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Mark Regan
Barra Roantree

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Born under a bad sign: the impact of finishing school when labour markets are weak

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Born under a bad sign: the impact of finishing school when labour markets are weak*

Mark Regan†, and Barra Roantree‡

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Abstract

This paper provides evidence that finishing school when labour markets are weak leads to poor subsequent labour market prospects, particularly those leaving school at younger ages. Using administrative register data from Denmark, we find that these scarring effects are larger and more persistent for young adults from the lowest-income backgrounds.

Keywords: unemployment, scarring, inequality

JEL codes: J23, J31, J64

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†Regan (mark.regan@esri.ie) is a Research Analyst at the Economic and Social Research Institute, Research Affiliate at Trinity College Dublin and a PhD student at University College Dublin.

‡Roantree (barra.roantree@esri.ie) is a Research Officer at the Economic and Social Research Institute, an adjunct Assistant Professor at Trinity College Dublin and a Research Associate at the Institute for Fiscal Studies.

1 Introduction

Recent recessions have brought with them concerns about "lost generations" of young adults who will end up bearing long-lasting scars from entering the labour market at an inopportune time (von Wachter, 2020a). This is grounded in the observation that the brunt of employment losses in these recessions have fallen on younger workers (Hoynes et al., 2012; Elsby et al., 2010), and that young workers who fail to find employment struggle to match the early career wage growth experienced by those who do (Murphy and Welch, 1990; Topel and Ward, 1992). Such concerns appear to be well founded, with a growing literature finding scarring effects in the labour market that last for up to ten years on average (Oreopoulos et al., 2012; Kahn, 2010; Schwandt and von Wachter, 2019; von Wachter, 2020b). These effects are thought to occur for reasons as varied as the depreciation of general human capital (Pissarides, 1992), psychological discouragement (Clark et al., 2001) and worse matches between workers and firms (Liu et al., 2016). In addition, there is evidence of impacts on crime (Bell et al., 2017), substance misuse (Maclean, 2015; Cutler et al., 2015) and mortality (Maclean, 2013; Schwandt and von Wachter, 2020).

However, much of this literature focuses on college graduates in the United States and Canada.[1] While this group has the attraction of having a relatively well-defined career structure and labour market entry date (making the identification of treatment effects more credible), there are reasons to think that they may endure smaller and more transitory scars than less advantaged groups. For one, those from less advantaged backgrounds are more exposed to weak labour market conditions than college graduates in part because of of the industries and sectors they are more likely to work in (Hoynes et al., 2012). If they also take longer to recover from labour market shocks, then it is likely that scarring effects will be more persistent.

[1]Notable exceptions include Speer (2016) and Schwandt and von Wachter (2019) - who examine scarring effects on college and non-college graduates in the United States - as well as Raaum and Røed (2006) and Haaland (2018) - who find that lower-educated and lower-ability men in Norway are more vulnerable to local business cycle conditions.

Using administrative register data from Denmark, the contribution of this paper is to show that scarring effects are indeed larger and more persistent for young adults from the lowest-income backgrounds, particularly those leaving school at younger ages. We exploit cross-cohort and regional variation in the initial labour market conditions faced by school leavers in Denmark at ages 18-21 to examine how much a weak initial labour market affects their subsequent labour market prospects.

Our estimates show that those finishing school aged 18 or 19 - 21% of those born in the 1980s - every percentage point increase in the not-in-education employment-or-training (NEET) rate among 18 or 19 year olds is associated with employment rates that are initially 2 percent lower than expected. While these fade over time, they remain 0.5 percent lower even 7-8 years after when these young adults are aged 26. This compares to an initial reduction in the probability of being in paid work of 0.6% for those finishing school aged 20 or 21 - 44% of those born in the 1980s - which fades completely by age 26.

Similarly, our estimates show that a percentage point increase in the NEET rate at school completion also leads to earnings losses for those that do find work. These are initially 3% lower for those leaving school at age 18, but only 1.4% lower for those leaving school at 21. While these effects fade entirely by age 26 for both younger and older school leavers, they do so faster for older school leavers (within 3 compared to 5 years).

We also estimate scarring effects separately by sex and family background. This is facilitated by the population-wide longitudinal coverage of our data, which contain sufficient sample sizes to look at smaller groups in addition - crucially - to information on the parental earnings of all individuals born between 1980 and 1992. We assign each individual to a cohort-specific quintile on the basis of the rank of their parents' combined earnings when they were 16 (i.e. between 1986 and 2008). These estimates suggest that scarring effects are much larger and more persistent for those from the lowest-income quintile. This is particularly the case for younger school leavers. For example, the estimated probability of being in paid work at age 26 is 0.9% lower for those from the lowest-income quintile leaving school at age 18 when the NEET rate is elevated, compared to 0.7% at age 19 for those from the highest-income quintile. We find are less pronounced differences in scarring by sex, though our estimates of the initial adverse effects on earnings are larger for men then women.

For older school leavers, our estimates suggest smaller scarring effects that heal faster than for similarly educated groups elsewhere. For example, we find that the scarring effect on earnings for those leaving school at ages 20 and 21 fade within 3 years compared to 6-10 years for those with at least some college education in the United States (Kahn, 2010; Altonji et al., 2015), Canada (Oreopoulos et al., 2012) and Norway (Liu et al., 2016). However, we find effects on employment for those with lower levels of education that are similarly sized if perhaps somewhat more persistent than in the United States (Schwandt and von Wachter, 2019) and Britain (Cribb et al., 2017). Furthermore, we find these effects are substantially larger and more persistent for young adults from lower-income backgrounds. This is a group for whom economic research - worryingly - suggests active labour market policies are typically least effective (Caliendo and Schmidl, 2016). Given this group are also more likely to work in sectors like hospitality and retail which have been disproportionately affected by the ongoing COVID-19 pandemic (Andersen et al., 2020), policymakers face a huge challenge in limiting its potential consequences.

This paper proceeds as follows. Section 2 outlines the empirical approach and data that we use. Section 3 presents our results and Section 4 concludes.

2 Empirical Approach and Data

Our goal is to estimate the effect that the initial state of the labour market has on the subsequent outcomes of labour market entrants. Ideally this would involve comparing the outcomes of a set of individuals who randomly enter labour markets of differing strengths, but who are otherwise identical.

However, there exists no such source of randomization in the real world, so we instead exploit variation in initial labour market conditions across birth cohorts and region. The basic idea is to compare individuals from the same area who face different initial labour markets due to exogenous changes in the business cycle, but who are born close enough together that they are otherwise identical.

We do this using the framework of Kahn (2010); Oreopoulos et al. (2012) and Schwandt and von Wachter (2019), amongst others. This involves regressing a measure of initial labour market conditions for an individual i of birth cohort c living in region r_0 at the time they enter the labour market on subsequent labour market outcomes at age t, $y_{i,t}$. We interact this measure of initial labour market conditions (n_{c,r_0}) with age (t), including fixed-effects for age (γ), birth cohort (η) and original region (λ) to control for the strong age gradient observed in employment and earnings, secular trends over time and differences across regions. That is, we estimate the equation:

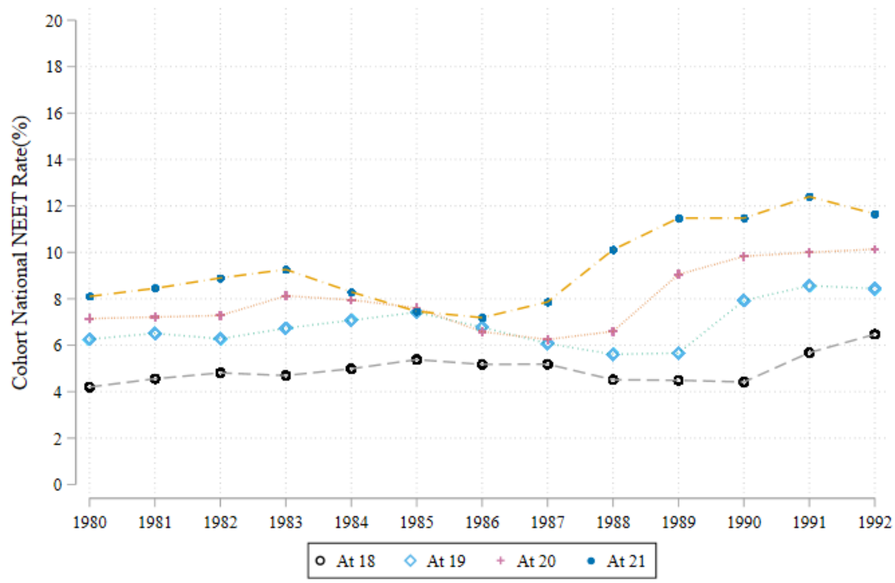
$$y_{i,t,c,r_0} = \sum_{t=t_{min}}^{t_{max}} \beta_t t.n_{c,r_0} + \boldsymbol{\gamma} t + \boldsymbol{\eta} c + \boldsymbol{\lambda} r_0 + \epsilon \quad (1)$$

The estimate of scarring effects are given by the β coefficients, the parameter associated with the interaction of initial labour market conditions and age. These can be interpreted as the deviation from the typical experience profile caused by completing education in a recession, subject to the subsequent typical evolution of local labour market conditions (von Wachter, 2020b).

We calculate initial local labour market conditions (n_{c,r_0}) using the regional not-in-education-or-employment (NEET) rate for each cohort at the age they leave education.[2] This is a more granular measure of initial labour market conditions than typically used in the literature, facilitated by our data that cover the entire population of those born from 1980 to 1992 (discussed below). These provide information on when each individual completes education and where they are living, avoiding the need to approximate this using

[2]Given we calculate this for each cohort at the age they leave education, our measure is equivalent to one minus the employment rate, capturing declines in labour market participation as well as unemployment.

Figure 1: **National variation in initial labour market conditions across cohorts**



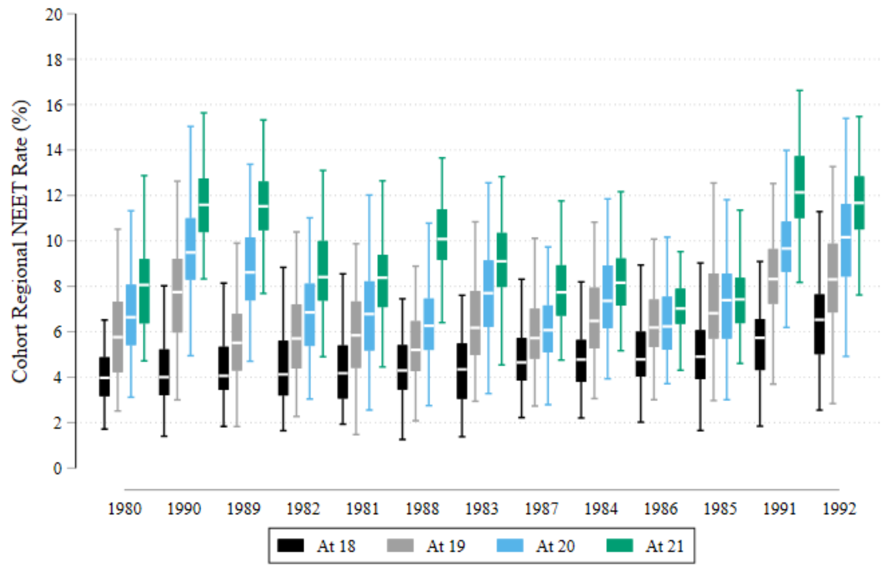
Source: Authors' calculations using data from Statistics Denmark.
Notes: We define a young adult as NEET (Not-in-Education-Employment-or-Training) if they had zero earnings in the calendar year and they were not register in any education or training course in an accredited Danish institution.

the region of birth and synthetic cohorts constructed from repeated cross-section data as in much of the literature. A drawback is that we are limited to examining the outcomes of just 12 year-of-birth cohorts.

We use administrative register data provided by Statistics Denmark (Denmarks Statistik) on all individuals living in Denmark born between 1980 to 1992. These contain information on region of residence (98 municipalities), earnings, education status and educational attainment over the years 1996 to 2018. They also contain information on the parents of these individuals and their earnings, which we use to construct a measure of family background. Specifically, we rank parents of individuals in a given birth cohort by household earnings at age 16 and divide these into quintiles. This allows us to estimate differences in the extent and persistence of scarring by family background. Further details on how we construct the variables used in our estimation are provided in the Appendix.

Figure 1 plots the variation in the national NEET rate at ages 18-21 faced by different

Figure 2: **Regional variation in initial labour market conditions across cohorts**

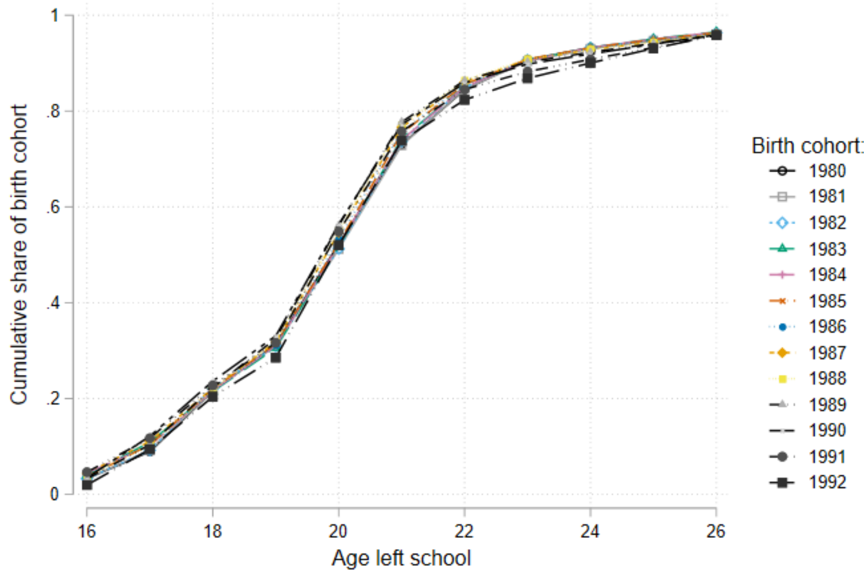


Source: Authors' calculations using data from Statistics Denmark.
Notes: Bars show median and interquartile range of municipal NEET rates at indicated age for indicated cohort. Whiskers show upper and lower adjacent values: the range of data points within 1.5 times the interquartile range of the upper/lower quartile (Tukey, 1977).

birth cohorts. The main source of cross-cohort variation at age 18 at the national level is between those born in the 1980s and those born in the 1990s. The latter unlucky cohorts had markedly higher NEET rates at age 18: 5.7% for the 1991 cohort and 6.5% for the 1992 cohort, compared to just 4% for those born in 1980. There is even more variation across cohorts at older ages. For example, the national NEET rate at age 21 rises from 8% for those born in 1980 to almost 10% for those born in 1983, before falling to below 8% for those born in 1986 and rising to 12% for those born in the 1990s.

While there is significant variation in NEET rates nationally, we are limited to a relatively small number of birth cohorts (12) from which to identify scarring effects. To provide additional variation and improve the precision of our estimates, our main results use regional variation in NEET rates across cohorts at ages 18, 19, 20 and 21. These are displayed in Figure 2, with boxplots showing the median, interquartile range and adjacent values of municipality level NEET rates by year of birth at these ages. Again these show that at age

Figure 3: **Cumulative share leaving school, by age and year of birth**



Source: Authors' calculations using data from Statistics Denmark.
Notes: First age at which individuals not observed in education.

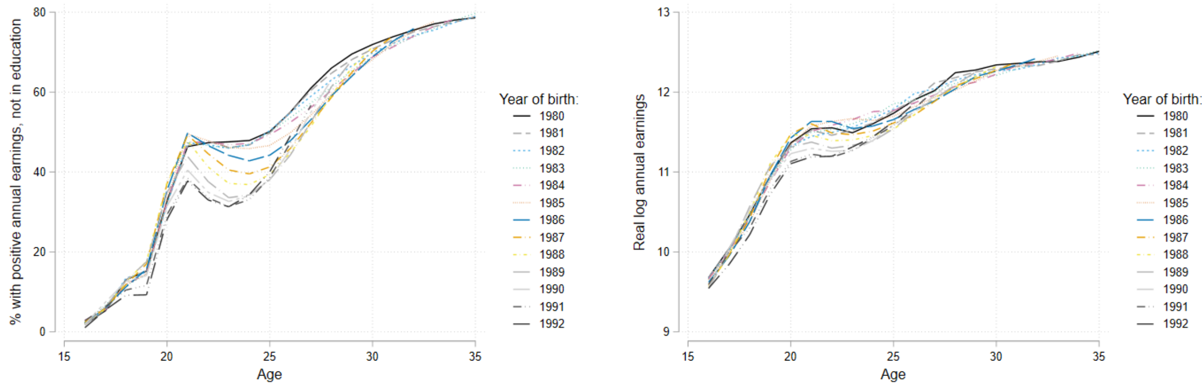
18 most variation is between those born before and after 1990, though there is also significant within-cohort (regional) variation with a lower (higher) adjacent value of below 2% (above 6%) for those born in 1980. Similarly, the median municipal NEET rate exhibits more variation at older than younger ages, but there is also significant within-cohort variation across municipalities. Table 1 in the Appendix also shows that this variation is not just due to certain regions having permanently low or high NEET rates. The R^2 of approximately 60% indicates that there is still substantial variation even after accounting for municipality and year fixed-effects in an ordinary least squares regression of municipality NEET rates.

Before proceeding to present our regression results, we first plot cross-cohort variation in the outcomes we examine by age. Figure 3 plots the cumulative share of each year of birth cohort who have left education for the first time by age. This shows that more than half of young Danes have left school by age 20 and more than 75% by age 21, with little variation across cohorts.

Figure 4: **Cross-cohort variation in earnings and employment by age**

(a) Employed (positive earnings, not in education)

(b) Mean annual log earnings



Source: Authors' calculations using data from Statistics Denmark.
Notes: Calculated over the universe of workers aged 16 to 35 and born between 1980 and 1992.

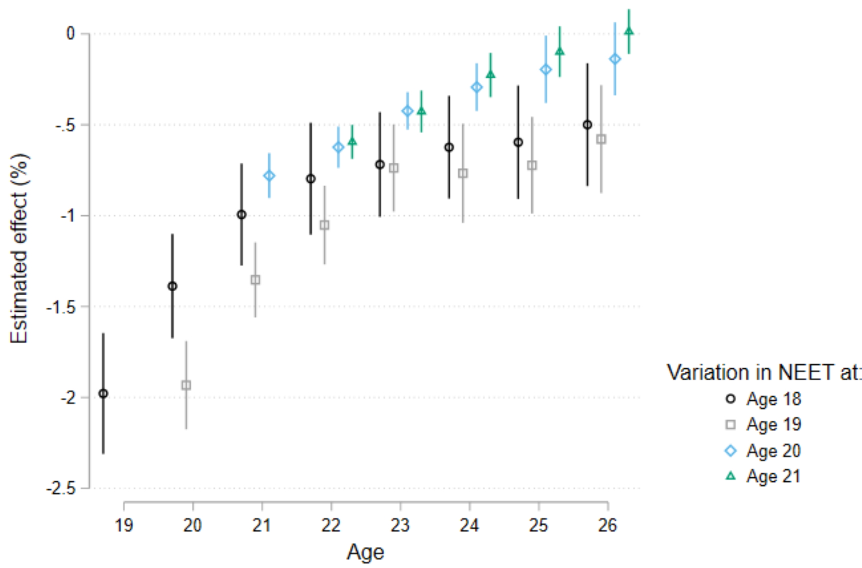
Panel A of Figure 4 shows that those who turned 20 over the course of the Great Recession (born in the late 1980s and early 1990s) experienced lower rates of employment throughout their 20s than those born in the early 1980s. Similarly, Panel B shows that those from cohorts more exposed to the Great Recession had lower earnings throughout their 20s, only converging to the levels of those born in the early 1980s after age 30.

3 Results

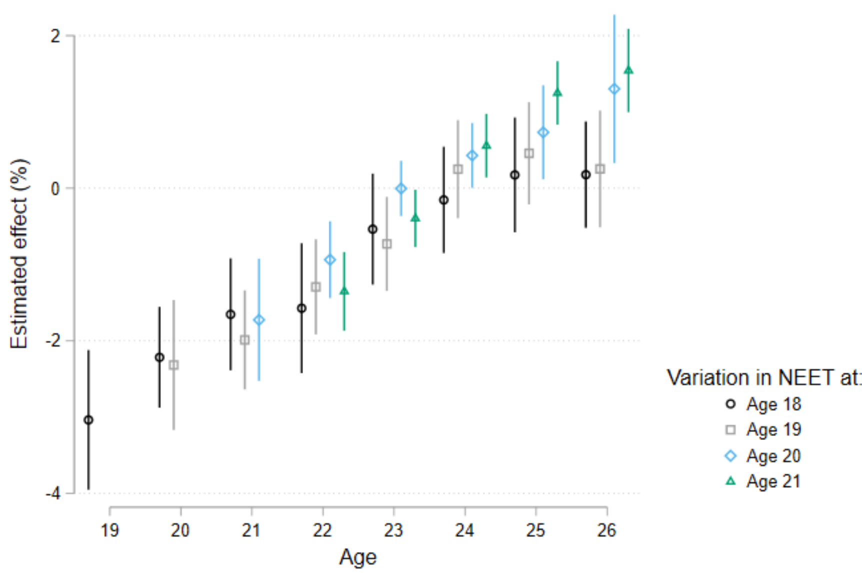
Our baseline estimates of scarring effects on employment and earnings outcomes are shown in Figure 5. The regression estimates are displayed separately for young adults who finished education at ages 18 to 21. For employment, the profile of the scarring process is steepest for young adults leaving education at age 18 or 19- they incur both the largest and most persistent decrease in employment prospects in early adulthood. For every percentage point (ppt.) increase in the municipal NEET rates at 18, school-leavers at 18 are 2% less likely to be employed at 19, This effect diminishes slowly over time, to -1.4% at age 20, 1% at age

Figure 5: **Estimated scarring effects on employment & earnings of young adults**

(a) Employment



(b) Log earnings



Source: Authors' calculations using data from Statistics Denmark.
Notes: Estimates show the scarring coefficients from Equation 1, scaled so as to be interpreted in percentage terms. Scarring effects are estimated separately for those leaving education at ages 18, 19, 20 and 21. The regression sample comprises all members of 1980-1992 birth cohorts who completed education between the age of 18 and 21. Standard errors are clustered at the municipality level. A 95% confidence interval surrounds the point estimate.

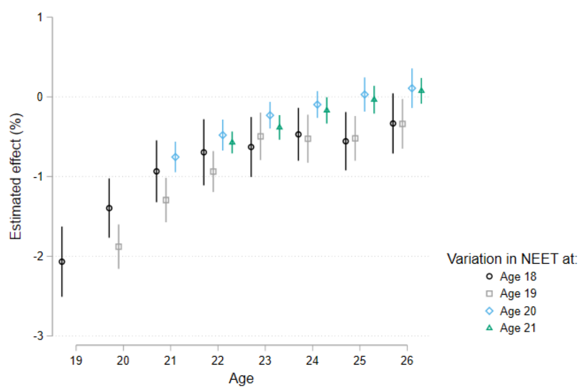
21 but even by age 26, these effects are relatively large at 0.5%. Those leaving school at 19 experience a similar scarring process- with a decrease in the probability of employment at age 20 of 1.9%, which slowly decreases to 0.6% by age 26. Employment prospects of school-leavers at 20 and 21 are less impacted by NEET rates at labour market entry conditions- with the probability of employment falling by 0.8 and 0.4% one year after labour market entry with these effects fading to zero by age 26.

A similar gradient in scarring effects across age groups is also evident in earnings, although these scars are less severe. Those leaving education at 18 (19) face penalties of 3.0 (2.3)% at age 19, but these converge to zero by age 23 (24). Initial scars are again lower for those leaving education at ages 20 and 21- falling by 1.7 and 1.3%. These penalties are short-lived and by age 24, these scarring coefficients are positive, indicating that those who find employment at these ages, even after being exposed to an initial NEET rate shock, tend to have slightly higher wages (+1% by age 26). Given there are employment scars up to age 25 for these groups, this earnings premia, is likely due to selection and could arise if adverse employment effects are mainly levied on lower-skilled young adults whose earnings would be lower than average if they were in-work.

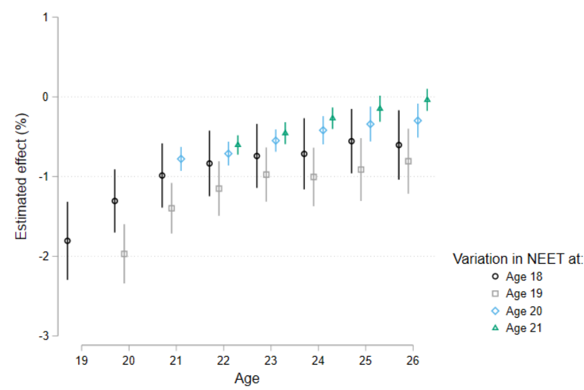
In Figure 6 we display the scarring effects by sex, which we estimate by estimating Equation 1 separately for men and women. These are within-sex scarring effects and are to be interpreted as how a ppt. increase in the municipality NEET rate affected men (women) who faced this shock relative to those that didn't. Overall, the magnitude of scarring effects tend to be quite similar across men and women but with women facing slightly larger employment scars and men facing larger earnings losses (particularly amongst the less educated) . For employment, less educated women leaving education at 18 (19) face an initial reduction in employment of 1.8 (2.0)% at age 19 (20), which falls steadily to -0.6 (-0.8)% by age 26. Women leaving education at 20, who would have received some post-secondary education incur employment scars of 0.7% at 21, decreasing to 0.3 by 26. For women leaving education at 21, the scars are less persistent - at 0.6% at 22, but already zero by 25, similar to the

Figure 6: **Estimated scarring effects on employment & earnings of young adults, by sex**

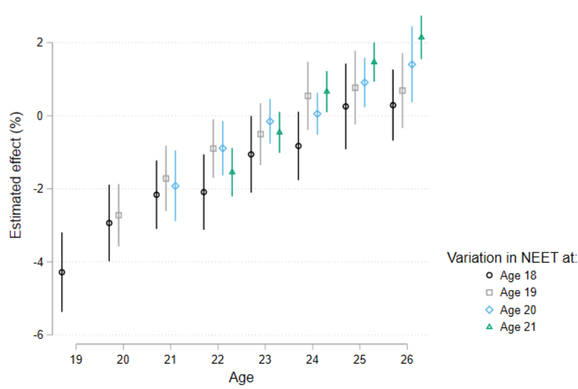
(a) Employment (men)



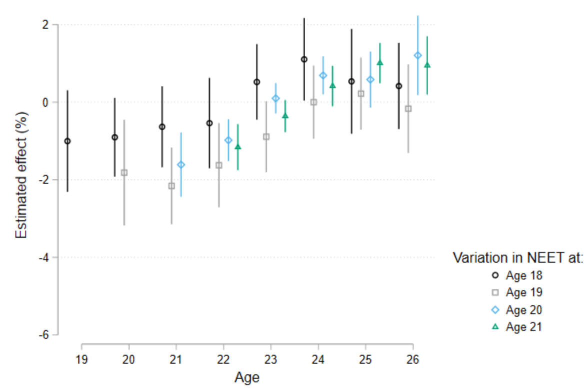
(b) Employment (women)



(c) Log earnings (men)



(d) Log earnings (women)



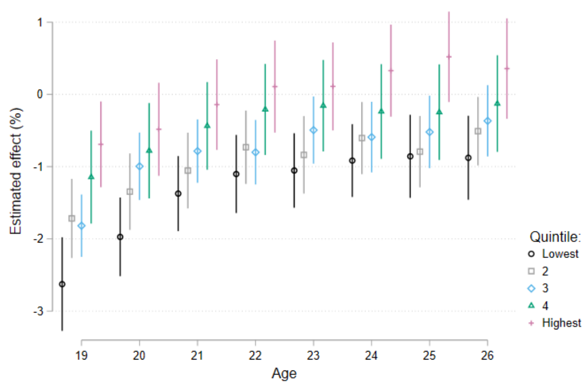
Source: Authors' calculations using data from Statistics Denmark.
Notes: Estimates show the scarring coefficients from Equation 1, scaled so as to be interpreted in percentage terms. Scarring effects are estimated separately for those leaving education at ages 18, 19, 20 and 21 and by gender. The regression sample comprises all members of 1980-1992 birth cohorts who completed education between the age of 18 and 21. Standard errors are clustered at the municipality level. A 95% confidence interval surrounds the point estimate.

trend observed in male scars. Scarring effects calculated on earning tend to vary by sex, with less-educated men bearing very large early career scars. Men leaving education at 18, face earnings losses of 4.2% at age 19 in response to a ppt. increase in municipality NEET rates. These scars are at 2.9, 2.2, 2.1 and 1.0% in the ensuing years and are zero by age 24. Men leaving education at 19 also face large losses (although not as large or persistent as the 18 year old cohort), of 2.8% at age 20, but these scars fade to zero by age 23. In contrast, women leaving education at 18 tend to not face any negative earnings scars. Those leaving at 19 do tend to face scars of 1.8% at 21, 2.6% at 22 and 1.6% at 23 however. Men and women leaving education at 20/21 tend to have comparable scarring effects, with earnings decreasing slightly (less than 2%) immediately after graduation, these scars then re-converge to zero quickly and small premia are evident in the mid-twenties.

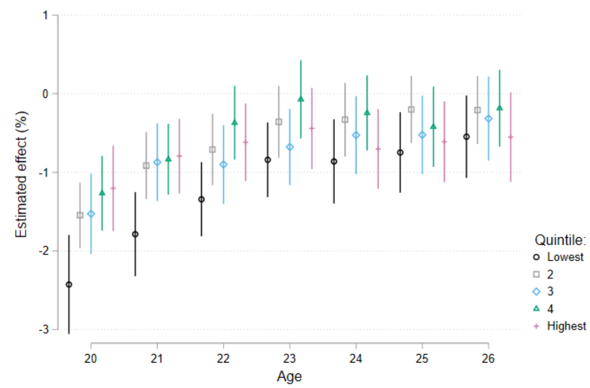
In Figures 7 and 8 we plot the scarring effects on earnings and employment by parental income at age 16. We rank children into quintiles, based on household income at 16, and estimate scarring models separately for each quintile. We see that the scarring effects for both employment and earnings are strongest for children from the bottom income group. In our baseline model, we found less-educated adults, those leaving school at 18/19, incurred lower employment prospects which were still significant at age 26. This employment risk is disproportionately levied on young adults from low-income background. Less-educated adults from a bottom-income quintile household face a decreased employment probability of 2.6 (2.4)% one year after graduation if they left education at age 18 (19). These scars decrease in age but are still larger than zero at age 26. Their cohort peers from a higher-income background smaller initial losses, 1.8% for those in the middle income quintile leaving school at 18, with this effect fading to zero by 26. Those from the highest income quintile face the smallest losses- of just 0.7% at 19, with no scarring effect evident at age 20 if they had left school at 18. For more-educated young adults, those leaving school at 20/21, there are also higher initial losses after graduation- but the gap across the income distribution is substantially more modest and these scars also re-converge to zero at a similar speed. Early

Figure 7: **Estimated scarring effects on employment, by parental income quintile**

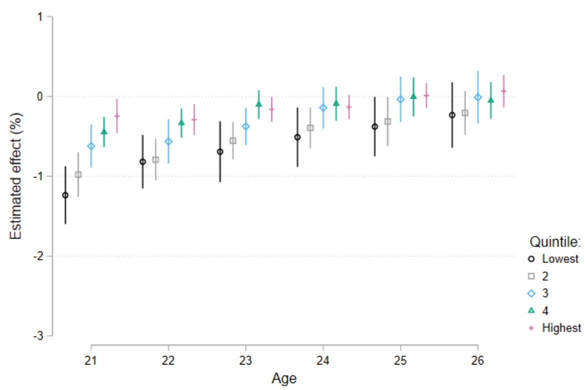
(a) Variation at age 18-employment



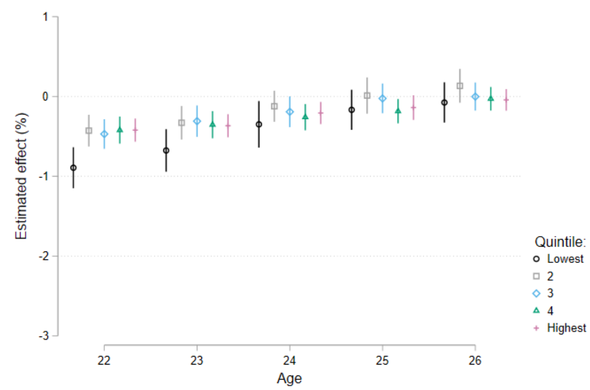
(b) Variation at age 19-employment



(c) Variation at age 20-employment

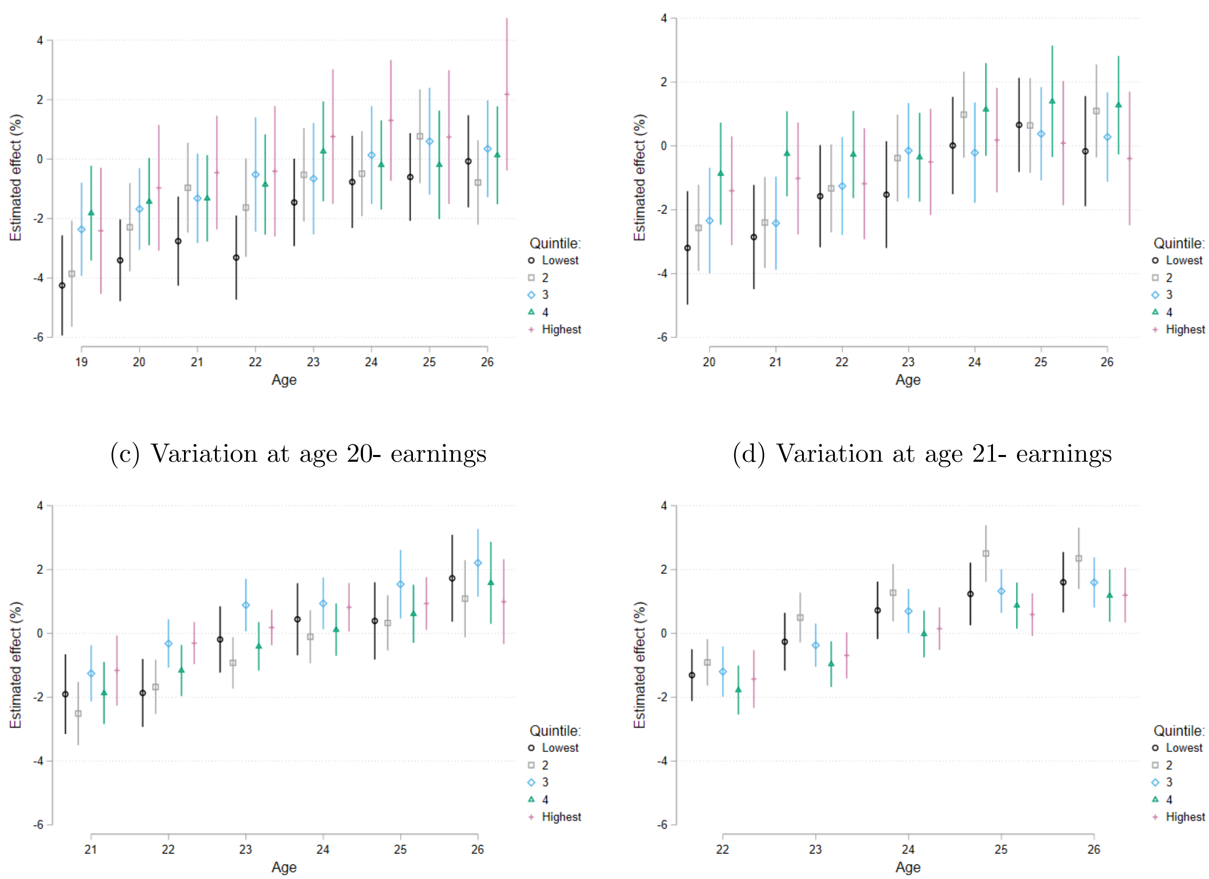


(d) Variation at age 21-employment



Source: Authors' calculations using data from Statistics Denmark.
Notes:Estimates show the scarring coefficients from Equation 1, scaled so as to be interpreted in percentage terms. Scarring effects are estimated separately for those leaving education at ages 18, 19, 20 and 21 and were living in a bottom to top quintile household at age 16. The regression sample comprises all members of 1980-1992 birth cohorts who completed education between the age of 18 and 21. Standard errors are clustered at the municipality level. A 95% confidence interval surrounds the point estimate.

Figure 8: **Estimated scarring effects on earnings, by parental income quintile**



(a) Variation at age 18- earnings

(b) Variation at age 19- earnings

(c) Variation at age 20- earnings

(d) Variation at age 21- earnings

Source: Authors' calculations using data from Statistics Denmark.
Notes: Estimates show the scarring coefficients from Equation 1, scaled so as to be interpreted in percentage terms. Scarring effects are estimated separately for those leaving education at ages 18, 19, 20 and 21 and were living ina bottom to top quintile household at age 16. The regression sample comprises all members of 1980-1992 birth cohorts who completed education between the age of 18 and 21. Standard errors are clustered at the municipality level. A 95% confidence interval surrounds the point estimate.

school leavers from a low-income background also bear the largest earnings scars, with those from the poorest background face losses of 4.3 (3.2) if leaving school at 18 (19). These losses are also more persistent, but fade to zero by age 22. Middle-income early school leavers face more muted initial losses, of just over 2% and these tend to zero by age 22. Those from the highest-income group face only transitory losses and scarring effects on earnings are zero by the age of 20.

3.1 Robustness checks

von Wachter (2020b) highlights possible threats to the internal validity of estimates that may arise if individuals respond to weak labour market conditions by delaying when they leave school or by moving to a different labour market. Endogenous migration is a concern particularly in cross-sectional data where researchers will not have access to an individual's full migration history. Individuals whom lived in region a at graduation, but migrated to region b in response to poor labour market opportunities may be sampled in a survey while residing in region b. These migration patterns increase the difficulty of identifying the scale of the relevant labour market shock by generating measurement error. In addition, if who decides to migrate in response to a shock is highly non-random, selection bias could result in cyclical variation in the quality of new workers in a given region. For example, only the least skilled workers may remain in region a after a large unemployment shock at graduation. Endogenous education may also lead to biased estimates if there is selection in the types of workers who chose to start their career in a recession (again, leading to cyclical variation in new worker quality).

With our detailed longitudinal administrative data, we can track individuals across the life-cycle and accurately identify the relevant unemployment shock meaning that migratory issues are less concerning. We address concerns in endogenous educational attainment by re-estimating our model using variation in NEET rates at 18-21 for all young adults, rather than just those who left education at ages 18-21. This allows us to circumvent possible cyclical variation in new worker quality, which is an issue if there is substantial selection in which young adults opt to continue their education when faced with a weak labour market close to graduation.

However, this approach induces an element of measurement error as impacts are estimated for all members of a birth cohort: both those still in-education and those participating in the labour market. As a result, we prefer the strategy employed in our baseline estimates which are computed over those who have finished their education, and so will not be impacted by trends in part-time employment of young adults primarily in-education. Overall, the approach amounts to exploiting variation in regional NEET rates across birth cohorts, as the variation is purely based on an age basis, rather than on an age finished education basis as in our baseline specification. Kahn (2010) and Oreopoulos et al. (2012) have both used this framework for college graduates, with the unemployment rate at age 22 being the relevant identifying shock as it corresponds to the modal graduation age of college graduates.

These results are shown in appendix Tables 16 and 17. The employment scars in Table 16 are smaller for all age groups than in our baseline specification (Figure 5 and also shown in Tables 2 and 3). Negative employment scars at younger ages - up to age 22 - are evident throughout. Convergence to zero occurs more quickly, particularly for 18 year olds, who faced employment losses up to the age of 26 in our baseline specification but now recover by the age of 23. The effects for 20 and 21 year olds are more comparable to our baseline specification for people leaving school at these ages.

This is likely because these young adults make up a larger share of each birth cohort than do those leaving at ages 18 and 19 (around 40 and 20% respectively), meaning the initial NEET rate at ages 20 and 21 is more relevant for the combined sample. The earning scars in Table 17 are also smaller than our baseline model estimates, but the pattern is similar with largest scars borne by early school leavers and convergence occurring by age 22. Small earnings premia are also evident from ages 23 onward for recession cohorts, which may arise for the reasons of selection discussed earlier.

4 Conclusion

We estimate the effect of regional labour market shocks on the early career trajectories, in terms of employment probability and earnings, for young Danish workers. Our results suggest that those leaving education, at ages 18 or 19, are particularly sensitiveness to the strength of the initial labour market. In response to a percentage increase in the NEET rate at graduation, 18 year olds incur a decrease in the likelihood of being employed at age 19 of 2%. There is also an earnings reduction of 3% for those lucky enough to find employment. Young men also tend to bear the brunt of these wage reductions- incurring the largest losses of 4.2% at age 19. These employment scars tend to be persistent, but do shrink over time and stand at 0.5% by age 26. In contrast, losses in earnings tend to be more transitory, and fade to zero by age 23. Increased educational attainment tends to insulate young adults from scarring effects- with those leaving school at 21 incurring a decrease in the probability of employment one year later of just 0.8% and an earnings reduction of 1.3%. These are very transitory losses, and are not different from zero by age 23. This finding indicate that increased educational attainment can substantially buffer a young adult from absorbing large financial losses during an early-career economic downturn. Using detailed register panel data we also find that early school leavers from low-income backgrounds are particularly affected by initial labour market conditions. For young adults from low-income households (bottom 20%) leaving school at 18, a percentage point increase in the municipality NEET rate at graduation decreases employment likelihood by 2.6% at 19 and also lowers earnings by 4%. Those leaving school at 18, but from a high-income household (top 20%) , experience smaller losses in employment, 0.7%, while earnings fall by 2%. These more fortunate young adults incurred temporary scars, with employment and earnings losses turning to zero by age 20. The low-income group incurred earnings scars until the age of 22 and employment scars are still evident at 26, the last age at which we analyse.

Our results are broadly consistent with those from existing research. For older school leavers, we find somewhat smaller scarring effects that heal faster than for similarly educated groups internationally. For example, we find that the scarring effect on earnings for those leaving school at ages 20 and 21 fade within 3 years compared to 6-10 years for those with at least some college education in the United States (Kahn, 2010; Altonji et al., 2015), Canada (Oreopoulos et al., 2012) and Norway (Liu et al., 2016). However, we find scarring on employment comparable to, and as persistent as, those observed in the United States (Schwandt and von Wachter, 2019) and Britain (Cribb et al., 2017). Of particular note, we find these effects are substantially larger and more persistent for young adults from lower-income backgrounds, particularly those from a low-income background whom leave education before the age of 20. This mirrors the findings in Schwandt and von Wachter (2019) where more economically vulnerable groups - ethnic minorities and non-college graduates - bore some of the largest labour market scars from a poor start in the labour market.

Such findings suggest that there are good reasons for policymakers to be concerned about the long-term impact of COVID-19 on the future prospect of recent school leavers. This is particularly given young adults are also more likely to work in sectors such hospitality and retail which have been disproportionately affected by the pandemic (Andersen et al., 2020), which comes on top of the Great Recessions and what Rothstein (2020) finds is a structural decline in employment rates among young adults entering the labour market in the United States. A key question for future research then is how we can best limit ameliorate the consequences spells of economic inactivity have for young adults: a group for whom economic research suggests active labour market policies are typically least effective (Caliendo and Schmidl, 2016).

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A Data Appendix

Analysis Population: Our regressions examine all individuals born between 1980 and 1992 who lived in Denmark between the ages of 18 and 26. These data are drawn from the population (bef) register. We exclude individuals who are not observed at the time of the relevant shock e.g. at age 18 when examining the effect of cohort-region NEET rates at 18 on future outcomes. Excluding these migrants (either immigrants or returning migrants) reduces measurement error from the treatment effect of exposure to high NEET rates at the cohort-region level as we have no information on these individuals' outcomes in other labour markets.

Incomes: The population (bef) register includes a unique social security number along with a household of residence identifier for each individual. We merge annual employee earnings from the annual income (ind) registers to track the earnings of individuals in these birth cohorts from 18 to 26. We also construct a measure of household income (from wages) in the household an individual lived in at age 16. For each cohort, we then create quintiles of households to rank an individual's parental income at age 16. We opt for age 16, as the majority of 16 year olds will be living with their parents and household income will be an accurate measure of pre-graduation socio-economic status.

Education: We use the Danish Education Register to determine when an individual completed their education. The register notes if an individual is currently in education, and if so, what degree/vocational education they are pursuing. The highest level of education an individual has received by the 1st of October of that year is also noted in each register. The highest education attained is at the degree level and is remarkably detailed. For instance, a masters degree in economics is coded distinctly from an undergraduate or PhD level degree in the subject. The register does not capture any education attained from institutions outside of Denmark.

Measuring variation in initial labour market conditions: We construct NEET rates (not-in-education-or-employment) at the municipality level across birth cohorts at ages

18 through to 21. We classify a young person as NEET if they have zero wages for the year and are also not currently enrolled in any education or training program at an accredited Danish institution.

Regions in Denmark: Municipalities (kommunes) in Denmark, were changed in 2007, when 270 municipalities in Denmark were consolidated into 98 larger municipalities. We use these 98 municipalities as the unit of analysis when we exploit regional cohort NEET rate variation.

B Additional Tables and Figures

Table 1: Variation in NEET rates net of region and year fixed-effects

	(1)	(2)	(3)	(4)
Observations	1274	1274	1274	1274
Region	FE	FE	FE	FE
Year	FE	FE	FE	FE
R_Squared	0.595	0.571	0.604	0.658

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: These results show the R-squared from a regression of municipality NEET rates at ages 18-21 (Columns 1-4) on municipality and year fixed-effects.

Table 2: Employment, by age left education

	(1)	(2)	(3)	(4)
Age=18 × exogvar	-0.0240***			
	(0.00254)			
Age=19 × exogvar	-0.0198***	-0.0233***		
	(0.00168)	(0.00235)		
Age=20 × exogvar	-0.0139***	-0.0193***	-0.00900***	
	(0.00145)	(0.00122)	(0.000506)	
Age=21 × exogvar	-0.00993***	-0.0135***	-0.00780***	-0.00975***
	(0.00141)	(0.00104)	(0.000621)	(0.00172)
Age=22 × exogvar	-0.00797***	-0.0105***	-0.00623***	-0.00594***
	(0.00155)	(0.00109)	(0.000572)	(0.000469)
Age=23 × exogvar	-0.00718***	-0.00738***	-0.00424***	-0.00427***
	(0.00145)	(0.00121)	(0.000519)	(0.000582)
Age=24 × exogvar	-0.00623***	-0.00767***	-0.00293***	-0.00226***
	(0.00142)	(0.00137)	(0.000661)	(0.000613)
Age=25 × exogvar	-0.00596***	-0.00723***	-0.00195*	-0.000984
	(0.00157)	(0.00134)	(0.000933)	(0.000702)
Age=26 × exogvar	-0.00499**	-0.00579***	-0.00138	0.000127
	(0.00170)	(0.00149)	(0.00101)	(0.000620)
Observations	827071	612399	1237193	1063272
controls_age	FE	FE	FE	FE
controls_yob	FE	FE	FE	FE
controls_reg	FE	FE	FE	FE
SE_cluster	kom	kom	kom	kom

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: The table shows the scarring estimates from Equation 1 where a dummy variable, employed, is the outcome of interest. The scarring effects are the interaction of age fixed-effects and the municipality NEET rate at the age left education (denoted as exogvar). The model is estimated as a linear probability model. Equation 1 is estimated separately for those leaving education at 18 (Column 1), 19 (Column 2), 20 (Column 3) and 21 (Column 4). All adults who completed education at these ages and were born between 1980 and 1992 are included in the regressions. fixed-effects in age, year of birth and municipality are also included. Standard errors are clustered at the municipality level.

Table 3: Log earnings, by age left education

	(1)	(2)	(3)	(4)
Age=18 × exogvar	-0.0467***			
	(0.00450)			
Age=19 × exogvar	-0.0304***	-0.0341***		
	(0.00461)	(0.00764)		
Age=20 × exogvar	-0.0222***	-0.0232***	-0.0203***	
	(0.00333)	(0.00429)	(0.00386)	
Age=21 × exogvar	-0.0165***	-0.0199***	-0.0172***	-0.0177***
	(0.00370)	(0.00327)	(0.00404)	(0.00253)
Age=22 × exogvar	-0.0157***	-0.0129***	-0.00936***	-0.0135***
	(0.00429)	(0.00314)	(0.00253)	(0.00260)
Age=23 × exogvar	-0.00536	-0.00730*	-0.0000298	-0.00395*
	(0.00367)	(0.00310)	(0.00182)	(0.00189)
Age=24 × exogvar	-0.00153	0.00250	0.00430*	0.00557**
	(0.00351)	(0.00323)	(0.00214)	(0.00210)
Age=25 × exogvar	0.00175	0.00458	0.00733*	0.0125***
	(0.00379)	(0.00337)	(0.00310)	(0.00209)
Age=26 × exogvar	0.00178	0.00253	0.0130**	0.0154***
	(0.00351)	(0.00385)	(0.00490)	(0.00275)
Observations	628769	467117	1083756	942877
controls_age	FE	FE	FE	FE
controls_yob	FE	FE	FE	FE
controls_reg	FE	FE	FE	FE
SE_cluster	kom	kom	kom	kom

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: The table shows the scarring estimates from Equation 1 where log earnings is the variable of interest. The scarring effects are the interaction of age fixed-effects and the municipality NEET rate at the age left education (denoted as exogvar). Equation 1 is estimated separately for those leaving education at 18 (Column 1), 19 (Column 2), 20 (Column 3) and 21 (Column 4). All adults who completed education at these ages and were born between 1980 and 1992 are included in the regressions. fixed-effects in age, year of birth and municipality are also included. Standard errors are clustered at the municipality level.

Table 4: Employment, by age left education (men)

	(1)	(2)	(3)	(4)
Age=18 × exogvar	-0.0264***			
	(0.00316)			
Age=19 × exogvar	-0.0207***	-0.0245***		
	(0.00222)	(0.00249)		
Age=20 × exogvar	-0.0140***	-0.0188***	-0.00829***	
	(0.00187)	(0.00140)	(0.000932)	
Age=21 × exogvar	-0.00934***	-0.0129***	-0.00755***	-0.00907***
	(0.00195)	(0.00140)	(0.000965)	(0.00134)
Age=22 × exogvar	-0.00695**	-0.00938***	-0.00480***	-0.00572***
	(0.00209)	(0.00129)	(0.000979)	(0.000694)
Age=23 × exogvar	-0.00629**	-0.00496**	-0.00231**	-0.00384***
	(0.00189)	(0.00150)	(0.000844)	(0.000776)
Age=24 × exogvar	-0.00470**	-0.00526***	-0.000965	-0.00170*
	(0.00167)	(0.00152)	(0.000847)	(0.000834)
Age=25 × exogvar	-0.00557**	-0.00521***	0.000294	-0.000356
	(0.00184)	(0.00141)	(0.00108)	(0.000876)
Age=26 × exogvar	-0.00334	-0.00339*	0.00108	0.000748
	(0.00190)	(0.00157)	(0.00125)	(0.000814)
Observations	437792	319107	525790	514395
controls_age	FE	FE	FE	FE
controls_yob	FE	FE	FE	FE
controls_reg	FE	FE	FE	FE
SE_cluster	kom	kom	kom	kom

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: The table shows the scarring estimates from Equation 1 where a dummy variable, employed, is the outcome of interest. The scarring effects are the interaction of age fixed-effects and the municipality NEET rate at the age left education (denoted as exogvar). The model is estimated as a linear probability model. Equation 1 is estimated separately for those leaving education at 18 (Column 1), 19 (Column 2), 20 (Column 3) and 21 (Column 4). All men who completed education at these ages and were born between 1980 and 1992 are included in the regressions. fixed-effects in age, year of birth and municipality are also included. Standard errors are clustered at the municipality level.

Table 5: Employment, by age left education (women)

	(1)	(2)	(3)	(4)
Age=18 × exogvar	-0.0206***			
	(0.00255)			
Age=19 × exogvar	-0.0181***	-0.0220***		
	(0.00247)	(0.00259)		
Age=20 × exogvar	-0.0131***	-0.0197***	-0.00931***	
	(0.00199)	(0.00187)	(0.000774)	
Age=21 × exogvar	-0.00986***	-0.0140***	-0.00778***	-0.0103***
	(0.00203)	(0.00160)	(0.000757)	(0.00224)
Age=22 × exogvar	-0.00835***	-0.0115***	-0.00712***	-0.00603***
	(0.00207)	(0.00172)	(0.000754)	(0.000614)
Age=23 × exogvar	-0.00741***	-0.00975***	-0.00549***	-0.00456***
	(0.00202)	(0.00171)	(0.000704)	(0.000694)
Age=24 × exogvar	-0.00715**	-0.0100***	-0.00419***	-0.00269***
	(0.00225)	(0.00185)	(0.000893)	(0.000678)
Age=25 × exogvar	-0.00556**	-0.00913***	-0.00342**	-0.00149
	(0.00204)	(0.00198)	(0.00110)	(0.000825)
Age=26 × exogvar	-0.00604**	-0.00807***	-0.00298**	-0.000384
	(0.00219)	(0.00205)	(0.00107)	(0.000699)
Observations	389279	293292	711403	548877
controls_age	FE	FE	FE	FE
controls_yob	FE	FE	FE	FE
controls_reg	FE	FE	FE	FE
SE_cluster	kom	kom	kom	kom

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: The table shows the scarring estimates from Equation 1 where a dummy variable, employed, is the outcome of interest. The scarring effects are the interaction of age fixed-effects and the municipality NEET rate at the age left education (denoted as exogvar). The model is estimated as a linear probability model. Equation 1 is estimated separately for those leaving education at 18 (Column 1), 19 (Column 2), 20 (Column 3) and 21 (Column 4). All men who completed education at these ages and were born between 1980 and 1992 are included in the regressions. fixed-effects in age, year of birth and municipality are also included. Standard errors are clustered at the municipality level.

Table 6: Log earnings, by age left education (men)

	(1)	(2)	(3)	(4)
Age=18 × exogvar	-0.0574***			
	(0.00679)			
Age=19 × exogvar	-0.0428***	-0.0430***		
	(0.00548)	(0.00464)		
Age=20 × exogvar	-0.0294***	-0.0272***	-0.0268***	
	(0.00528)	(0.00429)	(0.00404)	
Age=21 × exogvar	-0.0216***	-0.0172***	-0.0192***	-0.0233***
	(0.00473)	(0.00452)	(0.00489)	(0.00309)
Age=22 × exogvar	-0.0209***	-0.00898*	-0.00890*	-0.0155***
	(0.00520)	(0.00404)	(0.00376)	(0.00333)
Age=23 × exogvar	-0.0106*	-0.00504	-0.00153	-0.00455
	(0.00529)	(0.00427)	(0.00309)	(0.00284)
Age=24 × exogvar	-0.00826	0.00545	0.000537	0.00661*
	(0.00472)	(0.00470)	(0.00289)	(0.00284)
Age=25 × exogvar	0.00255	0.00768	0.00911**	0.0147***
	(0.00591)	(0.00509)	(0.00341)	(0.00271)
Age=26 × exogvar	0.00290	0.00689	0.0141**	0.0214***
	(0.00490)	(0.00517)	(0.00524)	(0.00300)
Observations	344083	249411	453435	454089
controls_age	FE	FE	FE	FE
controls_yob	FE	FE	FE	FE
controls_reg	FE	FE	FE	FE
SE_cluster	kom	kom	kom	kom

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: The table shows the scarring estimates from Equation 1 where log earnings is the variable of interest. The scarring effects are the interaction of age fixed-effects and the municipality NEET rate at the age left education (denoted as exogvar). Equation 1 is estimated separately for those leaving education at 18 (Column 1), 19 (Column 2), 20 (Column 3) and 21 (Column 4). All men who completed education at these ages and were born between 1980 and 1992 are included in the regressions. fixed-effects in age, year of birth and municipality are also included. Standard errors are clustered at the municipality level.

Table 7: log earnings, by age left education (women)

	(1)	(2)	(3)	(4)
Age=18 × exogvar	-0.0287***			
	(0.00677)			
Age=19 × exogvar	-0.0100	-0.0246		
	(0.00660)	(0.0125)		
Age=20 × exogvar	-0.00903	-0.0182**	-0.0159***	
	(0.00511)	(0.00686)	(0.00433)	
Age=21 × exogvar	-0.00633	-0.0216***	-0.0161***	-0.0121***
	(0.00526)	(0.00498)	(0.00417)	(0.00299)
Age=22 × exogvar	-0.00539	-0.0162**	-0.00978***	-0.0116***
	(0.00587)	(0.00547)	(0.00271)	(0.00300)
Age=23 × exogvar	0.00523	-0.00890	0.00101	-0.00358
	(0.00491)	(0.00461)	(0.00197)	(0.00209)
Age=24 × exogvar	0.0111*	0.0000149	0.00692**	0.00417
	(0.00536)	(0.00475)	(0.00248)	(0.00263)
Age=25 × exogvar	0.00538	0.00221	0.00585	0.0101***
	(0.00680)	(0.00469)	(0.00364)	(0.00261)
Age=26 × exogvar	0.00418	-0.00167	0.0121*	0.00948*
	(0.00559)	(0.00576)	(0.00516)	(0.00379)
Observations	284686	217706	630321	488788
controls_age	FE	FE	FE	FE
controls_yob	FE	FE	FE	FE
controls_reg	FE	FE	FE	FE
SE_cluster	kom	kom	kom	kom

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: The table shows the scarring estimates from Equation 1 where log earnings is the variable of interest. The scarring effects are the interaction of age fixed-effects and the municipality NEET rate at the age left education (denoted as exogvar). Equation 1 is estimated separately for those leaving education at 18 (Column 1), 19 (Column 2), 20 (Column 3) and 21 (Column 4). All women who completed education at these ages and were born between 1980 and 1992 are included in the regressions. fixed-effects in age, year of birth and municipality are also included. Standard errors are clustered at the municipality level.

Table 8: Employment, by parental income quintile (variation at age 18)

	(1)	(2)	(3)	(4)	(5)
Age=18 × exogvar	-0.0296***	-0.0252***	-0.0225***	-0.0140***	-0.0126***
	(0.00448)	(0.00339)	(0.00248)	(0.00335)	(0.00331)
Age=19 × exogvar	-0.0263***	-0.0172***	-0.0182***	-0.0114***	-0.00691*
	(0.00326)	(0.00276)	(0.00217)	(0.00324)	(0.00299)
Age=20 × exogvar	-0.0197***	-0.0135***	-0.00995***	-0.00779*	-0.00483
	(0.00274)	(0.00267)	(0.00235)	(0.00333)	(0.00324)
Age=21 × exogvar	-0.0137***	-0.0105***	-0.00785***	-0.00436	-0.00142
	(0.00262)	(0.00264)	(0.00221)	(0.00305)	(0.00315)
Age=22 × exogvar	-0.0110***	-0.00732**	-0.00801***	-0.00209	0.00109
	(0.00272)	(0.00256)	(0.00225)	(0.00317)	(0.00321)
Age=23 × exogvar	-0.0105***	-0.00837**	-0.00494*	-0.00156	0.00111
	(0.00259)	(0.00270)	(0.00234)	(0.00319)	(0.00307)
Age=24 × exogvar	-0.00916***	-0.00604*	-0.00591*	-0.00237	0.00329
	(0.00254)	(0.00251)	(0.00246)	(0.00330)	(0.00321)
Age=25 × exogvar	-0.00857**	-0.00793**	-0.00520*	-0.00247	0.00520
	(0.00289)	(0.00249)	(0.00253)	(0.00333)	(0.00315)
Age=26 × exogvar	-0.00877**	-0.00509*	-0.00366	-0.00128	0.00357
	(0.00293)	(0.00239)	(0.00249)	(0.00337)	(0.00350)
Observations	227388	191374	164178	131475	90519
controls_age	FE	FE	FE	FE	FE
controls_yob	FE	FE	FE	FE	FE
controls_reg	FE	FE	FE	FE	FE
SE_cluster	kom	kom	kom	kom	kom

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: The table shows the scarring estimates from Equation 1 where a dummy variable, employed, is the outcome of interest. The scarring effects are the interaction of age fixed-effects and the municipality NEET rate at the age 18 for those who left education at age 18 (denoted as exogvar). The model is estimated as a linear probability model. Equation 1 is estimated separately for by parental income quintile at age 16. The column numbers are the quintiles, with the lowest income quintile shown in column 1 while the highest is shown in column 5. All adults who completed education at age 18, observed living with their parents at age 16, and who born between 1980 and 1992 are included in the regressions. fixed-effects in age, year of birth and municipality are also included. Standard errors are clustered at the municipality level.

Table 9: Employment, by parental income quintile (variation at age 19)

	(1)	(2)	(3)	(4)	(5)
Age=19 × exogvar	-0.0286***	-0.0210***	-0.0211***	-0.0157***	-0.0156***
	(0.00388)	(0.00280)	(0.00343)	(0.00272)	(0.00356)
Age=20 × exogvar	-0.0243***	-0.0155***	-0.0153***	-0.0127***	-0.0120***
	(0.00318)	(0.00210)	(0.00258)	(0.00240)	(0.00274)
Age=21 × exogvar	-0.0179***	-0.00915***	-0.00871***	-0.00834***	-0.00793**
	(0.00269)	(0.00215)	(0.00249)	(0.00227)	(0.00239)
Age=22 × exogvar	-0.0134***	-0.00710**	-0.00900***	-0.00370	-0.00618*
	(0.00237)	(0.00229)	(0.00252)	(0.00236)	(0.00248)
Age=23 × exogvar	-0.00841***	-0.00358	-0.00677**	-0.000716	-0.00443
	(0.00239)	(0.00230)	(0.00244)	(0.00251)	(0.00260)
Age=24 × exogvar	-0.00862**	-0.00330	-0.00527*	-0.00245	-0.00703**
	(0.00270)	(0.00236)	(0.00250)	(0.00240)	(0.00255)
Age=25 × exogvar	-0.00747**	-0.00200	-0.00524*	-0.00421	-0.00611*
	(0.00258)	(0.00215)	(0.00251)	(0.00257)	(0.00259)
Age=26 × exogvar	-0.00547*	-0.00208	-0.00317	-0.00185	-0.00552
	(0.00264)	(0.00218)	(0.00269)	(0.00247)	(0.00287)
Observations	156791	130510	117318	97260	76775
controls_age	FE	FE	FE	FE	FE
controls_yob	FE	FE	FE	FE	FE
controls_reg	FE	FE	FE	FE	FE
SE_cluster	kom	kom	kom	kom	kom

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: The table shows the scarring estimates from Equation 1 where a dummy variable, employed, is the outcome of interest. The scarring effects are the interaction of age fixed-effects and the municipality NEET rate at the age 19 for those who left education at age 19 (denoted as exogvar). The model is estimated as a linear probability model. Equation 1 is estimated separately for by parental income quintile at age 16. The column numbers are the quintiles, with the lowest income quintile shown in column 1 while the highest is shown in column 5. All adults who completed education at age 19, observed living with their parents at age 16, and who born between 1980 and 1992 are included in the regressions. fixed-effects in age, year of birth and municipality are also included. Standard errors are clustered at the municipality level.

Table 10: Employment, by parental income quintile (variation at age 20)

	(1)	(2)	(3)	(4)	(5)
Age=20 × exogvar	-0.0155***	-0.0100***	-0.00610***	-0.00356***	-0.00179*
	(0.00167)	(0.00128)	(0.00125)	(0.000934)	(0.000695)
Age=21 × exogvar	-0.0124***	-0.00979***	-0.00621***	-0.00446***	-0.00246*
	(0.00183)	(0.00140)	(0.00136)	(0.000948)	(0.00108)
Age=22 × exogvar	-0.00818***	-0.00791***	-0.00564***	-0.00333***	-0.00291**
	(0.00169)	(0.00131)	(0.00139)	(0.000928)	(0.000977)
Age=23 × exogvar	-0.00692***	-0.00555***	-0.00376**	-0.00101	-0.00161*
	(0.00192)	(0.00118)	(0.00118)	(0.000909)	(0.000784)
Age=24 × exogvar	-0.00510**	-0.00393**	-0.00141	-0.000916	-0.00134
	(0.00187)	(0.00129)	(0.00131)	(0.00107)	(0.000780)
Age=25 × exogvar	-0.00377*	-0.00314*	-0.000355	-0.0000447	0.000118
	(0.00187)	(0.00156)	(0.00144)	(0.00123)	(0.000791)
Age=26 × exogvar	-0.00232	-0.00206	-0.000100	-0.000512	0.000658
	(0.00207)	(0.00138)	(0.00165)	(0.00116)	(0.00102)
Observations	169052	217055	229608	247329	331915
controls_age	FE	FE	FE	FE	FE
controls_yob	FE	FE	FE	FE	FE
controls_reg	FE	FE	FE	FE	FE
SE_cluster	kom	kom	kom	kom	kom

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: The table shows the scarring estimates from Equation 1 where a dummy variable, employed, is the outcome of interest. The scarring effects are the interaction of age fixed-effects and the municipality NEET rate at the age 18 for those who left education at age 18 (denoted as exogvar). The model is estimated as a linear probability model. Equation 1 is estimated separately for by parental income quintile at age 16. The column numbers are the quintiles, with the lowest income quintile shown in column 1 while the highest is shown in column 5. All adults who completed education at age 18, observed living with their parents at age 16, and who born between 1980 and 1992 are included in the regressions. fixed-effects in age, year of birth and municipality are also included. Standard errors are clustered at the municipality level.

Table 11: Employment, by parental income quintile (variation at age 21)

	(1)	(2)	(3)	(4)	(5)
Age=21 × exogvar	-0.0105***	-0.00419***	-0.00485***	-0.00327***	-0.00325***
	(0.00124)	(0.000973)	(0.000746)	(0.000731)	(0.000614)
Age=22 × exogvar	-0.00893***	-0.00428***	-0.00470***	-0.00422***	-0.00422***
	(0.00129)	(0.00100)	(0.000934)	(0.000852)	(0.000730)
Age=23 × exogvar	-0.00676***	-0.00329**	-0.00309**	-0.00354***	-0.00367***
	(0.00134)	(0.00106)	(0.000992)	(0.000859)	(0.000725)
Age=24 × exogvar	-0.00349*	-0.00123	-0.00192	-0.00260**	-0.00208**
	(0.00147)	(0.000981)	(0.000967)	(0.000829)	(0.000701)
Age=25 × exogvar	-0.00167	0.000112	-0.000248	-0.00185*	-0.00139
	(0.00127)	(0.00114)	(0.000937)	(0.000765)	(0.000774)
Age=26 × exogvar	-0.000752	0.00133	-0.0000167	-0.000290	-0.000427
	(0.00127)	(0.00107)	(0.000885)	(0.000744)	(0.000680)
Observations	132908	189457	202812	237905	248819
controls_age	FE	FE	FE	FE	FE
controls_yob	FE	FE	FE	FE	FE
controls_reg	FE	FE	FE	FE	FE
SE_cluster	kom	kom	kom	kom	kom

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: The table shows the scarring estimates from Equation 1 where a dummy variable, employed, is the outcome of interest. The scarring effects are the interaction of age fixed-effects and the municipality NEET rate at the age 18 for those who left education at age 18 (denoted as exogvar). The model is estimated as a linear probability model. Equation 1 is estimated separately for by parental income quintile at age 16. The column numbers are the quintiles, with the lowest income quintile shown in column 1 while the highest is shown in column 5. All adults who completed education at age 18, observed living with their parents at age 16, and who born between 1980 and 1992 are included in the regressions. fixed-effects in age, year of birth and municipality are also included. Standard errors are clustered at the municipality level.

Table 12: Log earnings, by parental income quintile (variation at age 18)

	(1)	(2)	(3)	(4)	(5)
Age=18 × exogvar	-0.0560***	-0.0538***	-0.0435***	-0.0406***	-0.0220
	(0.00773)	(0.0106)	(0.00884)	(0.00887)	(0.0117)
Age=19 × exogvar	-0.0425***	-0.0385***	-0.0236**	-0.0182*	-0.0241*
	(0.00849)	(0.00900)	(0.00791)	(0.00803)	(0.0107)
Age=20 × exogvar	-0.0341***	-0.0229**	-0.0168*	-0.0143	-0.00965
	(0.00693)	(0.00749)	(0.00692)	(0.00739)	(0.0106)
Age=21 × exogvar	-0.0276***	-0.00963	-0.0132	-0.0132	-0.00455
	(0.00755)	(0.00761)	(0.00758)	(0.00732)	(0.00963)
Age=22 × exogvar	-0.0331***	-0.0163	-0.00518	-0.00857	-0.00409
	(0.00712)	(0.00834)	(0.00970)	(0.00850)	(0.0110)
Age=23 × exogvar	-0.0146	-0.00528	-0.00658	0.00260	0.00758
	(0.00740)	(0.00792)	(0.00944)	(0.00846)	(0.0114)
Age=24 × exogvar	-0.00769	-0.00489	0.00135	-0.00196	0.0130
	(0.00780)	(0.00719)	(0.00828)	(0.00756)	(0.0102)
Age=25 × exogvar	-0.00604	0.00767	0.00598	-0.00194	0.00741
	(0.00743)	(0.00796)	(0.00906)	(0.00918)	(0.0113)
Age=26 × exogvar	-0.000745	-0.00787	0.00346	0.00130	0.0218
	(0.00781)	(0.00715)	(0.00820)	(0.00830)	(0.0129)
Observations	148826	148015	132474	111061	76984
controls_age	FE	FE	FE	FE	FE
controls_yob	FE	FE	FE	FE	FE
controls_reg	FE	FE	FE	FE	FE
SE_cluster	kom	kom	kom	kom	kom

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: The table shows the scarring estimates from Equation 1 where log earnings is the outcome of interest. The scarring effects are the interaction of age fixed-effects and the municipality NEET rate at the age 18 for those who left education at age 18 (denoted as exogvar). The model is estimated as a linear probability model. Equation 1 is estimated separately for by parental income quintile at age 16. The column numbers are the quintiles, with the lowest income quintile shown in column 1 while the highest is shown in column 5. All adults who completed education at age 18, observed living with their parents at age 16, and who born between 1980 and 1992 are included in the regressions. fixed-effects in age, year of birth and municipality are also included. Standard errors are clustered at the municipality level.

Table 13: Log earnings, by parental income quintile (variation at age 19)

	(1)	(2)	(3)	(4)	(5)
Age=19 × exogvar	-0.0483***	-0.0346***	-0.0270**	-0.0229*	-0.0262*
	(0.0111)	(0.00969)	(0.00949)	(0.00985)	(0.0125)
Age=20 × exogvar	-0.0320***	-0.0257***	-0.0234**	-0.00871	-0.0141
	(0.00895)	(0.00681)	(0.00834)	(0.00806)	(0.00858)
Age=21 × exogvar	-0.0286***	-0.0240**	-0.0242**	-0.00248	-0.0102
	(0.00822)	(0.00719)	(0.00735)	(0.00670)	(0.00883)
Age=22 × exogvar	-0.0158	-0.0133	-0.0126	-0.00271	-0.0119
	(0.00806)	(0.00693)	(0.00773)	(0.00688)	(0.00876)
Age=23 × exogvar	-0.0153	-0.00383	-0.00148	-0.00357	-0.00505
	(0.00842)	(0.00686)	(0.00750)	(0.00701)	(0.00837)
Age=24 × exogvar	0.000101	0.00977	-0.00213	0.0114	0.00181
	(0.00768)	(0.00678)	(0.00792)	(0.00731)	(0.00824)
Age=25 × exogvar	0.00656	0.00639	0.00377	0.0139	0.000859
	(0.00742)	(0.00746)	(0.00735)	(0.00879)	(0.00979)
Age=26 × exogvar	-0.00168	0.0109	0.00277	0.0127	-0.00396
	(0.00868)	(0.00734)	(0.00707)	(0.00777)	(0.0105)
Observations	105692	101561	94749	81565	65929
controls_age	FE	FE	FE	FE	FE
controls_yob	FE	FE	FE	FE	FE
controls_reg	FE	FE	FE	FE	FE
SE_cluster	kom	kom	kom	kom	kom

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: The table shows the scarring estimates from Equation 1 where log earnings is the outcome of interest. The scarring effects are the interaction of age fixed-effects and the municipality NEET rate at the age 19 for those who left education at age 19 (denoted as exogvar). The model is estimated as a linear probability model. Equation 1 is estimated separately for by parental income quintile at age 16. The column numbers are the quintiles, with the lowest income quintile shown in column 1 while the highest is shown in column 5. All adults who completed education at age 19, observed living with their parents at age 16, and who born between 1980 and 1992 are included in the regressions. fixed-effects in age, year of birth and municipality are also included. Standard errors are clustered at the municipality level.

Table 14: Log earnings, by parental income quintile (variation at age 20)

	(1)	(2)	(3)	(4)	(5)
Age=20 × exogvar	-0.0213***	-0.0243***	-0.0105	-0.0201***	-0.0145**
	(0.00553)	(0.00512)	(0.00582)	(0.00402)	(0.00517)
Age=21 × exogvar	-0.0190**	-0.0251***	-0.0125**	-0.0187***	-0.0116*
	(0.00629)	(0.00499)	(0.00443)	(0.00490)	(0.00553)
Age=22 × exogvar	-0.0187***	-0.0168***	-0.00318	-0.0116**	-0.00306
	(0.00537)	(0.00428)	(0.00381)	(0.00404)	(0.00332)
Age=23 × exogvar	-0.00191	-0.00923*	0.00885*	-0.00409	0.00184
	(0.00523)	(0.00406)	(0.00414)	(0.00382)	(0.00281)
Age=24 × exogvar	0.00441	-0.00109	0.00938*	0.00115	0.00817*
	(0.00569)	(0.00418)	(0.00408)	(0.00414)	(0.00382)
Age=25 × exogvar	0.00391	0.00327	0.0154**	0.00611	0.00935*
	(0.00609)	(0.00434)	(0.00541)	(0.00459)	(0.00417)
Age=26 × exogvar	0.0172*	0.0108	0.0221***	0.0158*	0.00993
	(0.00686)	(0.00609)	(0.00533)	(0.00646)	(0.00670)
Observations	136196	189453	203777	224757	305223
controls_age	FE	FE	FE	FE	FE
controls_yob	FE	FE	FE	FE	FE
controls_reg	FE	FE	FE	FE	FE
SE_cluster	kom	kom	kom	kom	kom

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: The table shows the scarring estimates from Equation 1 where log earnings is the outcome of interest. The scarring effects are the interaction of age fixed-effects and the municipality NEET rate at the age 20 for those who left education at age 20 (denoted as exogvar). The model is estimated as a linear probability model. Equation 1 is estimated separately for by parental income quintile at age 16. The column numbers are the quintiles, with the lowest income quintile shown in column 1 while the highest is shown in column 5. All adults who completed education at age 20, observed living with their parents at age 16, and who born between 1980 and 1992 are included in the regressions. fixed-effects in age, year of birth and municipality are also included. Standard errors are clustered at the municipality level.

Table 15: Log earnings, by parental income quintile (variation at age 21)

	(1)	(2)	(3)	(4)	(5)
Age=21 × exogvar	-0.0210***	-0.0152***	-0.0172***	-0.0189***	-0.0157***
	(0.00446)	(0.00433)	(0.00402)	(0.00357)	(0.00398)
Age=22 × exogvar	-0.0131**	-0.00911*	-0.0120**	-0.0178***	-0.0143**
	(0.00409)	(0.00366)	(0.00396)	(0.00387)	(0.00455)
Age=23 × exogvar	-0.00262	0.00494	-0.00372	-0.00964**	-0.00692
	(0.00455)	(0.00393)	(0.00341)	(0.00360)	(0.00364)
Age=24 × exogvar	0.00721	0.0127**	0.00696*	-0.000199	0.00146
	(0.00453)	(0.00453)	(0.00350)	(0.00370)	(0.00335)
Age=25 × exogvar	0.0123*	0.0250***	0.0132***	0.00872*	0.00587
	(0.00495)	(0.00446)	(0.00344)	(0.00364)	(0.00337)
Age=26 × exogvar	0.0160**	0.0235***	0.0159***	0.0118**	0.0120**
	(0.00476)	(0.00485)	(0.00395)	(0.00411)	(0.00434)
Observations	112630	169680	184037	219166	230096
controls_age	FE	FE	FE	FE	FE
controls_yob	FE	FE	FE	FE	FE
controls_reg	FE	FE	FE	FE	FE
SE_cluster	kom	kom	kom	kom	kom

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: The table shows the scarring estimates from Equation 1 where log earnings is the outcome of interest. The scarring effects are the interaction of age fixed-effects and the municipality NEET rate at the age 21 for those who left education at age 18 (denoted as exogvar). The model is estimated as a linear probability model. Equation 1 is estimated separately for by parental income quintile at age 16. The column numbers are the quintiles, with the lowest income quintile shown in column 1 while the highest is shown in column 5. All adults who completed education at age 21, observed living with their parents at age 16, and who born between 1980 and 1992 are included in the regressions. fixed-effects in age, year of birth and municipality are also included. Standard errors are clustered at the municipality level.

Table 16: Robustness check: Employment estimates, using NEET rate at various ages

	(1)	(2)	(3)	(4)
Age=18 × exogvar	-0.0104***			
	(0.000744)			
Age=19 × exogvar	-0.0111***	-0.0127***		
	(0.000838)	(0.000779)		
Age=20 × exogvar	-0.00634***	-0.00906***	-0.0112***	
	(0.000760)	(0.000470)	(0.000457)	
Age=21 × exogvar	-0.00352***	-0.00588***	-0.00927***	-0.0110***
	(0.000678)	(0.000470)	(0.000374)	(0.000463)
Age=22 × exogvar	-0.00170**	-0.00360***	-0.00672***	-0.00895***
	(0.000590)	(0.000403)	(0.000337)	(0.000371)
Age=23 × exogvar	-0.000786	-0.00185***	-0.00429***	-0.00684***
	(0.000491)	(0.000376)	(0.000315)	(0.000354)
Age=24 × exogvar	-0.000433	-0.00116**	-0.00233***	-0.00413***
	(0.000519)	(0.000410)	(0.000368)	(0.000353)
Age=25 × exogvar	-0.000247	-0.000765	-0.00118*	-0.00221***
	(0.000596)	(0.000521)	(0.000482)	(0.000393)
Age=26 × exogvar	-0.0000504	-0.000291	-0.000171	-0.000551
	(0.000822)	(0.000727)	(0.000648)	(0.000465)
Observations	6979977	6221240	5465329	4728100
controls_age	FE	FE	FE	FE
controls_yob	FE	FE	FE	FE
controls_reg	FE	FE	FE	FE
SE_cluster	kom	kom	kom	kom

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: The table shows the scarring estimates from Equation 1 where a dummy variable, employed, is the outcome of interest. The scarring effects are the interaction of age fixed-effects and the municipality NEET rate at the various ages (denoted as exogvar). The model is estimated as a linear probability model. Equation 1 is estimated separately using municipality-NEET rates at 18 (Column 1), 19 (Column 2), 20 (Column 3) and 21 (Column 4). fixed-effects in age, year of birth and municipality are also included. Standard errors are clustered at the municipality level.

Table 17: Robustness check: Log earnings, using NEET rate at various ages

	(1)	(2)	(3)	(4)
Age=18 × exogvar	-0.0181***			
	(0.00326)			
Age=19 × exogvar	-0.0176***	-0.0180***		
	(0.00327)	(0.00328)		
Age=20 × exogvar	-0.0145***	-0.0180***	-0.0163***	
	(0.00272)	(0.00253)	(0.00235)	
Age=21 × exogvar	-0.0106***	-0.0134***	-0.0205***	-0.0157***
	(0.00294)	(0.00238)	(0.00167)	(0.00216)
Age=22 × exogvar	0.000449	-0.00344	-0.0141***	-0.0176***
	(0.00221)	(0.00200)	(0.00167)	(0.00200)
Age=23 × exogvar	0.00881***	0.00417**	-0.00369**	-0.00777***
	(0.00148)	(0.00129)	(0.00132)	(0.00156)
Age=24 × exogvar	0.0119***	0.00896***	0.00308*	0.000237
	(0.00181)	(0.00165)	(0.00143)	(0.00135)
Age=25 × exogvar	0.00996***	0.0106***	0.00951***	0.00790***
	(0.00230)	(0.00179)	(0.00162)	(0.00137)
Age=26 × exogvar	0.00809**	0.00914***	0.0140***	0.0152***
	(0.00288)	(0.00234)	(0.00205)	(0.00173)
Observations	5880749	5259139	4631383	3983916
controls_age	FE	FE	FE	FE
controls_yob	FE	FE	FE	FE
controls_reg	FE	FE	FE	FE
SE_cluster	kom	kom	kom	kom

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: The table shows the scarring estimates from Equation 1 where log earnings is the outcome of interest. The scarring effects are the interaction of age fixed-effects and the municipality NEET rate at the various ages (denoted as exogvar). The model is estimated as a linear probability model. Equation 1 is estimated separately using municipality-NEET rates at 18 (Column 1), 19 (Column 2), 20 (Column 3) and 21 (Column 4). fixed-effects in age, year of birth and municipality are also included. Standard errors are clustered at the municipality level.