 Concluding remarks

Past unemployment lowers earnings for the rest of a worker's life. These long term effects are extensively documented for the US (Table 1 in Couch and Placzeck 2010, p 574, summarises studies using both administrative and survey panel dataset), the UK (Arulampalam et al 2001 reviews a number of papers, all of which report evidence of scar), in Japan (Genda et al 2010), and in Sweden (Eliason and Storrie 2006) among other countries. The paper by Schmillen and Möller (2012), which follows cohorts of American men born between 1950 and 1954, highlights the importance of early shocks for

[13] Using the income of equivalent women to categorise men into quintiles overlooks the importance of child-bearing and part time work as determinants of women's incomes. It seems, however, preferable to using the same data and model, both to categorise individuals into quintiles and to estimate the effects for each quintile.

lifetime labour market outcomes. Our paper contributes to this literature by confirming the UK studies with a different dataset, and, more innovatively, by documenting that not all youth unemployment is equal. We report the distinct, much more serious, effects of being unemployed at the very beginning of one's working life. A period of unemployment at this stage causes a permanent large loss of earnings.

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A1 Appendix: Decomposing the effect of unemployment

We can rewrite the regression model, (21), estimated in each of columns (1)-(3) in Table 1 separately for each column, omitting the coefficients restricted to 0 in each case. Thus, we have, for the earnings at age t, $t =$ 23-34, $\ldots$, 39-40:

$$\ln w_i^t = \beta^t_{E,(1)} uw_{1820} + \lambda_1(X) + \varepsilon_1 \tag{A1}$$

$$\ln w_i^t = \beta^t_{E,(2)} uw_{1820} + \beta^t_{Y,(2)} uw_{2123} + \lambda_2(X) + \varepsilon_2 \tag{A2}$$

$$\ln w_i^t = \beta^t_{E,(3)} uw_{1820} + \beta^t_{Y,(3)} uw_{2123} + \beta^t_{A,(3)} uw_{2426} + \lambda_3(X) + \varepsilon_3. \tag{A3}$$

In the above, the coefficients β are those in (21), and the subscript in the brackets is the column of Table 1 from which it is obtained. Differentiating, and indicating with a subscript, with slight abuse of notation, the equation from which the partial derivative is derived, we obtain:

$$\frac{dw_i^t}{duw_{1820}} = \left.\frac{\partial w_i^t}{\partial uw_{1820}}\right|_{\text{(A1)}}$$

$$\frac{dw_i^t}{duw_{1820}} = \left.\frac{\partial w_i^t}{\partial uw_{1820}}\right|_{\text{(A2)}} + \left.\frac{\partial w_i^t}{\partial uw_{2123}}\right|_{\text{(A2)}} \frac{\partial uw_{2123}}{\partial uw_{1820}}$$

$$\frac{dw_i^t}{duw_{1820}} = \left.\frac{\partial w_i^t}{\partial uw_{1820}}\right|_{\text{(A3)}} + \left.\frac{\partial w_i^t}{\partial uw_{2123}}\right|_{\text{(A3)}} \frac{\partial uw_{2123}}{\partial uw_{1820}} + \left.\frac{\partial w_i^t}{\partial uw_{2426}}\right|_{\text{(A3)}} \left(\frac{\partial uw_{2426}}{\partial uw_{2123}}\frac{\partial uw_{2123}}{\partial uw_{1820}} + \frac{\partial uw_{2426}}{\partial uw_{1820}}\right).$$

Substituing now the values from (A1)-(A3), the above can be written as:

$$\frac{dw_i^t}{duw_{1820}} = \beta^t_{E,(1)} \tag{A4}$$

$$\frac{dw_i^t}{duw_{1820}} = \beta^t_{E,(2)} + \beta^t_{Y,(3)} \frac{\partial uw_{2123}}{\partial uw_{1820}} \tag{A5}$$

$$\frac{dw_i^t}{duw_{1820}} = \beta^t_{E,(3)} + \beta^t_{Y,(3)} \frac{\partial uw_{2123}}{\partial uw_{1820}} + \beta^t_{A,(3)} \left(\frac{\partial uw_{2426}}{\partial uw_{2123}}\frac{\partial uw_{2123}}{\partial uw_{1820}} + \frac{\partial uw_{2426}}{\partial uw_{1820}}\right). \tag{A6}$$

Equating the RHS of (A4) and (A5), we obtain

$$\frac{\partial uw_{2123}}{\partial uw_{1820}} = \frac{\beta^t_{E,(1)} - \beta^t_{E,(2)}}{\beta^t_{Y,(2)}}.$$

A similar process with only the last two equations would yield the corresponding factor:

$$\frac{\partial uw_{2426}}{\partial uw_{2123}} = \frac{\beta^t_{Y,(2)} - \beta^t_{Y,(3)}}{\beta^t_{A,(3)}}.$$

And so (A6) can be written as:

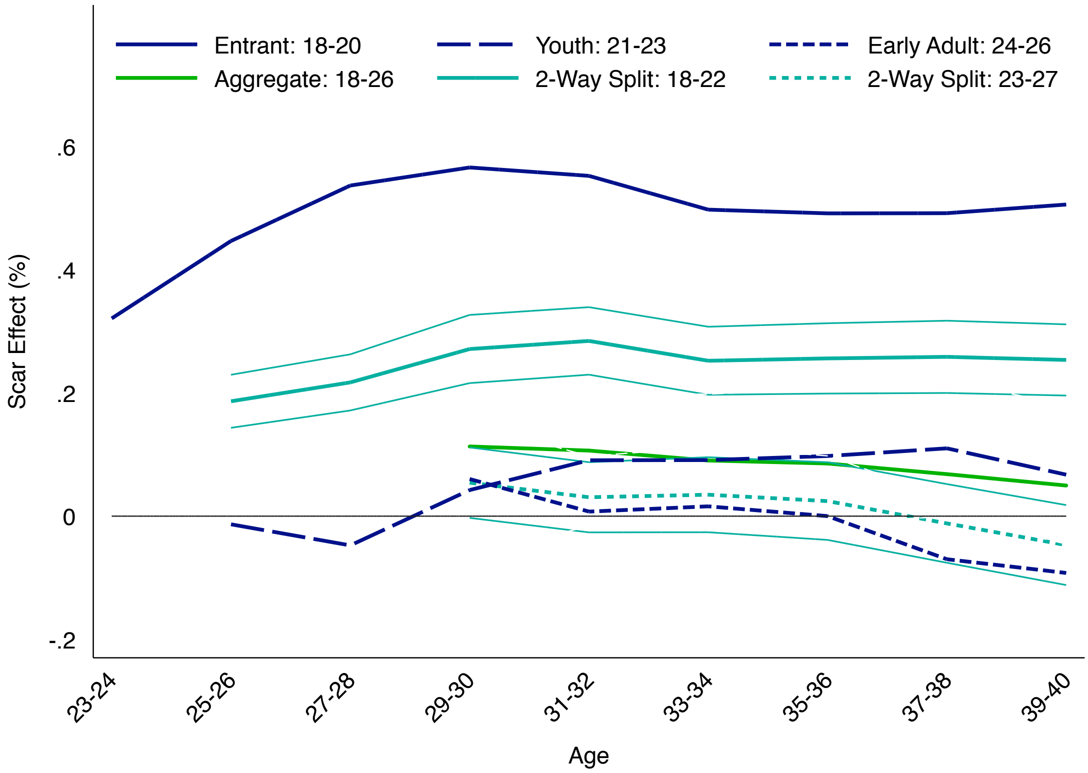
$$\beta^t_{E,(1)} = \beta^t_{E,(3)} + \beta^t_{Y,(3)} \frac{\beta^t_{E,(1)} - \beta^t_{E,(2)}}{\beta^t_{Y,(2)}} + \beta^t_{A,(3)} \left(\frac{\beta^t_{Y,(2)} - \beta^t_{Y,(3)}}{\beta^t_{A,(3)}} \frac{\beta^t_{E,(1)} - \beta^t_{E,(2)}}{\beta^t_{Y,(2)}} + \frac{\partial uw_{2426}}{\partial uw_{1820}} \right),$$

from which we can derive $\frac{\partial uw_{2426}}{\partial uw_{1820}}$:

$$\frac{\partial uw_{2426}}{\partial uw_{1820}} = \frac{\beta^t_{E,(2)} - \beta^t_{E,(3)}}{\beta^t_{A,(3)}}. \tag{A7}$$

A2 Appendix: Additional Tables and Figures

Figure A.1:
The scar effect of youth unemployment



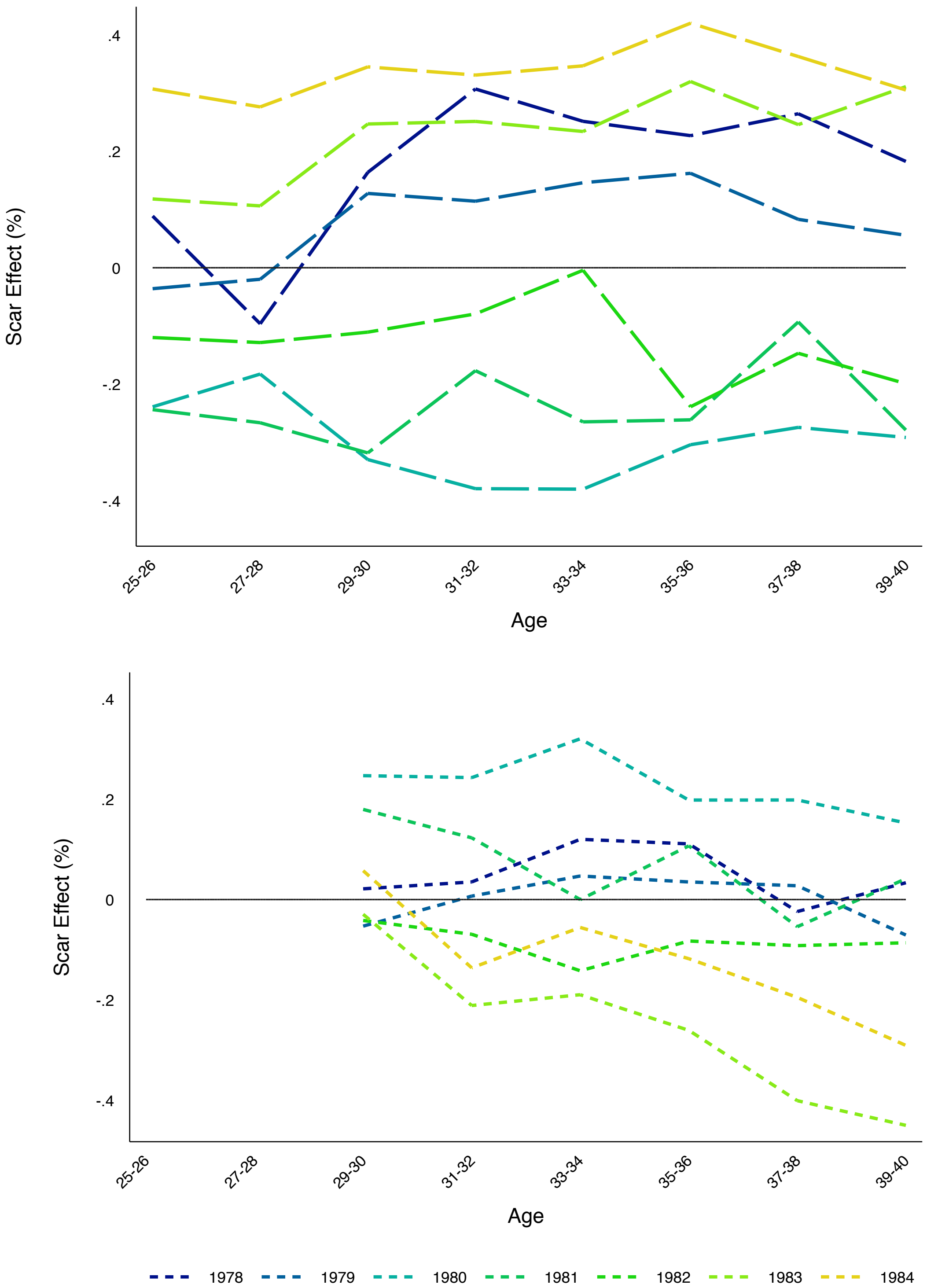
Note: The blue lines report the estimated coefficients from equation (21) for the effect of Entrant, Youth, and early Adulthood unemployment, β_E^t (solid line), β_Y^t (dashed line), and β_A^t (dotted line). The light gren line depicts the coefficients when (21) is estimated with the restrictions (22)-(23). These are the same lines as in Figure 3, without the confidence intervals, to avoid cluttering the drawing. The aquamarine lines are the coefficients of the 2-way split, that is when (21) is estimated with the restrictions (25)-(27). For these we do we include the thin lines showing the 10% confidence intervals.

Table A1:
Summary statistics for individuals in sample for Table 1.

	1960	1961	1962	1963	1964	1965	1966	**Total**
Unemployment at age								
18-20	9.66	13.25	18.59	22.11	25.50	25.78	23.10	**19.58**
sd	19.76	23.73	28.91	31.74	32.78	32.07	29.81	**29.24**
21-23	16.60	19.02	20.36	20.40	20.70	18.93	16.02	**18.88**
sd	29.17	30.90	31.72	31.46	30.63	29.89	27.81	**30.32**
24-26	15.08	15.00	14.25	13.77	14.29	15.85	16.31	**14.92**
sd	29.48	28.68	27.78	27.31	28.46	29.51	30.03	**28.75**
Earnings at age								
23-24	12229	11998	11936	11932	12454	13114	13313	**12409**
sd	6875	7235	7929	7649	8163	8693	8221	**7848**
25-26	13800	13890	14417	14778	14791	14544	14023	**14316**
sd	8476	8687	9728	9040	9722	10614	9544	**9418**
27-28	16233	16881	16850	16095	15494	15405	15546	**16093**
sd	10624	10783	11446	11370	11400	12040	11883	**11376**
29-30	18306	18208	17337	16631	16737	16869	16508	**17242**
sd	11763	14924	12915	12274	13979	13191	14337	**13396**
31-32	18378	18416	18269	17524	17521	17729	18042	**17991**
sd	12441	12905	13557	14306	15170	15640	16952	**14463**
33-34	19205	19441	18795	17972	18529	19914	20876	**19236**
sd	13710	15307	14416	15829	15476	18793	21797	**16644**
35-36	19451	19821	19695	19591	20709	22203	22675	**20559**
sd	14389	17442	16460	18019	18760	23908	23121	**19094**
37-38	20461	21659	21830	21857	22041	23414	22401	**21936**
sd	16010	24366	20003	27207	20625	24809	20905	**22273**
39-40	22704	23462	23058	22236	22202	24444	23302	**23053**
sd	22904	25356	20691	26052	23458	32200	26050	**25398**
41-42	23638	23877	23394	22036	22075	0	0	**23019**
sd	20546	27446	23736	22485	22663	0	0	**23533**
43-44	23794	23936	23818	0	0	0	0	**23850**
sd	21963	22492	26957	0	0	0	0	**23935**
45-46	24348	0	0	0	0	0	0	**24348**
sd	28231	0	0	0	0	0	0	**28231**
Receiving benefits at age								
23-24	0.29	0.31	0.33	0.33	0.33	0.30	0.29	**0.31**
25-26	0.26	0.27	0.26	0.25	0.28	0.31	0.31	**0.28**
27-28	0.22	0.21	0.23	0.26	0.29	0.31	0.30	**0.26**
29-30	0.20	0.23	0.27	0.28	0.30	0.30	0.30	**0.26**
31-32	0.24	0.25	0.27	0.30	0.29	0.28	0.26	**0.27**
33-34	0.26	0.26	0.28	0.28	0.28	0.26	0.26	**0.27**
35-36	0.26	0.25	0.25	0.28	0.28	0.28	0.27	**0.27**
37-38	0.24	0.24	0.25	0.29	0.29	0.27	0.25	**0.26**
39-40	0.25	0.25	0.26	0.28	0.27	0.24	0.23	**0.26**
41-42	0.26	0.25	0.24	0.25	0.25	0	0	**0.25**
43-44	0.24	0.22	0.24	0	0	0	0	**0.23**
45-46	0.22	0	0	0	0	0	0	**0.22**
N	2065	2154	2164	2089	1985	1966	2001	**14424**

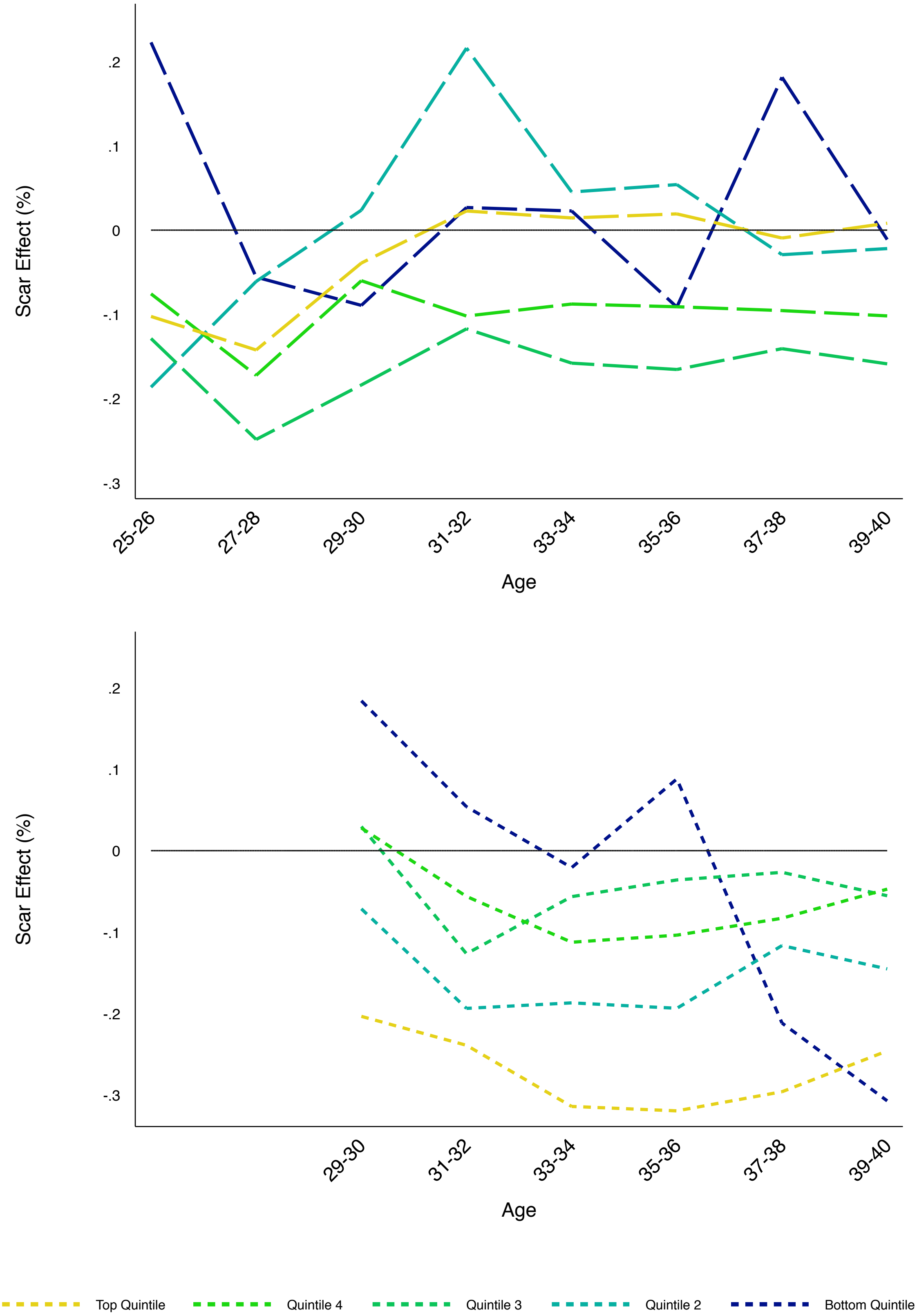
Note: The upper part reports the unemployment rate of UK male individuals born in 1960-1966 at age 18-20, 21-23 and 24-26. the middle part their average yearly earnings, measured in 2004 pounds, at ages 23-24 to 45-46. The third part is the proportion who claimed some of the benefits available

Figure A.2:
Scar Effects of Youth and Early Adult Unemployment for Different Cohorts



Note: The lines report the estimated coefficients from (21) for the effect of Youth, and Early Adulthood unemployment corresponding to those in Figure 5. That is the coefficients β_Y^t and β_A^t, calculated from each subsample of individuals in the same cohort in the sample of the main regression, column (3) in Table 1.

Figure A.3:
Scar Effects of Youth and Early Adult Unemployment on
Individuals of Different Abilities.



Note: The lines report the estimated coefficients from (21) for the effect of Youth, and Early Adulthood unemployment corresponding to those in Figure 6. That is the coefficients β_Y^t and β_A^t, calculated for each subsample of individuals in the same ability quintile determined according to the earnings of women who have lived in the same places at the same time.

Table A2:
Different cut-off ages; different splits of the period of youth.

	(1)	(2)	(3)	(4)	(5)	(6)
	Sample 18-40	Sample 18-42	Sample 18-44	Sample 18-46	Whole Youth	Entrant + Early Adult
Current Unemployment	2.318***	2.288***	2.235***	2.067***	2.222***	2.279***
	(0.051)	(0.057)	(0.069)	(0.115)	(0.051)	(0.051)
Entrant Unemployment (18-20)						
On Earnings Aged 23-24	0.321***	0.342***	0.307***	0.155		
	(0.040)	(0.043)	(0.053)	(0.087)		
On Earnings Aged 25-26	0.447***	0.500***	0.479***	0.388***		
	(0.051)	(0.056)	(0.071)	(0.103)		
On Earnings Aged 27-28	0.537***	0.608***	0.571***	0.472***		
	(0.052)	(0.057)	(0.069)	(0.109)		
On Earnings Aged 29-30	0.566***	0.641***	0.631***	0.527***		
	(0.054)	(0.058)	(0.073)	(0.100)		
On Earnings Aged 31-32	0.552***	0.597***	0.593***	0.444***		
	(0.053)	(0.059)	(0.071)	(0.106)		
On Earnings Aged 29-30	0.498***	0.530***	0.540***	0.441***		
	(0.053)	(0.058)	(0.073)	(0.114)		
On Earnings Aged 35-36	0.492***	0.540***	0.553***	0.463***		
	(0.055)	(0.060)	(0.073)	(0.121)		
On Earnings Aged 37-38	0.492***	0.543***	0.564***	0.406***		
	(0.056)	(0.060)	(0.074)	(0.110)		
On Earnings Aged 39-40	0.506***	0.565***	0.599***	0.449***		
	(0.056)	(0.061)	(0.074)	(0.115)		
On Earnings Aged 41-42		0.535***	0.553***	0.336***		
		(0.053)	(0.065)	(0.100)		
On Earnings Aged 43-44			0.574***	0.406***		
			(0.065)	(0.102)		
On Earnings Aged 45-46				0.457***		
				(0.102)		
Youth Unemployment (21-23)						
On Earnings Aged 25-26	−0.013	−0.067	−0.033	0.078		
	(0.045)	(0.052)	(0.063)	(0.097)		
On Earnings Aged 27-28	−0.047	−0.113*	−0.090	−0.106		
	(0.046)	(0.054)	(0.061)	(0.100)		
On Earnings Aged 29-30	0.042	−0.031	0.022	0.144		
	(0.053)	(0.062)	(0.075)	(0.115)		
On Earnings Aged 31-32	0.091	0.020	0.052	0.264*		
	(0.055)	(0.064)	(0.076)	(0.125)		
On Earnings Aged 29-30	0.091	0.022	0.046	0.180		
	(0.055)	(0.065)	(0.077)	(0.120)		
On Earnings Aged 35-36	0.098	−0.005	0.062	0.179		
	(0.056)	(0.065)	(0.076)	(0.129)		
On Earnings Aged 37-38	0.110	0.029	0.051	0.244*		
	(0.056)	(0.066)	(0.077)	(0.121)		
On Earnings Aged 39-40	0.067	−0.023	0.036	0.196		
	(0.057)	(0.066)	(0.078)	(0.126)		
On Earnings Aged 41-42		−0.007	0.060	0.317**		
		(0.056)	(0.066)	(0.107)		
On Earnings Aged 43-44			0.049	0.287**		
			(0.066)	(0.108)		
On Earnings Aged 45-46				0.317**		
				(0.109)		
Early Adulthood Unempl. (24-26)						
On Earnings Aged 29-30	0.060	0.070	0.061	0.042		
	(0.047)	(0.055)	(0.073)	(0.127)		
On Earnings Aged 31-32	0.007	0.078	0.081	0.050		
	(0.046)	(0.052)	(0.068)	(0.134)		
On Earnings Aged 29-30	0.016	0.074	0.146*	0.143		
	(0.049)	(0.056)	(0.071)	(0.129)		
On Earnings Aged 35-36	0.000	0.086	0.104	0.116		
	(0.050)	(0.056)	(0.074)	(0.153)		
On Earnings Aged 37-38	−0.070	0.023	0.062	−0.028		
	(0.051)	(0.058)	(0.075)	(0.139)		
On Earnings Aged 39-40	−0.092	0.016	0.028	0.012		
	(0.051)	(0.057)	(0.074)	(0.142)		

Continued on next page

Table A2 – continued from previous page

	(1)	(2)	(3)	(4)	(5)	(6)
	Sample 18-40	Sample 18-42	Sample 18-44	Sample 18-46	Whole Youth	Entrant + Early Adult
On Earnings Aged 41-42		-0.026	-0.001	-0.070		
		(0.044)	(0.058)	(0.115)		
On Earnings Aged 43-44			0.014	-0.076		
			(0.058)	(0.116)		
On Earnings Aged 45-46				-0.108		
				(0.116)		
Whole Youth Unemployment (18-26)						
On Earnings Aged 29-30					0.113^{***}	
					(0.013)	
On Earnings Aged 31-32					0.106^{***}	
					(0.013)	
On Earnings Aged 33-34					0.090^{***}	
					(0.014)	
On Earnings Aged 35-36					0.086^{***}	
					(0.014)	
On Earnings Aged 37-38					0.068^{***}	
					(0.015)	
On Earnings Aged 39-40					0.050^{***}	
					(0.015)	
Entrant (18-22) Unemployment						
On Earnings Aged 25-26						0.187^{***}
						(0.022)
On Earnings Aged 27-28						0.217^{***}
						(0.023)
On Earnings Aged 29-30						0.271^{***}
						(0.028)
On Earnings Aged 31-32						0.285^{***}
						(0.028)
On Earnings Aged 33-34						0.252^{***}
						(0.028)
On Earnings Aged 35-36						0.256^{***}
						(0.029)
On Earnings Aged 37-38						0.259^{***}
						(0.030)
On Earnings Aged 39-40						0.254^{***}
						(0.029)
Youth Unemployment (23-27)						
On Earnings Aged 29-30						0.054
						(0.029)
On Earnings Aged 31-32						0.031
						(0.029)
On Earnings Aged 29-30						0.035
						(0.031)
On Earnings Aged 35-36						0.024
						(0.032)
On Earnings Aged 37-38						-0.012
						(0.033)
On Earnings Aged 39-40						-0.047
						(0.033)
N	319481	249465	163725	56621	319481	319481
Number of Individuals	14348	10326	6264	2017	14348	14348

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Columns (1)-(4) report estimated coefficients from (21) for different samples. Therefore Column (1) is the same as column (3) in Table 1, and is the regression run on a sample which contains seven cohorts. The next three columns are for smaller samples, containing respectively five, three and one cohort only. Column (5) contains the estimated coefficients when the entire period from age 18 to age 26 is treated as homogeneous, that is when (21) is estimated with the restrictions (22)-(23). These coefficients are drawn as the light green line in Figure 3, and in Figure A.1. Finally, Column (6) reports the estimated coefficients when youth is split into two periods, with restrictions (25)-(27). The resulting coefficients are drawn as the aquamarine lines in Figure A.1.

Table A3:
Results For Different Ability Quintiles

	(1) Bottom Quartile	(2) 2nd Quartile	(3) 3rd Quartile	(4) 4th Quartile	(5) Top Quartile
Current Unemployment	4.453^{***}	1.822^{***}	0.887^{***}	0.742^{***}	0.381^{**}
	(0.205)	(0.153)	(0.136)	(0.137)	(0.124)
Entrant Unemployment (18-20)					
On Earnings Aged 23-24	0.487^{*}	0.276	0.056	0.158	0.166
	(0.225)	(0.186)	(0.167)	(0.145)	(0.145)
On Earnings Aged 25-26	0.541	0.425^{*}	0.237	0.211	0.351^{*}
	(0.289)	(0.208)	(0.215)	(0.181)	(0.177)
On Earnings Aged 27-28	0.795^{**}	0.371	0.351	0.261	0.287
	(0.289)	(0.220)	(0.235)	(0.163)	(0.173)
On Earnings Aged 29-30	1.061^{***}	0.423	0.266	0.205	0.271
	(0.318)	(0.216)	(0.204)	(0.169)	(0.173)
On Earnings Aged 31-32	0.741^{*}	0.353	0.227	0.263	0.216
	(0.331)	(0.234)	(0.206)	(0.161)	(0.168)
On Earnings Aged 29-30	0.694^{*}	0.344	0.222	0.259	0.233
	(0.337)	(0.222)	(0.200)	(0.158)	(0.168)
On Earnings Aged 35-36	0.722^{*}	0.421	0.202	0.228	0.219
	(0.338)	(0.224)	(0.197)	(0.155)	(0.169)
On Earnings Aged 37-38	0.616	0.475^{*}	0.203	0.254	0.220
	(0.356)	(0.219)	(0.197)	(0.155)	(0.165)
On Earnings Aged 39-40	0.610	0.382	0.266	0.249	0.205
	(0.357)	(0.231)	(0.202)	(0.157)	(0.164)
Youth Unemployment (21-23)					
On Earnings Aged 25-26	0.223	−0.186	−0.129	−0.076	−0.102
	(0.230)	(0.173)	(0.188)	(0.172)	(0.142)
On Earnings Aged 27-28	−0.056	−0.061	−0.248	−0.172	−0.142
	(0.249)	(0.182)	(0.198)	(0.152)	(0.144)
On Earnings Aged 29-30	−0.089	0.024	−0.184	−0.060	−0.039
	(0.340)	(0.194)	(0.184)	(0.174)	(0.144)
On Earnings Aged 31-32	0.027	0.216	−0.117	−0.102	0.023
	(0.347)	(0.204)	(0.166)	(0.166)	(0.139)
On Earnings Aged 29-30	0.023	0.045	−0.158	−0.088	0.014
	(0.359)	(0.189)	(0.167)	(0.160)	(0.137)
On Earnings Aged 35-36	−0.091	0.054	−0.165	−0.091	0.019
	(0.384)	(0.189)	(0.167)	(0.164)	(0.140)
On Earnings Aged 37-38	0.181	−0.029	−0.141	−0.096	−0.009
	(0.402)	(0.191)	(0.169)	(0.167)	(0.139)
On Earnings Aged 39-40	−0.011	−0.022	−0.159	−0.102	0.008
	(0.381)	(0.211)	(0.173)	(0.164)	(0.144)
Early Adulthood Unemployment (24-26)					
On Earnings Aged 29-30	0.184	−0.071	0.030	0.028	−0.204
	(0.264)	(0.160)	(0.133)	(0.132)	(0.138)
On Earnings Aged 31-32	0.054	−0.194	−0.127	−0.056	−0.239
	(0.262)	(0.159)	(0.121)	(0.134)	(0.139)
On Earnings Aged 29-30	−0.021	−0.187	−0.056	−0.113	-0.314^{*}
	(0.289)	(0.146)	(0.118)	(0.133)	(0.136)
On Earnings Aged 35-36	0.088	−0.194	−0.036	−0.104	-0.320^{*}
	(0.303)	(0.145)	(0.117)	(0.136)	(0.136)
On Earnings Aged 37-38	−0.212	−0.117	−0.027	−0.083	-0.296^{*}
	(0.316)	(0.149)	(0.125)	(0.138)	(0.136)
On Earnings Aged 39-40	−0.308	−0.145	−0.055	−0.047	−0.246
	(0.326)	(0.163)	(0.121)	(0.128)	(0.132)
Observations	64,009	63,832	63,952	63,852	63,835
Number of Individuals	3,059	2,839	2,827	2,811	2,812

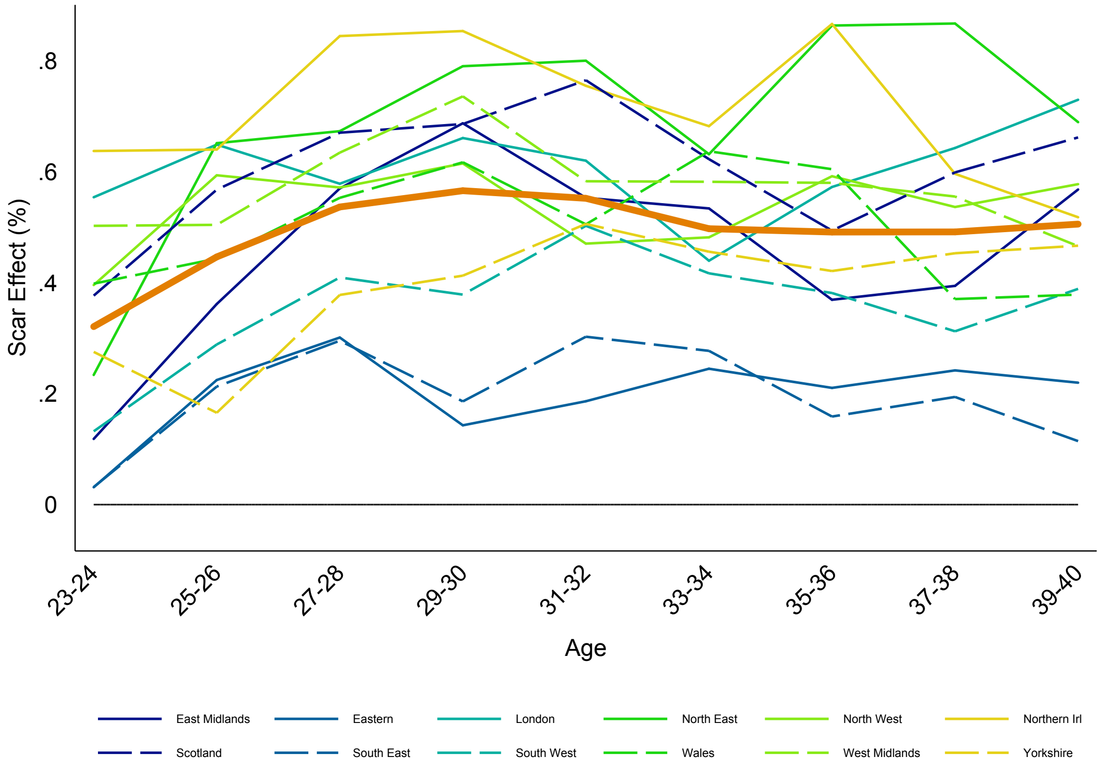
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Coefficients for the estimation of (21), the same as the main regression, column (3) in Table 1, estimated from each subsample of individuals in the same ability quintile according to the rank determined by their earnings potential. The coefficients in the top block are plotted in Figure 6, those in the other two blocks in Figure A.3.

Table A4:
Results For Individual Cohorts

	(1) 1978	(2) 1979	(3) 1980	(4) 1981	(5) 1982	(6) 1983	(7) 1984
Current Unemployment	2.050***	2.124***	2.388***	2.381***	2.439***	2.489***	2.557***
	(0.131)	(0.118)	(0.142)	(0.141)	(0.139)	(0.149)	(0.125)
Entrant Unemployment (18-20)							
On Earnings Aged 23-24	0.137	0.343***	0.389***	0.331***	0.536***	0.272	0.102
	(0.085)	(0.085)	(0.102)	(0.095)	(0.114)	(0.143)	(0.182)
On Earnings Aged 25-26	0.367***	0.506***	0.541***	0.421***	0.752***	0.302	−0.048
	(0.100)	(0.127)	(0.141)	(0.119)	(0.132)	(0.170)	(0.204)
On Earnings Aged 27-28	0.451***	0.546***	0.684***	0.675***	0.731***	0.348*	−0.080
	(0.112)	(0.116)	(0.138)	(0.136)	(0.146)	(0.167)	(0.212)
On Earnings Aged 29-30	0.502***	0.617***	0.763***	0.570***	0.857***	0.338	−0.043
	(0.103)	(0.118)	(0.154)	(0.137)	(0.140)	(0.181)	(0.210)
On Earnings Aged 31-32	0.424***	0.489***	0.830***	0.552***	0.787***	0.421*	0.084
	(0.113)	(0.114)	(0.148)	(0.144)	(0.139)	(0.169)	(0.210)
On Earnings Aged 29-30	0.397**	0.477***	0.739***	0.506***	0.655***	0.367*	0.151
	(0.124)	(0.120)	(0.144)	(0.137)	(0.135)	(0.166)	(0.216)
On Earnings Aged 35-36	0.431***	0.446***	0.763***	0.488***	0.703***	0.314	0.075
	(0.130)	(0.125)	(0.136)	(0.145)	(0.139)	(0.177)	(0.215)
On Earnings Aged 37-38	0.399***	0.564***	0.708***	0.450**	0.722***	0.313	−0.004
	(0.120)	(0.129)	(0.151)	(0.151)	(0.141)	(0.173)	(0.223)
On Earnings Aged 39-40	0.452***	0.574***	0.749***	0.503***	0.646***	0.284	0.020
	(0.125)	(0.130)	(0.152)	(0.152)	(0.145)	(0.182)	(0.223)
Youth Unemployment (21-23)							
On Earnings Aged 25-26	0.089	−0.036	−0.239	−0.244*	−0.120	0.118	0.307**
	(0.095)	(0.104)	(0.130)	(0.122)	(0.152)	(0.127)	(0.119)
On Earnings Aged 27-28	−0.096	−0.020	−0.183	−0.266	−0.129	0.106	0.276*
	(0.099)	(0.098)	(0.126)	(0.155)	(0.163)	(0.127)	(0.120)
On Earnings Aged 29-30	0.164	0.128	−0.329*	−0.318	−0.111	0.247	0.345**
	(0.112)	(0.123)	(0.163)	(0.180)	(0.167)	(0.158)	(0.116)
On Earnings Aged 31-32	0.307*	0.114	−0.379*	−0.177	−0.079	0.251	0.331*
	(0.133)	(0.121)	(0.162)	(0.183)	(0.189)	(0.152)	(0.129)
On Earnings Aged 29-30	0.251	0.146	−0.380*	−0.265	−0.004	0.234	0.347**
	(0.129)	(0.129)	(0.159)	(0.184)	(0.176)	(0.155)	(0.123)
On Earnings Aged 35-36	0.227	0.162	−0.304	−0.261	−0.239	0.320*	0.420**
	(0.137)	(0.123)	(0.159)	(0.180)	(0.178)	(0.149)	(0.131)
On Earnings Aged 37-38	0.264*	0.083	−0.274	−0.093	−0.147	0.246	0.363**
	(0.131)	(0.130)	(0.170)	(0.192)	(0.176)	(0.154)	(0.126)
On Earnings Aged 39-40	0.183	0.056	−0.291	−0.279	−0.199	0.311*	0.305*
	(0.133)	(0.129)	(0.180)	(0.189)	(0.182)	(0.155)	(0.134)
Early Adulthood Unemployment (24-26)							
On Earnings Aged 29-30	0.021	−0.053	0.247*	0.179	−0.042	−0.029	0.057
	(0.127)	(0.135)	(0.121)	(0.103)	(0.126)	(0.143)	(0.120)
On Earnings Aged 31-32	0.035	0.007	0.243*	0.123	−0.069	−0.211	−0.136
	(0.146)	(0.115)	(0.112)	(0.097)	(0.137)	(0.143)	(0.125)
On Earnings Aged 29-30	0.120	0.047	0.320**	−0.000	−0.142	−0.190	−0.056
	(0.139)	(0.132)	(0.117)	(0.116)	(0.150)	(0.144)	(0.132)
On Earnings Aged 35-36	0.111	0.035	0.198	0.107	−0.083	−0.261	−0.118
	(0.165)	(0.127)	(0.119)	(0.111)	(0.137)	(0.143)	(0.139)
On Earnings Aged 37-38	−0.024	0.027	0.198	−0.054	−0.092	−0.401**	−0.195
	(0.151)	(0.138)	(0.133)	(0.117)	(0.142)	(0.136)	(0.138)
On Earnings Aged 39-40	0.033	−0.071	0.152	0.041	−0.086	−0.450**	−0.291*
	(0.154)	(0.137)	(0.128)	(0.113)	(0.153)	(0.138)	(0.143)
N	46222	48013	48222	46073	43583	43203	44165
Number of Individuals	2057	2143	2152	2076	1972	1954	1994

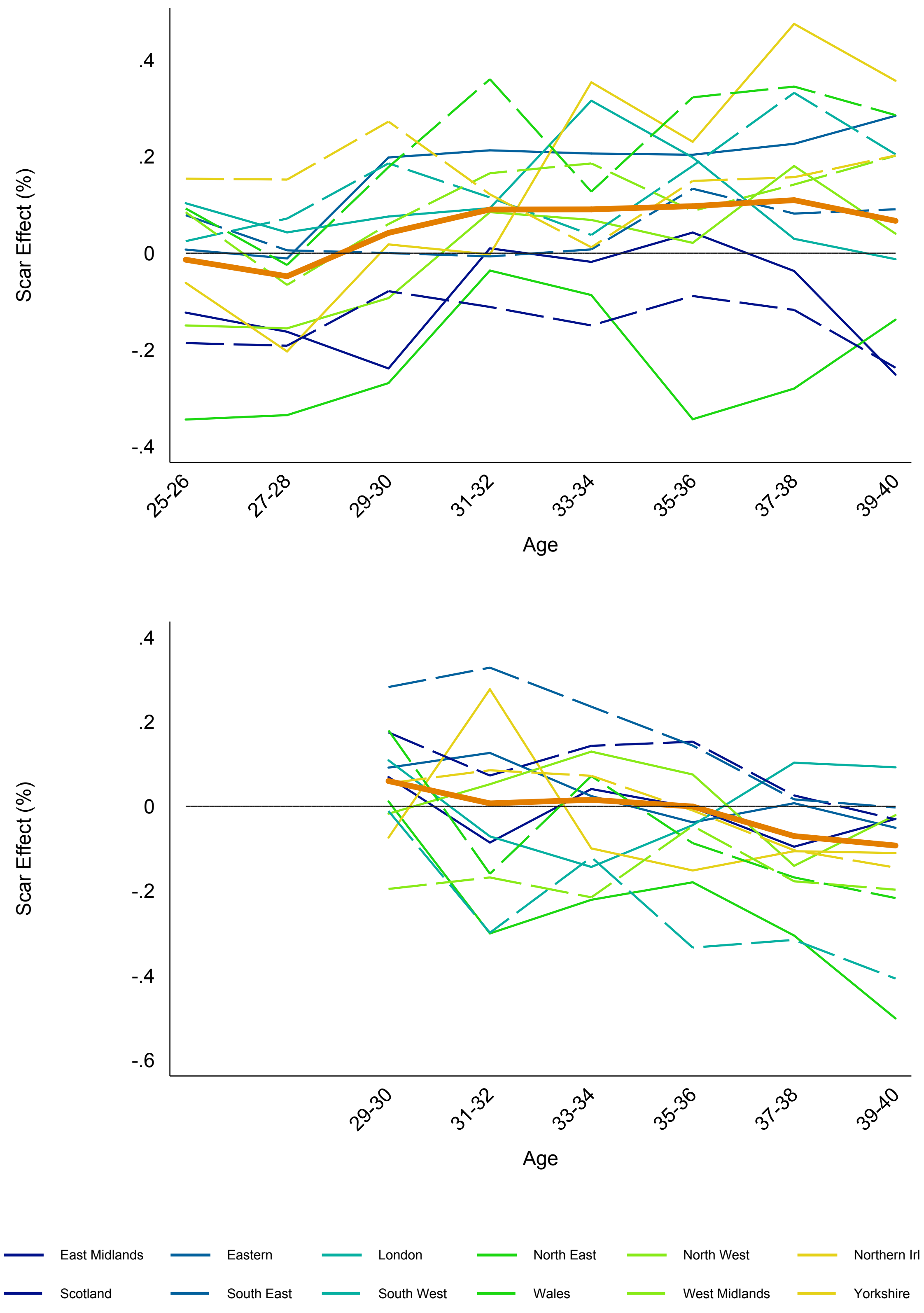
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Coefficients for the estimation of (21), the same as the main regression, column (3) in Table 1, estimated from each subsample of individuals according to the year of entry in the labour market. The coefficients in the top block are plotted in Figure 5, those in the other two blocks in Figure A.2.

Figure A.4:
Scar Effects of Entry Unemployment in Different Regions.



Note: The lines report the estimated coefficients from (21) for the effect of Entry unemployment corresponding to those in Figure 6. That is, the coefficients β_E^t are calculated for each subsample of individuals in the same region at the time of entry in the labour market.

Figure A.5:
Scar Effects of Youth and Early Adult Unemployment in Different Regions.



Note: The lines report the estimated coefficients from (21) for the effect of Youth, and Early Adulthood unemployment corresponding to those in Figure 6. That is, the coefficients β^t_{Y} and β^t_A are calculated from each subsample of individuals in the same region at the time of entry in the labour market.