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Abstract:
Utilizing registry data for all Norwegian males born in 1959–1973, I demonstrate that local unemployment rates at the typical age of graduation from compulsory school (age 16) and high-school (age 19) have persistent, negative effects on males' earnings, employment, and disability pension utilization when measured as late as age 35. With data on every male IQ, I study how labor market conditions at age of graduation have differential effects for low- and high-ability males. As one would expect, low-ability males are particularly vulnerable to business cycles at the time of labor market entry.

Keywords: Business cycle, graduation, careers

JEL classification: E32, J31, J24

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Sammendrag

Ved å benytte registerdata for alle norske menn født i 1959-1973, viser jeg at den lokale arbeidsledigheten unge møter i den tiden de vanligvis fullfører ungdomskolen (16 år) og videregående (19 år) gir en vedvarende negativ effekt på menns inntekt og yrkestilknytning, samt en høyere sannsynlighet for å bli uføretrygdet, i voksen alder. Med andre ord ser vi at betingelser på arbeidsmarkedet en møter som ung, kan ha langvarige konsekvenser. Evnedata («IQ» fra sesjon) gjør det mulig å studere om unge menn med høyere og lavere kognitive evner rammes ulikt av arbeidsledigheten de møter når de er ferdige med ungdomskolen og videregående skole. Som forventet viser resultatene at de med lave kognitive evner er ekstra sårbare og kan falle ut av arbeidsmarkedet.

1 Introduction

The financial crisis has forced a large fraction of youth into unemployment. The unemployment rate among youth aged 15–24 reached 21 percent in the European Union and 18.4 percent in the United States in the fourth quarter of 2010. From the fourth quarter of 2007, this represents an increase of 6 and 7.3 percentage points for Europe and the United States, respectively. Even today,[1] following a recovery for some countries, the youth unemployment rate is still high in the European Union, 21.6 percent, and 50.6–32.9 percent in some of the most critical euro areas: Greece, Spain, and Portugal (OECD, 2015).

Youth are often called "the population at risk," as they have little work experience, and during recessions they are often the last to be hired and the first to be fired. Research on youth vulnerability shows that they experience more unemployment and underemployment and less employment than adults during recessions (see e.g. Bell and Blanchflower, 2011a,b; Hoynes et al., 2012). Moreover, unemployment may affect the quality of a youth's first job, and thereby influence that youth's opportunities for the learning and accumulation of human capital, with their associated impacts on future wages and job opportunities.[2]

Some groups seem to be especially vulnerable during recessions. In particular, in the US, Black and Hispanic workers, as well as low-educated workers, experience higher increases in unemployment rates during a recession (see e.g. Hines Jr. et al., 2002; Elsby et al., 2010; Hoynes et al., 2012). Devereux (2002) also shows that the low-skilled suffer more in terms of job quality when unemployment rates are high. In this paper I investigate the effects of the labor market conditions faced by youth at the time of typical graduation from upper and lower secondary school, on long-term labor market outcomes, with a particular focus on low-ability youth.

There are at least three important mechanisms through which poor labor market entry conditions can affect long-term labor market outcomes. First, if job search is costly and workers are immobile across companies, then future earnings might be affected through a low initial wage contract with insufficient wage adjustment (Milton and Holmstrom, 1982; Beaudry and DiNardo, 1991). Second, poor labor market entry conditions may lead to unemployment or poor job quality. Experiencing unemployment or a period in a poor-quality job may lead to a reduction in the accumulation of human capital, which may have a negative effect on long-term earnings (Becker, 1962). Last, poor labor market opportunities might reduce the opportunity cost of schooling and thereby encourage youth to complete their current educational track or undertake higher education, which in turn could improve future labor market outcomes (Becker, 1962;

[1] In the third quarter of 2014

[2] There is a large body of theoretical literature on cyclical occupational upgrading that explains this (see e.g. Reder, 1955; Okun et al., 1973; Devereux, 2002; McLaughlin and Bils, 2001).

Micklewright et al., 1990).

Labor market conditions at the time of graduation can affect high- and low-ability individuals differently. First, it could be more difficult for low- than high-ability individuals to find a high-quality job, or any job for that matter, if the unemployment rate is high at graduation time. Such initial differences could could persist or become amplified in the long run if low-ability individuals struggle to escape the low-quality job, or if a low-quality job hampers their human capital accumulation. We may also expect differential effects on long-term labor market outcomes if, for example, high-ability individuals facing poor labor market entry conditions are better than low-ability individuals at catching up with individuals within the same ability category facing good labor market entry conditions, through a greater search intensity and job mobility: thus resulting in a differential effect on long-term earnings even if there were no initial differences. (see e.g. Oreopoulos et al., 2008). Second, the replacement rate of benefits from welfare programs are often a concave and capped function of prior earnings, giving a higher ratio for low-income workers than that for high-income workers. This could provide low-ability individuals who graduate in bad times stronger incentives to leave the labor force.[3] Finally, the loss in the opportunity cost of schooling might depend on the ability type, providing differential incentives to continue with education.

The time at which to measure labor market entry conditions is not straightforward. Both the year of observed employment entry and the year of completed education are endogenous. Individuals might experience prolonged unemployment when the unemployment rate is high, which will delay entry into the first job. Moreover, several empirical studies have documented an increase in school enrollment rates and school completion during recessions (Gustman and Steinmeier, 1981; Clark, 2009; Öckert, 2011; Johnson, 2013; Reiling and Strøm, 2015). In the empirical strategy, I follow Raaum and Røed (2006) and address such endogeneity problems by including all men (regardless of educational achievements) born in 1959–1973, and by looking at unemployment rates at the typical age when Norwegian men complete school and enter the labor market (and not the time of actual entry).[4] Norwegian youth are scheduled to graduate from junior high school and high school at ages 16 and 19, respectively. I estimate how the labor market outcomes in mature adulthood are affected by the local unemployment rate that adolescents face at these two ages.

The empirical model includes regional and year fixed effects. The estimates are identified from differ-

[3] A change in long-term earnings for low-ability workers, who are more likely to be low-income workers, could have a larger effect on the long-term replacement faced by these workers than for high-ability workers. Higher replacement rates are expected to increase the duration of unemployment spells, through lower search costs (see e.g. Atkinson and Micklewright, 1991; Røed and Zhang, 2003)

[4] In the sample, 71 percent have secondary education as their highest obtained educational level at age 34, consisting of 23 percent completing junior high school and 47 percent completing high school. In Norway as of 2011, more than 63 percent of the men between 30–39 years of age have a secondary education (junior high school 18.4 percent and high school 44.3 percent) as their highest obtained education (Statistics Norway, 2011).

ences in how the local unemployment rates change over time across regions. The analysis uses high-quality registry data covering the entire Norwegian population. Importantly, the data include information about IQs. This allows me to investigate heterogeneous effects across a measure of ability that is available for everyone, and not only for those who have entered college, as in Oreopoulos et al. (2012) or Liu et al. (2012). It also allows me to measure ability directly, avoiding issues of, e.g., measurement error arising from having to predict the individual's skills, as in Raaum and Røed (2006).

I find that local unemployment rates at the typical age of graduation from compulsory school (age 16) and high school (age 19) have persistent, negative effects on males' earnings and employment, and increases disability pension use, when measured as late as age 35. As one would expect, effects differ with ability. For low-ability youth, a 1 percentage point increase in the local unemployment rate at age 16 reduces earnings at age 35 by about 4 percent and increases the likelihood of being on a disability pension by about 20 percent.[5] For high-ability youth there are little or no effects on employment, disability use, or earnings in general, except that high unemployment rates at age 19 reduce their likelihood of ending up with particularly high earnings at age 35. While I find that unemployment rates at ages 16 and 19 have no general effect on educational attainment, there is a small but positive effect on the likelihood that high ability individuals will undertake a college education.[6]

There is a large body of recent literature on the effects that labor market entry conditions have on long-term labor market outcomes (Burgess et al., 2003; Oyer, 2006; Raaum and Røed, 2006; Kondo, 2007; Stevens, 2008; Genda et al., 2010; Kwon et al., 2010; Kahn, 2010; Oreopoulos et al., 2012; Liu et al., 2012; Brunner and Kuhn, 2014). The present paper is related to Stevens (2008); Genda et al. (2010); Brunner and Kuhn (2014), which investigate the effect of local labor market entry conditions on long-term earnings for low-skilled individuals. The present paper is also closely related to Raaum and Røed (2006). Using Norwegian data, they find that young men who face a high local unemployment rate at the time they are 16 and 19 are more likely to suffer from non-employment in adulthood. My investigations of employment effects are consistent with the estimates of Raaum and Røed (2006). Moreover, Raaum and Røed (2006) investigated the differential effects of unemployment at ages 16 and 19 on unemployment and non-employment incidences across less advantaged and more advantaged youth based on family characteristics. Surprisingly,

[5]In the data, 1 percentage point represents just below one standard deviation of the unemployment rate at age 16. At age 19, the standard deviation is somewhat larger (1.3), meaning that 1 percentage point is less than one standard deviation.

[6]The rich panel data allow me to explore the effects of unemployment rates at several stages, not only ages 16 and 19, but also later ages up to 35. Oreopoulos et al. (2012) show, for a restricted sample, that the unemployment rates in the second and third year following graduation have a much smaller effect on long-term earnings than that of the unemployment rate experienced at graduation. I include similar investigations, and, moreover, the rich individual-level data allow me to take this one step further and investigate how 19 years of subsequent unemployment rates (up to age 35) continue to influence long-term earnings for a large subsample of cohorts.

they find that the effects of unemployment at ages 16 and 19 for particularly less advantaged youth are not very different from the average effects for all youth. A few recent studies have explored the differential effects of labor market entry conditions on earnings for low-skilled workers across gender (Kondo, 2007; Hershbein, 2012), blue- and white-collar workers Brunner and Kuhn (2014), and ethnic groups (Kondo, 2007). In general these studies reveal that males and blue-collar workers experience more persistent negative effects on earnings if they face poor labor market conditions at labor market entry than do females or white-collar workers.[7]

The present paper makes two main contributions: the first one is the benefit of having a direct measure of ability (IQ) that is available for everyone. Thus, I am not looking at how effects differ with various measures of socioeconomic background. Moreover, I do not have to apply predetermined family or individual characteristics to estimate more or less relevant proxies for skills or abilities, with the associated potential for attenuation bias accruing from measurement errors in these estimates. This direct measure of ability also circumvents issues of endogenous sample selection that could arise if educational achievements were used to define the low- and high-ability groups.[8] Since those youth with the lowest abilities may not even complete high school and hardly enter college, using such observed measures of educational achievements to proxy for ability would also restrict the sample under investigation to the relatively advantaged groups of youth. Having the ability measurements for everyone, I thus avoid disregarding the effects on those who are believed to be most seriously hit by poor labor market entry conditions. Second, in addition to long-term outcome measures like earnings and employment status, which have been applied in most previous studies, I also look at drawing from a disability pension. While drawing from a disability pension could be related to health effects of labor market entry conditions, it is also clear that the economic incentives for entering a disability pension are affected by earnings (and expectations about future earnings) (see e.g. Black et al., 2002; Autor and Duggan, 2003; Eliason and Storrie, 2006; Rege et al., 2009), which depend on entry conditions. Moreover, while the overall effects on high-ability individuals are minor, I also examine the effects for the upper part of the earnings distribution. Overall, the present paper thus provides new evidence for heterogeneous effects on earnings, employment, disability use, and educational attainment for individuals

[7] For immigrants or black workers, the effects on long-term earnings seem to be slightly less persistent than for native workers (See e.g Kondo, 2007). The author argues that one explanation could be that they are more likely to be employed in jobs that have diminishing marginal returns to human capital. Hence, when the economy improves, the less advantaged individuals who experienced a recession can more easily catch up with the luckier counterparts who experienced a booming economy.

[8] The unemployment rates, or the expectations thereof for the future, could affect an individual's decision to complete high school or to enter college. See Oreopoulos et al. (2008, 2012) for careful discussions about such potential endogenous sample selection, and possibly evolving estimation biases, when using the population of individuals who have decided to enter college. They construct the subsamples for lower and higher-quality colleges, using information about college type, program, and length of study.

of different cognitive abilities.

In line with other studies I show that the main results are robust to a number of specification tests. For example, other studies have shown that controlling for the full local unemployment rate history does not change the estimated effect that the unemployment rate faced by graduating youth has on earnings (Oreopoulos et al., 2012). My results are also robust to such inclusions of unemployment rate histories.

2 Theoretical Considerations

2.1 Why Should We Expect Long-Term Effects on Labor Market Outcomes?

There are many mechanisms through which the labor market opportunities faced by youth could affect long-term labor market outcomes. First, future earnings can be affected by a low wage established in the initial contract.[9] Furthermore, such wage disparities might persist for several years if long-term contracts lead to insufficient wage adjustment (e.g. Beaudry and DiNardo, 1991).

Second, there might be an effect on human capital accumulation through work experience. In the human capital model of Becker (1962), on-the-job training through improving skills or learning new ones will raise the worker's future productivity, which can translate into higher long-term wages. Time spent unemployed or in a poor-quality job with few opportunities for learning could imply no or low accumulation of human capital. The level of acquired human capital could also affect the level of employment in adulthood. A labor supply model would support this. If two individuals have the same initial ability and same preference for working, but different amounts of productive human capital, then the most productive worker has a higher likelihood of being employed.

Notably, however, in contrast to the human capital literature, another body of literature argues that it is the learning about the worker's unobservables, such as work ethic, willingness to work, and ability, that determines increases in wages (Baker et al., 1994; Farber and Gibbons, 1996). This would imply that a worker experiencing a poor job match will be assigned to better matches when information about the worker's abilities becomes evident.[10] If there are diminishing marginal returns to human capital, then there might not be any effect on earnings in the long term.[11]

[9] Several empirical studies have maintained that unemployment rates are negatively associated with individuals' wages (see Nijkamp and Poot, 2005).

[10] Models of job change predict that workers who face a poor job match, in which their productivity is shown to be relatively low, select themselves out of the jobs (Jovanovic, 1979). Thus, we could expect an increase in job mobility for the cohort facing poor labor market opportunities. If so, investment in firm- or task-specific human capital, which makes them more valuable for the current employer/position than others, could go unused in the new job (see e.g. Gibbons and Waldman, 2006).

[11] Consistently, Oreopoulos et al. (2012) show that for college students graduating during a recession, there is a gradual recovery in earnings through mobility into better quality firms. Moreover, Topel and Ward (1992) show that early mobility is an important

Third, and related to the first and the second mechanisms, lower earnings and expectations thereof for the future could also effect the incentives to work. To conceptualize this, assume that individuals enter the labor market if the expected benefits from entering exceed the expected benefits of not entering (leisure time, etc.). Lower wages could reduce the expected benefit from working, and some individuals might decide to work fewer hours or not to work at all.[12] Moreover, the size of government transfers, such as unemployment benefits or disability benefits, are linked to the utility gain of reentering employment.[13] Consequently, there could be a more persistent effect on labor market attachment of labor market entry conditions in countries with more generous welfare benefits.

A fourth mechanism that can affect long-term labor market outcomes is the effect on human capital through education. In the standard human capital model by Becker (1962), the cost of continuing with education is characterized as the forgone earnings in the market during the time in school (the opportunity cost of schooling) and the direct cost, such as tuition fees. Poor labor market opportunities increase the likelihood of facing unemployment or a poor-quality job, thereby reducing the opportunity costs of schooling.[14] The benefits from continuing with higher education are an increase in productivity, which can translate into higher wages and a lower probability of unemployment (Becker, 1962). If poor entry conditions induce youth to enter (or remain in) higher education, then we may expect positive and persistent effects on long-term earnings.

2.2 Heterogeneity in the Effect on Long-Term Earnings Across Ability

The effect of youth labor market opportunities on long-term labor market outcomes can be heterogeneous. First, as emphasized in Section 1, low-skilled youth are likely to suffer the most during a recession in terms of unemployment (Devereux, 2002; Hoynes et al., 2012) and job quality (see e.g. Devereux, 2002). Likewise, Öckert (2011) found that in terms of unemployment, a recession hits low-ability youth much harder. The initial differential effect on earnings could persist or become amplified in the long run if they consequently suffer larger losses to their human capital accumulation and do not manage to switch into better

mechanism for explaining the wage growth for young workers. In particular, more than one-third of the average wage growth during the first ten years of a young worker's career can be attributed to job changes. This suggests that increased job shopping works as an adjustment mechanism for future wages, and again there might not be any sustained impact on future earnings.

[12]For example, a growing literature has provided empirical evidence suggesting a causal relation between the value of labor market participation and the drawing of a disability pension (see e.g. Black et al., 2002; Autor and Duggan, 2003; Rege et al., 2009). Hence, we might also expect the local labor market entry conditions to affect the use of disability programs.

[13]There is a large body of theoretical literature about search intensity and how non-employment subsidies can reduce the income return of getting a job (see e.g. Mortensen, 1977). Consistently with this, Røed and Zhang (2003) show that a decrease in unemployment compensation increases the escape rate from unemployment.

[14]Notably, Micklewright et al. (1990) argue in a theoretical model that the effect that unemployment has on school leaving rates is ambiguous for several reasons. For example, high unemployment rates reduce family income, which can restrict access to family credit and hence discourage further school enrollment.

jobs as the economy improves.[15] Alternatively, even without any initial differential effect, a differential effect on long-term earnings could reflect a larger catch-up effect through job mobility or promotion for high-ability individuals (see e.g. Oreopoulos et al., 2008, 2012).

Second, variation in local unemployment rates could provide differential incentives for high- and low-ability individuals to work. For example, if there is a negative effect on long-term earnings from poor labor market entry conditions, then a concave replacement rate in welfare programs would provide low-ability individuals with stronger incentives to stay out of work. This suggests that low-ability individuals, who are also more likely to be the low-earners, will face a lower opportunity cost of exiting the labor market into welfare programs. Hence, we might expect a more pronounced effect of entry conditions on the long-term labor market attachment of low-ability individuals.[16]

Last, the loss in opportunity cost of schooling can depend on one's ability. Öckert (2011) argued that there can be a larger reduction in the opportunity cost of schooling for low-ability youth than for high-ability youth, since the former are more likely to suffer unemployment. On the other hand, although high-ability individuals are less likely to suffer unemployment during a recession, they could still be subject to a larger earnings loss if they become unemployed or enter a lower-quality job. Thus, the heterogeneity in the reduction in opportunity cost is ambiguous. However, when assuming that the loss in opportunity costs is equal for all individuals, we would then expect that the demand for higher education increases for all youth. If the increase in demand is not met by an increased capacity in universities, then this can result in higher admission standards during recessions. Öckert (2011) demonstrated that Swedish college enrollment rates are countercyclical, meaning that more students enroll when unemployment is high. Moreover, based on the students' compulsory school grade-point averages (GPA), he showed that the response to the unemployment rates is almost entirely driven by the top one-third of the students.

The rich individual-level data employed in this study allow me to explore the existence of such heterogeneous differential effects across ability levels on long-term earnings, labor market attachment, disability program utilization and educational attainment.

[15] Notably, there might also be situations where we predict a larger long-term effect on the earnings of high-ability individuals. Becker (1962) argued for a positive relation between ability and human capital investment. Thus low-ability individuals would be more likely to be employed in jobs where there are more diminishing returns to human capital or fewer training opportunities, independently of the labor market conditions, than the high-ability individuals. Then, as the economy recovers, the unlucky low-ability individuals more quickly catch up with the low-ability individuals who entered the labor market when the economy was booming, while the high-ability individuals suffer higher losses to their human capital accumulation. Consistently with this, Genda et al. (2010) suggest that the labor market entry condition have more persistent effect on the long-term earnings of college graduates than on those of high school graduates.

[16] Unemployment experience might also effect long term health, and this could translate into lower long-term labor market attachment for low-ability individuals. (see e.g. Tella et al., 2003; McKee-Ryan et al., 2005; Rege et al., 2009; Sullivan and von Wachter, 2009).

3 Background

This section describes some of the relevant features of Norwegian institutions. As mentioned in Section 1, I avoid the endogeneity in the timing of actual labor market entry by looking at unemployment rates at the time when Norwegian men typically leave compulsory school (age 16) and high school (age 19). In Norway, compulsory education amounts to 10 years of schooling (seven years in primary school and three years in secondary school). Children start compulsory education at the age of six and are then expected to finish at the age of 16.[17] Immature students are given extra and special tutoring. Thus, unlike some countries, such as the U.S., it is extremely rare for students in Norway to graduate from compulsory school at ages other than 16. After graduation from secondary school, a youth can choose to continue with education (high school) for three years (preparing for academic education), or for three to four years of vocational schooling [18], typically finishing around the age of 19.[19] Unlike graduation from compulsory school, there is thus more variation in the age of the students at graduation from high school.

Appendix Figure B.1 shows the distribution of completed years of education for the cohorts included in the sample. We see that the largest share of individuals in the sample have either 10 or 13 years of education, 23 percent and 40 percent, respectively. This suggests that the time when the youth are 16 and 19 represents critical ages with respect to labor market entry, especially for low-ability individuals.[20]

A young person can choose to enter the labor market following primary or secondary education, or continue with higher education. But in addition to primary education, Norwegian military service is mandatory for every male in Norway and lasts for one year. The typical age of military conscription is from 18 to 20. Hence, it is expected that a large proportion of Norwegian youth do not enter the labor market immediately after graduating from high school. But even so, the time between ages 16 and 19 represents an important period at which decisions can affect their adult labor market outcomes. In particular, it is the time when youth decide on whether to complete high school and then undertake higher education, or to make a transition

[17] In 1997, a large primary school reform was implemented in Norway, where the school starting age changed from seven to six. The new system also increased the number of years spent in primary education from nine to ten. However, the age when youth finish compulsory education did not change.

[18] This could entail schooling and apprenticeship, but it might be as little as one year of schooling.

[19] A large school reform was implemented between 1961 and 1972, changing the years of mandatory education from seven to nine years. Some of the cohorts born before 1966 would typically graduate from primary school at the age of 14. In some municipalities, youth could continue with one or two more years of primary education. Secondary education was either a three- or five-year track for the cohort born before 1965, finishing at the ages of 17 to 19. In Appendix Table A.2, I show that restricting the sample to cohorts born after 1965 produces essentially the same estimated effect of unemployment rates at ages 16 and 19.

[20] During the analyzed period, there was a large expansion in the number of student slots in higher education, by about 50,000, an increase of 45 percent from 1988 to 1992 (NOU, 1994). Since the proportion of youth undertaking higher education increases over time in the sample, we might expect that the point when most youth enter the labor market changes over time. However, the effect does not seem to differ noticeably between the subsamples of older and younger cohorts (see Appendix Table A.2).

from school to work.[21]

The Norwegian higher educational system, including colleges and universities, is publicly provided and free of charge, and the welfare state also offers generous scholarships and loans that can cover living expenses during the studies (from high school through university). Recall from Section 2.1 that the effects that poor labor market conditions have on family income could lower the effects that labor market entry conditions have on educational attainment. But, as education is free, family income will be less important for a youth's decision to undertake more education. Hence, for the Norwegian population, unlike the population of countries where education is not free of charge, we might expect unemployment rates at ages 16 and 19 to have a larger positive effect on educational attainment.

On the other hand, the return on education is found to be quite low in Norway (Hunnes et al., 2009). The marginal return to one extra year of education is approximately 5 percent in an ordinary least squares Mincer regression (see e.g., Barth and Røed, 2001). This low rate of return suggests that for the Norwegian population, labor market entry conditions might have a less pronounced positive effect on earnings if we consider the indirect effect from undertaking higher education.

In Norway, the public welfare system is universal and generous. As discussed in Section 2.1, a reduction in future earnings could also effect long-term labor market attachment, and the magnitude of this effect is linked to the size of the replacement rates of welfare programs. The public welfare services in Norway are mainly provided by the Norwegian National Insurance Program. Some of the important services provided are unemployment insurance, disability pensions, sick-leave compensation, rehabilitation pensions, and means-tested social assistance. The earnings replacement rate for unemployment insurance or the disability pension is high in Norway, above 60 percent, compared to less than 40 percent in the U.S. (30 percent replacement rate for a fully disabled person living alone in the the United States and the United Kingdom, according to Blondal and Pearson (1995)). Because of these generous non-employment subsidies in Norway, the long-term effects on labor market outcomes of entering the labor market in a recession might be more pronounced than for countries with less generous welfare systems. Consistently with this, Genda et al. (2010) found a very small and only marginally significant negative effect on long-term employment for less educated American men, while Raaum and Røed (2006) found that labor market entry rates have a permanent and sizable effect on the incidence of unemployment and non-employment for Norwegian men facing

[21] In Appendix Table A.4, I include the unemployment rates at age 17 and age 20, and demonstrate that the low and medium ability individuals are most vulnerable at the time when they are scheduled to graduate from junior high school and high school at ages 16 and 19. Column 4 of Appendix Table A.4 investigates an alternative specification and only includes the unemployment rates at ages 12 and 23. As expected, we see that earnings at age 35 are not strongly related to the unemployment rate youth faced at age 12 or 23.

high unemployment rates at ages 16 or 19 years.[22]

4 Data

To investigate the impact of labor market entry conditions on adult labor market outcomes, I have used several registry databases provided by Statistics Norway. This gives me a rich longitudinal dataset containing records for every Norwegian from 1967 to 2009. The available variables include socioeconomic data (earnings, years of education) and demographic information (sex, age, number of children, ethnicity). There are also geographic identifiers for municipality of residence.

I focus this analysis on the 1959 to 1973 male cohorts, to ensure the availability of outcome measures when the individual reaches the age of 35. Since one of the main features of this paper is to study differential effects across ability types, I restrict the sample to men, as I only have IQ measurements for them. These cohorts amount to 466,753 native men who were alive at age 16. I drop 2,727 men who could not be matched to a region of residence at age 16. To focus on the differential effects of the local unemployment rate across ability types, I drop 27,755 men for whom the data on their IQ is missing. I also drop 3,496 men without reported information about education, which is done to ensure that the sample is the same for all the dependent variables in the analysis. Last, I drop 5,368 men who cannot be matched to both parents, in order to ensure clean covariates for birth order and family size.[23] The final sample includes 427,407 men.

The key outcome variable is the log of the individual's annual earnings at age 35.[24] Annual earnings include labor-related income from wages, self-employment, and work-related transfers such as sickness benefits and unemployment benefits. The earnings variable is adjusted for inflation and real wage growth using yearly earnings thresholds defined by the Norwegian Social Insurance Scheme. I focus on earnings at age 35 for several reasons. First, almost all individuals have completed their education by this time. Second, at this age, I am more likely to capture returns to schooling that could accrue if some individuals decided to undertake higher education when they faced a high unemployment rate at ages 16 or 19.[25] I will also look

[22] The empirical evidence for college graduates echoes these findings. For example, Kahn (2010); Oreopoulos et al. (2012) found no effect on long-term employment for college graduates in North America, while Liu et al. (2012) show that labor market entry conditions have a permanent effect on the incidence of unemployment for college graduates in Norway.

[23] In Appendix Table A.5, I replicate the estimated effect from Table 2 column 1 for an extended sample including men with unreported education, IQ, or parental identifier. The estimated effects on the extended sample are essentially the same as those produced with the main sample. From columns 3 through 6 we also see that mortality and migration out of the country are not driving the results.

[24] To include individuals with zero annual earnings in the log earnings transformation, I replace earnings less than 100,000 NOK with this amount. In Appendix Table A.6, I include several analyses where I change the censoring of the earnings variable to show that the censored results are essentially the same as those in the linear model.

[25] As emphasized by Bhuller et al. (2011), there is a substantial life-cycle bias in the returns to schooling if current earnings are measured before the age of 30 or after the age of 40. Moreover, they suggest looking at earnings at ages 30–35 to circumvent the

at earnings at other times in life, for example mean earnings at ages 30–35 and the accumulated earnings in the time period when the individuals are between 19–35.

Other measures of labor market outcomes include employment, full-time employment, and disability pension use. The data do not cover wages and work hours for the relevant time period: hence I use information on annual earnings to approximate employment. In line with previous studies using the same variable (Havnes and Mogstad, 2011a,b), I define employment and full-time employment as earning more than twice and four times the "basic amount". The "basic amount" determines the magnitude of current and future pensions in the universal (and mandatory) Norwegian National Insurance Scheme. It is adjusted annually by the Norwegian Parliament, and typically has been growing more than prices but less than wages. One basic amount corresponds to 70,006 NOK (approximately 13,017 USD) measured in fixed 2009 prices.

To consider the effect that labor market entry conditions has on educational attainment, I employ two outcomes: high school completion and higher education.[26] *High school completion* indicates more than 12 years of completed education and *higher education* indicates more than 14 years of completed education.

The key explanatory variable is the local unemployment rate faced at age 16 (*UR16*) and that faced at age 19 (*UR19*). The region of residence and the local unemployment rate are based on the regional classification standard used by Statistics Norway for the level between municipality (419 in our data) and county (19 in Norway), and there are 89 such regions in Norway. The main criteria used for defining the regions are the labor market and trade. By using regions, I mitigate the problem of migration between smaller municipalities, because individuals are less likely to migrate between regions than municipalities.

Based on the annual unemployment data for each municipality, I constructed a measure of regional unemployment rates. This was calculated as the proportion of individuals registered as unemployed in each region.[27] Information about the number of individuals registered as unemployed in each municipality is not available before 1975, thus restricting this sample to individuals who were 16 years old in the years 1975–89 and 35 in 1994–2008. Moreover, I approximate a measure of the labor force by including all individuals in each region in the age range between 16 and 66 years.[28] This unemployment rate is merged with the region of residence at age 16. The unemployment rate for the full population, rather than the youth unemployment rate, is used because the municipal-level data on the number of individuals registered as unemployed is not available by the relevant age categories.

problem with life-cycle bias when lifetime earnings are not observed.

[26] In contrast to all other outcomes, which are measured at age 35, education is measured at age 34. This is because I do not observe educational attainment after 2007.

[27] Individuals who are in an active labor market program are not included because this information is not available at a disaggregated level for the years 1975–95.

[28] Information about the actual labor force in each municipality is not available for the analysis period 1977–95.

Based on the time when an individual was 16, a large number of individual and parental characteristics are included in the models to capture child and parental characteristics. Unless otherwise stated, I include the following set of control variables in all models: dummy variables for birth order, maternal education, paternal education, and family size; linear and quadratic terms for maternal age at child birth; log of paternal mean earnings when the child was from 8 to 10 years of age; and indicator variables for IQ.[29] I also include fixed effects for region of residence at age 16 and birth cohort.

The main goal of this analysis is to study heterogeneous effects across individuals of different ability levels. To do this, the local unemployment rates at ages 16 and 19 will be interacted with two variables indicating ability type. To construct indicators for ability type, I use information about IQ. Admittedly, IQ is not a perfect measure of ability, for example, it does not capture important non-cognitive skills such as perseverance or emotional intelligence, which also matter for labor market success (See e.g Heckman and Rubinstein, 2001; Heckman et al., 2006; Bowles et al., 2001). As an additional (possibly noisier) measure of ability, I have also followed Raaum and Røed (2006) and constructed subsamples based on several exogenous parental and individual characteristics. See Appendix A for a more detailed description and a discussion of the results obtained from this model. The IQ is a variable constructed from the Norwegian Army ability tests administered at the time of military conscription (normally at age 18).[30] Military conscription is mandatory for every Norwegian man (but not for the cohorts of women in the data period).[31] The test is based on the sum of scores from three tests: math, figures, and word similarities. The score ranges from 1 to 9, and follows the Stanine method (Standard NINE), which scales test scores to a mean of 5 and a standard deviation of 2. The mean and median IQ in the sample for these analyses are 5. Based on IQ, I construct subsamples that represent three categories: low ability, medium ability, and high ability (<3, 3–4, ≥ 5). The low-ability subsample is constructed to capture the individuals with particularly low IQs, and as outlined in Section 2.2, they are expected to be particularly vulnerable to the local unemployment rate at time of labor market entry. Notably, the reference group, which will be the high-ability individuals, not only consists of those with particularly high IQs, but also those with average IQs. These ability categories are constructed to focus specifically on the lower parts of the ability distribution, which is likely not included in previous studies restricted to individuals who have attended college (Liu et al., 2012; Oreopoulos et al., 2012).[32] This

[29] I focus on paternal earnings when the child was 8 to 10 years old, as we do not observe earnings before 1967, and earnings after this age are more likely to be correlated with the local unemployment rate at the time the child is 16 years old.

[30] Notably, since the IQ is measured at age 18, it does not fully reflect innate ability, as ability measured by the IQ tends to be malleable up to the age of 10 (Hopkins and Bracht, 1975). When IQ is measured at such a late age it is likely to also capture environmental factors such as family and community.

[31] I would like to thank the Norwegian Armed Forces for access to these data. The views and conclusions expressed in this paper are those of the author and cannot in any way be attributed to the Norwegian Armed Forces.

[32] See, for example, Cawley et al. (2001), who establish that various measures of cognitive ability are strong predictors of

construction also implies that the majority of individuals in each of the categories would typically enter the labor market at age 19 or earlier (less than 14 years of education). Hence, the unemployment rates at ages 16 and 19 would be relevant for the majority of these individuals (Notably, more of the individuals in the high-ability group tend to undertake additional education). Appendix Figure B.2 presents a detailed description of the educational attainment for each subsample broken down by ability. For the high-and medium-ability subsamples, the largest share of individuals has 13 years of education, and are therefore expected to enter the labor market around age 19. We also see that the largest share of the low-ability individuals has 10 years of education, which suggests that 16 is a critical age for most individuals in this category.

Table 1 gives summary statistics for the key variables of interest. I present separately the means and standard deviations for the low-ability, medium-ability, and high-ability groups. We can see that at age 35, the higher-ability individuals have higher earnings, are more likely to be employed, are far less likely to be on disability, and have attained a higher level of education. We also see that the parents of higher-ability individuals have obtained higher levels of education, are older at time of the child's birth, have fewer children, and the fathers have higher earnings.

5 Empirical Strategy

Using ordinary least squares (OLS), I estimate the effect of the regional unemployment rate at ages 16 (UR16) and 19 (UR19) on long-term earnings.

$$LMO_i = \alpha_c + R_r + \beta UR_{r,c} + \lambda x_i + \varepsilon_i, \tag{1}$$

Here, LMO_i denotes the individual's long-term labor market outcome (e.g., yearly earnings, employment, education, or drawing a disability pension), α_c is a vector of cohort fixed effects included to control for national trends over time, R_r is a vector of regional fixed effects included to control for time-invariant regional characteristics, $UR_{r,c}$ is a vector of the regional unemployment rate which each cohort faces at different ages (particularly ages 16 and 19) and x_i is a vector of individual and parental characteristics (such as IQ, birth order, family size, parental education, parental age at birth of child, and paternal earnings).

education. They argue that few individuals with high cognitive abilities have low educational levels, and that we cannot, for example, determine the effect on wages from dropping out of high school across high- and low-ability individuals, but that one can determine the differential effects that dropping out of high school has on the wages of individuals of moderate ability as opposed to low ability. The differences in educational level between ability types could challenge our differential analysis if, for example, the high-ability individuals were not affected by the local unemployment rate at ages 16 and 19, because the majority of these individuals do not enter the labor market at this time, but undertake higher education independently of local unemployment.

Table 1: Summary statistics

	Low IQ	Medium IQ	High IQ
Earnings at age 35	332.7	394.2	475.2
	(188.0)	(193.9)	(229.9)
Employment at age 35	0.691	0.788	0.843
	(0.462)	(0.409)	(0.364)
DP recipient at age 35	0.0708	0.0274	0.0113
	(0.257)	(0.163)	(0.106)
Education years at age 34	11.03	12.02	13.94
	(1.453)	(1.799)	(2.506)
$\leq$13 years of education	0.986	0.919	0.594
	(0.116)	(0.273)	(0.491)
Paternal education years	9.745	10.40	11.82
	(2.049)	(2.336)	(3.007)
Maternal education years	9.447	9.891	10.88
	(1.547)	(1.764)	(2.316)
Paternal earnings (Child's age 8–10)	351.9	379.5	427.4
	(133.2)	(141.0)	(162.4)
Father's age at birth	30.27	30.15	30.54
	(7.178)	(7.036)	(6.896)
Mother's age at birth	26.59	26.71	27.30
	(6.081)	(6.024)	(5.909)
Maternal birth cohort (year)	1939.9	1939.7	1938.7
	(7.534)	(7.635)	(7.883)
Birth cohort (year)	1966.4	1966.4	1966.0
	(3.828)	(3.954)	(4.375)
Birth order	2.295	2.166	1.993
	(1.271)	(1.192)	(1.107)
Family size	3.165	3.036	2.905
	(1.324)	(1.234)	(1.151)
IQ	1.704	3.615	6.251
	(0.456)	(0.486)	(1.207)
Observations	31,544	117,497	278,366

Notes: Standard deviations in parentheses for mean statistics. Earnings are measured in NOK (2009)/1000. DP indicates use of disability pension. Family size refers to number of children in family.

Standard errors are clustered at the regional level.[33] In this model, the region of residence is determined at age 16.[34]

The coefficients of interest, β, capture the incremental increase in annual earnings from a 1 percentage point reduction in the local unemployment rate youth face at the given age (in particular UR16 and UR19). The OLS estimator of β will be unbiased provided that the local unemployment rate at the time of graduation is determined by exogenous economic shocks and is independent of unobservable determinants of adult labor market performance. Inclusion of cohort fixed effects prevents permanent differences across cohorts, such as cohort sizes or trends in educational attainment, from biasing the parameter of interest β. It also removes variation from annual cyclical changes in unemployment rates. Given the regional fixed effects, the primary remaining source of variation is thus that different regions are subject to different changes in the local unemployment rate compared to the overall annual variation.

In addition to including regional fixed effects, I also follow previous studies (e.g. Oreopoulos et al., 2012) in controlling for the regional unemployment rates at times other than ages 16 and 19. In particular, as a precaution against the effect of the unemployment rate at age 35 being loaded onto the effect of the unemployment rate at age 16 (or 19), I control for the unemployment rate at age 35 in all regressions.[35]

After accounting for regional and cohort fixed effects, the crucial identifying assumption is that the difference in earnings observed between regions with high and low unemployment rates would be the same if they did not experience the difference in the local unemployment rate. This assumption could be violated if regions of high unemployment had different time trends from regions of low unemployment. For example, there could be a decrease in parental education over time in the regions if, for example, poor labor market prospects caused selective migration. Hence, over time, there might be a systematic compositional change in the characteristics between the cohorts residing in high- and low-unemployment regions, and this compositional change could also be related to the youth (adult) labor market outcomes. To investigate the plausibility of compositional changes between cohorts, I include the vector x of observable characteristics expected to influence adult labor market performance. All variables in the x vector are measured prior to the age of 16. Variables observed after age 16 could be influenced by UR16 and UR19 (e.g., work experience, educational

[33] As noted by Bertrand et al. (2004), standard errors might suffer from serial correlation. Hence, I follow Liang and Zeger (1986); Arellano (1987) and employ a model with one-level-up clustering (clustering on the 89 regions).

[34] Notably, the region of residence at this age could be endogenous to UR16 if, for example, high-ability individuals decide to migrate to another region when the unemployment rate is high, thus leaving a negatively selected group of individuals behind. I address this in the empirical analysis, where I provide an additional robustness analysis using the region of birth instead of the region of residence at age 16.

[35] The coefficient of β would be biased upwards (downwards) if the length of the business cycle causes youth facing high UR16 or UR19 to be more (less) likely to face a high unemployment rate in the year when their earnings and employment outcomes are measured.

attainment, marital status, number of dependents, etc.) and hence are not included in the regression.[36]

The identifying assumption could also be undermined if there were an underlying structural change in some regions. One example of such a structural change would be an underlying trend in the educational attainment in some regions, which resulted in lower regional unemployment. Moreover, such a trend in educational attainment could also boost earnings in these regions. To investigate the plausibility of this, I include interactions between the regional indicators and a linear time trend. This controls for linear time trends in earnings that are specific to a region.[37] These region-specific linear time trends remove a substantial part of the variation used to identify any effect of UR16 and UR19 on long-term earnings, with a possible loss of precision.

To investigate whether local labor market conditions faced by youth with varying abilities at ages of 16 and 19 have heterogeneous effects on labor market outcomes, I use the OLS model

$$LMO_i = \alpha_c + R_r + \eta UR_{r,c} + \theta Low_i + \rho Med_i + \beta Low_i UR_{r,c} + \gamma Med_i UR_{r,c} + \lambda x_i + \varepsilon_i \qquad (2)$$

where Low_i and Med_i are indicators of low- and medium-ability types, as defined in Section 4. I also interact the ability type variables with the α_c and R_r, since there could be fundamental differences in labor earnings between the ability types.[38] With this inclusion, I end up with essentially the same estimated effect as I would have obtained by exploring the effect for each ability type in a subsample analysis. However, I can now directly investigate potential heterogeneous effects on LMO_i across ability types, as revealed by the coefficients β and γ. The coefficients β capture the differential effects of the local unemployment rates (at various ages) on the low-ability type compared with the high-ability type, and γ captures the differential effects of the local unemployment rate (at various ages) on the medium-ability type compared with the high-ability type.

[36]The analysis where I use birth region would also serve as a robustness test for exploring whether selective migration could bias the estimates.

[37]Although I indeed control for parental education in Equation 1, the trend in average educational attainment in each region could potentially develop in a different pattern in some regions over the period when the cohorts are 16, as there is a very high increase in overall educational attainment over this period.(NOU, 1994) Nonetheless, as educational attainment is probably endogenous to the local unemployment rate, this variable cannot be included as a covariate.

[38]For example, assume that the low-ability type individuals are more likely to live in non-densely populated regions where the distances to alternative jobs are longer. Then a high unemployment rate could be more harmful for low-ability individuals. This emphasizes the importance of interacting the ability type with the region of residence.

6 Empirical Results

6.1 Main Results for Earnings

The estimated effects of the labor market conditions at ages 16 and 19 on youth earnings at age 35 are presented in Table 2. The first column presents the results based on Equation 1 without covariates (x). We can see in column 1 of Table 2 that the adult's earnings at age 35 are negatively affected by the unemployment rate the youth faced at age 19.

As discussed in Section 5, a concern for the empirical strategy is unobserved compositional change in the cohorts in different regions that is systemically correlated with UR16 and UR19. If this happens, then including covariates for the individuals' and their parents' observable characteristics in the regression model could change the estimates. As we see in column 2, the inclusion of these covariates only has a modest impact on the coefficients, suggesting that such compositional changes are not seriously affecting the estimates.

Theory described in Section 2.2, suggests that youth might react to business cycles in different ways. Low-ability youth might be more likely to experience unemployment in recessions or to be downgraded to a lower-quality job. This could again affect their future employment or earnings. To investigate this, I stratify the sample by ability. Column 3 of Table 2 gives the results of using Equation 2 on the three ability subsamples defined in Section 4. We see that the low-ability individuals suffer a substantially larger earnings loss if they are subject to a high unemployment rate at age 16 than do the high-ability individuals. The interaction between medium ability and the local unemployment rate at age 19 is also large in magnitude and statistically significant. For the high-ability individuals, the estimated effects produced by this model suggest that a 1 percentage point increase in the local unemployment rate at age 19 resulted in a long-term earnings decrease of 0.54 percent. In the sample, the standard deviations in the local unemployment rate at ages 19 and 16 are about 1.3 and 1.0, respectively. For the low-ability youth looking at the local unemployment rate at age 16,[39] we see that earnings loss is 3.7 percent (0.0338+0.0029).

As mentioned in Section 5, the effects that UR16 and UR19 have on long-term earnings might systematically vary by region over time for reasons that are independent of labor market opportunities, such as unemployment experience or job quality. To explore this, column 4 includes region-specific linear time trends. This reduces the estimated effects somewhat. In particular, for high-ability individuals, the coefficient is positive but insignificant.[40] The results still reveal differential effects across ability types, suggesting

[39]Recall from Section 4 that the critical age for the high-ability individuals was 19, while it was age 16 for the low-ability youth.
[40]This could be explained through different underlying trends in educational attainment in the regions with high and low un-

Table 2: Main Results

	(1)	(2)	(3)	(4)	(5)
UR16	-0.0007	-0.0043	-0.0029	-0.0001	-0.0040
	(0.0040)	(0.0032)	(0.0042)	(0.0042)	(0.0036)
UR19	-0.0079**	-0.0069*	-0.0054+	0.0020	-0.0061+
	(0.0027)	(0.0027)	(0.0029)	(0.0035)	(0.0031)
UR35	-0.0176**	-0.0175**	-0.0173**	-0.0207**	-0.0061
	(0.0038)	(0.0034)	(0.0040)	(0.0041)	(0.0040)
Low ability×UR16			-0.0338**	-0.0211+	-0.0258*
			(0.0105)	(0.0120)	(0.0101)
Low ability×UR19			-0.0036	-0.0015	-0.0018
			(0.0081)	(0.0087)	(0.0078)
Low ability×UR35			-0.0133	-0.0251	-0.0020
			(0.0158)	(0.0186)	(0.0128)
Medium ability×UR16			0.0006	0.0015	-0.0028
			(0.0061)	(0.0049)	(0.0061)
Medium ability×UR19			-0.0086+	-0.0175**	-0.0097*
			(0.0045)	(0.0047)	(0.0040)
Medium ability×UR35			-0.0000	-0.0001	0.0009
			(0.0070)	(0.0082)	(0.0066)
Additional covars		x	x	x	x
Regional-specific linear time trend				x	
Observations	427,407	427,407	427,407	427,407	427,407

Notes: OLS regressions, with robust standard errors clustered by region in parentheses. Significance levels are indicated as follows: + significant at 10 percent; *significant at 5 percent; **significant at 1 percent.

Dependent variable in columns 1–4 is log of earnings at age 35. In column 5 the dependent variable is mean earnings when the individual is 30 to 35. All models include regional and birth cohort fixed effects. Additional covariates are ability type based on IQ divided into the three groups of low-, medium- and high-ability (<3, 3–4, ≥ 5); Mother's and father's education; years of education (<10, 10–11, 12–15, ≥ 16 and missing) in 5x2 categories; indicators for birth order and family size (representing 1,2,3,4,5,6+); linear and quadratic terms for mother's age at child birth and paternal earnings (log of paternal mean earnings from the period when the child is aged 8–10). See Section 4 for details defining the three ability categories. In columns 3–5, ability types are also interacted with the birth cohort and regional fixed effects.

that low- and medium-ability types are more vulnerable than high-ability types to the local unemployment rate faced at age 16 or 19.

In column 5, I substitute the dependent variable with a variable capturing mean earnings for individuals aged 30 to 35. I do this to investigate whether I observe a similar effect of UR16 and UR19 on earnings when looking at earnings over a longer time period. Comparing columns 6 and 3, we see that the effect of UR16 and UR19 on average earnings is essentially the same as in the results on earnings at age 35.[41]

There are some alternative interpretations for the observed effect of UR16 and UR19 in Table 2 column 2, and the observed differential effects across ability types (Table 2 column 3). First, subsequent exposure to a high unemployment rate might hurt someone just as much as did UR16 and UR19. For example, the later unemployment rate could prevent promotions or wage growth through job mobility, independently of the unemployment rate faced at ages 16 or 19. This could potentially confound the estimates, given that business-cycle shocks might be correlated with the local labor market conditions at the time of labor market entry.[42] Second, low- or medium-ability youth are in general more likely to enter the labor market at ages between 16 to 19, and the unemployment rate could be less important for the high-ability youth who would undertake higher education independently of the labor market conditions they faced at this age. Meanwhile the unemployment rate at the time of graduation from college, typically at age 22, could be particularly important for the high-ability youth.[43]

The rich registry data allows me to investigate this by including the full local unemployment rate history. In Table 3 I isolate the effect of UR16 and UR19 from the effect of the local unemployment situation at a later stage and investigate how local unemployment rates at other ages affect long-term earnings. Column 1 of Table 3 is similar to the results in column 2 of Table 2, although I also include the full history of the local unemployment rate with a three-year span between each included UR. As suggested by Oreopoulos et al. (2012), I do not include the unemployment rate each year from age 16 to age 35, as the strong correlation in the local unemployment rates across years would produce imprecise estimates.[44]

Comparing column 2 of Table 2 with column 1 Table 3, we see that the estimated effect of UR16 and

employment. Moreover, the increase in educational attainment could be most relevant for high-ability individuals. Thus, the unemployment rate seems somewhat less relevant for high-ability individuals when we include the region-specific time trend in the model.

[41] I have also looked at the effect on accumulated earnings for the time period 19–35: the coefficient produced by this model echo the findings from Table 2. Data for earning at ages 16 to 18 is not available.

[42] This is particularly concerning for the unemployment rate at the time of measuring the outcome variable (age 35), and in Table 2 I have thus followed previous studies in controlling for the unemployment rate at that time. However, the effects of unemployment rates between ages 19 and 35 could also load onto the estimates for UR16 and UR19.

[43] However, this line of interpretation does not seem to be of primary importance in explaining the differential effects of UR16 and UR19 on earnings across ability types. Recall from Table 1 that 60 percent of the high-ability individuals are predicted to graduate on or before age 19, as they have 13 or fewer years of education. Hence, the unemployment rate at age 19 is relevant also for the individuals in this subsample. Also, in Appendix Figure B.1, we see that there are no clear spikes in education years when

Table 3: Effect of Subsequent Unemployment Rate on Earnings

	(1)		(2)		(3)	
	Estimate	SE	Estimate	SE	Estimate	SE
UR16	-0.0070*	(0.0033)	-0.0064	(0.0040)	-0.0026	(0.0045)
UR19	-0.0071*	(0.0028)	-0.0055+	(0.0030)	-0.0065+	(0.0034)
UR22	-0.0042	(0.0026)	-0.0045+	(0.0026)	-0.0044	(0.0035)
UR25	-0.0037	(0.0024)	-0.0050+	(0.0030)	-0.0066+	(0.0036)
UR28	-0.0033	(0.0026)	-0.0047	(0.0032)	-0.0048	(0.0039)
UR31	-0.0022	(0.0034)	0.0026	(0.0040)	0.0055	(0.0044)
UR35	-0.0188**	(0.0034)	-0.0196**	(0.0039)	-0.0201**	(0.0049)
Low ability×UR16			-0.0291**	(0.0100)	-0.0304**	(0.0102)
Low ability×UR19			0.0011	(0.0085)	-0.0005	(0.0084)
Low ability×UR22			-0.0034	(0.0087)	-0.0035	(0.0090)
Low ability×UR25			0.0051	(0.0100)	0.0051	(0.0101)
Low ability×UR28			0.0192+	(0.0102)	0.0194+	(0.0103)
Low ability×UR31			-0.0061	(0.0092)	-0.0118	(0.0094)
Low ability×UR35			-0.0054	(0.0159)	-0.0069	(0.0151)
Medium ability×UR16			0.0056	(0.0053)	0.0031	(0.0058)
Medium ability×UR19			-0.0075	(0.0048)	-0.0077	(0.0055)
Medium ability×UR22			0.0038	(0.0049)	0.0029	(0.0054)
Medium ability×UR25			0.0082	(0.0058)	0.0105+	(0.0058)
Medium ability×UR28			0.0081	(0.0063)	0.0088	(0.0065)
Medium ability×UR31			-0.0105	(0.0066)	-0.0145*	(0.0069)
Medium ability×UR35			0.0043	(0.0074)	0.0028	(0.0085)
Observations	427,407		427,407		316,284	

Notes: OLS regressions, with robust standard errors clustered by region in parentheses (+$p < 0.10$, *$p < 0.05$, **$p < 0.01$). Dependent variable is log earnings at age 35. The model in column 1 is identical to column 2 in Table 2 but with the inclusion of the subsequent unemployment rates at ages 22, 25 and 31. In columns 2 and 3 the models are identical to the models in columns 3 and 5 of Table 2. The sample in column 3 is restricted to individuals with less than 14 years of education.

UR19 is only modestly influenced by the inclusion of the full unemployment rate history. In column 2 I explore the existence of heterogeneous effects on earnings across ability types, using the preferred model from column 3 in Table 2 with the inclusion of subsequent unemployment rate. Here too, the estimates for UR16 and UR19, as well as the interactions with the ability types, are only modestly affected by the inclusion of subsequent unemployment rates. Hence, I find little evidence that the effects on long-term earnings of UR16 and UR19 are mainly explained by correlations in the local unemployment rate at expected age of graduation with those later in life.

For the high-ability individuals in column 2, long-term earnings seem to be somewhat affected by the local unemployment rates at ages 16–28. Meanwhile, the interaction between low- (medium-) ability type and UR25 and UR28 turns positive. However, it is only marginally significant for UR28 interacted with low-ability type. So we cannot determine heterogeneous effects of the subsequent unemployment rates across ability types. Nevertheless, the estimates in column 2 suggest that for the low- (medium-) ability types, the full effect of unemployment at ages between 25 and 28 is close to zero and insignificant, while the full effect of the UR16 for the low-ability type is large in magnitude and statistically significant.[45] This emphasizes that the unemployment rate at the time when they typically enter the labor market is particularly important in determining their long-term earnings.

One explanation for the long-term effects on earnings of the subsequent unemployment rate for the high-ability type could be that high unemployment rates prevent wage growth through promotion or job mobility, and that this is most important for high-ability workers.[46] An alternative interpretation is that highly educated individuals tend to enter the labor market at ages 22–28. If high-ability individuals are more affected by the local unemployment rate at ages 22–28 (because this also represents a time of labor market entry following graduation from higher education), then I would expect the same estimate to be weaker in a sample of only those with lower education. In column 3 I thus restrict the sample to individuals with less than 14 years of schooling. Comparing columns 2 and 3 in Table 3, we see that the coefficients of interest are largely unaffected by this sample restriction. These results support the idea that a high unemployment rate early in one's career could depress one's wage increases that would otherwise have occurred through, for example, a process of ladder climbing. Notably, the estimated coefficients produced by this model need to be interpreted with caution, as the sample selection criteria could be endogenous to the local unemployment

we look at years of education above 13 years.

[44]There is still a substantial correlation between the unemployment rates included with the three-year span: hence multicollinearity between the included covariates could still produce imprecise estimates. See Appendix Table A.8 for an extended analysis.

[45]The full effect for low-ability types of UR22 is negative but smaller in magnitude than the coefficient of UR16.

[46]Related to this, Kwon et al. (2010) show that cohorts entering the labor market during a boom are promoted faster than those entering during a recession.

rate. In particular, some high-ability individuals might be encouraged to complete their current educational track or undertake higher education, which would yield an upward bias in the estimated effect in column 3.

6.2 Robustness

One potential concern regarding the estimates presented in Table 2 is that the region of residence at age 16 could be endogenous to the local unemployment rate at age 16. For example, based on unobservable characteristics, some youth (potentially the more productive ones) might decide to migrate to a region with a lower expected unemployment rate if they foresee a high unemployment rate at age 16. This could potentially bias the OLS estimates of β and γ in Equation 2 because of selection. In particular, if the more productive individuals foresee a high unemployment rate, they might be more likely to migrate to a region with a lower unemployment rate, something which would leave a negatively selected group of low productivity individuals behind. If so, the correlation between the unemployment rate at age 16 and earnings at age 35 could be explained by a compositional change in the distribution of the productivity of the cohort facing the high unemployment rate.

The plausibility of this is examined in the first three columns of Table 4. Column 1 shows the exact same results as in the preferred model in column 3 of Table 2. In column 3, I assign the individual to the unemployment rates in their birth region (instead of the region of actual residence). Notably, birth region is missing for some individuals, therefore, I replicate the model in column 1 on the sample where the birth region is not missing, in column 2.[47] Comparing the estimates from the model with the actual region of residence (column 2) with the estimates from the model using the birth region (column 3), we see that the estimates are largely the same.

An additional robustness test is employed in column 4, where I use the unemployment rates in the municipality (419) instead of the region (89) of residence at age 16. The resulting estimates are essentially the same as the main estimates shown in column 1, although the precision tends to increase, since there is more variation in the data.[48]

In columns 5 and 6 I investigate directly whether migration before age 16 is "affected" by the local unemployment rates at ages 16 and 19. The dependent variable is now, first, whether the individual migrated out of the region of birth before age 16 (column 5), and second, whether the individual migrated out of the

[47] I expect that using the birth region instead of the actual region of residence could result in an attenuation bias and less precision, as the unemployment rate in the birth region will not be relevant for individuals who have migrated.

[48] While the unemployment rates in the relevant labor market (region) should be more pertinent than the unemployment rate in the municipality, one concern with this model is that selective migration could be more prevalent. Indeed, we see from the mean of the dependent variables in columns 5 and 6 that migration out of the municipality of birth by age 16 is substantially larger than out of the region of birth.

Table 4: Robustness and Selective Migration

	(1)	(2)	(3)	(4)	(5)	(6)
		Log of earnings at age 35			Mig1	Mig2
UR16	-0.0029	-0.0006	-0.0011	-0.0037	-0.0077	0.0061
	(0.0042)	(0.0042)	(0.0037)	(0.0031)	(0.0064)	(0.0049)
UR19	-0.0054+	-0.0054+	-0.0032	-0.0058**	0.0031	0.0019
	(0.0029)	(0.0030)	(0.0023)	(0.0022)	(0.0047)	(0.0050)
UR35	-0.0173**	-0.0160**	-0.0130**	-0.0124**		
	(0.0040)	(0.0041)	(0.0043)	(0.0030)		
Low ability×UR16	-0.0338**	-0.0379**	-0.0372**	-0.0223**	0.0092	0.0015
	(0.0105)	(0.0114)	(0.0105)	(0.0084)	(0.0089)	(0.0070)
Low ability×UR19	-0.0036	-0.0051	-0.0061	0.0028	0.0080	0.0074
	(0.0081)	(0.0091)	(0.0076)	(0.0060)	(0.0082)	(0.0077)
Low ability×UR35	-0.0133	-0.0147	-0.0183	0.0013		
	(0.0158)	(0.0160)	(0.0134)	(0.0097)		
Medium ability×UR16	0.0006	0.0002	-0.0023	0.0032	0.0076	0.0000
	(0.0061)	(0.0057)	(0.0061)	(0.0046)	(0.0048)	(0.0038)
Medium ability×UR19	-0.0086+	-0.0072	-0.0070+	-0.0034	-0.0015	0.0007
	(0.0045)	(0.0045)	(0.0041)	(0.0038)	(0.0051)	(0.0045)
Medium ability×UR35	-0.0000	0.0009	-0.0012	0.0039		
	(0.0070)	(0.0077)	(0.0081)	(0.0051)		
Region/Munic of residence:	reg(16)	reg(16)	reg(birth)	Munic(16)	reg(16)	Munic(16)
Mean of DepVar for Low ability					0.267	0.520
Mean of DepVar for Medium ability					0.275	0.513
Mean of DepVar for High ability					0.329	0.524
Observations	427,407	390,332	390,332	427,407	390,332	390,332

Notes: OLS regressions, with robust standard errors clustered by region in parentheses (+$p < 0.10$, *$p < 0.05$, **$p < 0.01$). Dependent variable (*DepVar*) is log earnings at age 35 in columns 1–4. In columns 5–6 the dependent variable is a variable indicating whether the individual migrated between large regions (column 5) and small regions (column 6) in the time period from birth until age 16. Region/Municipality of residence is the location used to identify where the individual grew up, determined at age 16 or at birth (the unemployment rates at ages 16 and 19 are measured at the same regional or municipal level). In columns 2 and 3 the sample is restricted to include individuals with non-missing birth region.

municipality of birth before age 16 (column 6). The estimates in columns 5 and 6 are close to zero and insignificant, suggesting that the local unemployment rates matter little for such migration.

6.3 Results for Disability Pension, Employment and Education

In Table 5 I investigate the possible mechanisms through which the local unemployment rates at the time of typical labor market entry could cause differential effects on long-term earnings for individuals of different ability types. I will first look at adult employment as a possible mechanism affecting long-run earnings. A youth's unemployment or having a poor quality job may reduce that youth's future productivity, thereby increasing the likelihood of facing unemployment or underemployment in the future. We know that the unemployment rates faced by youth at ages 16 and 19 have a substantial and persistent effect on adult employment prospects (Raaum and Røed, 2006).

In Section 2.2 I argued that the negative effects on earnings, employment and use of a disability pension would be most pronounced for low-ability youth. In columns 1 and 2 of Table 5, I explore whether we can detect differential effects on employment across the ability types (see Section 4 for definitions). First, we can see that the estimated effect of the unemployment rate at ages 16 and 19 on employment and full-time employment is small in magnitude and insignificant for the high-ability individuals. However, the estimates of the interaction effects (cf. β and γ in Equation 2) suggest that there are differential effects on adult employment with differing ability type. In particular, we see that low-ability individuals are less likely to be employed in adulthood if they faced a high unemployment rate at age 16. Interpreting the baseline estimate for low-ability youth ($\eta+\beta$) in columns 1 and 2 as a percentage of change from the outcome mean, we have a 3 percent decrease in the adult (full-time) employment if the local unemployment rate they faced at age 16 was higher by 1 percentage point.

As outlined in Sections 2.1 and 2.2, we may expect the local unemployment rate that youth face at ages 16 and 19 to affect the likelihood of entering the disability pension program in adulthood, and this effect could differ with the ability type. I investigate this in column 3: the estimates in column 3 align well with these expectations. First, we see that the estimated effect for high-ability individuals is small in magnitude and only marginally significant. Second, we do not observe any differential effects between the high-ability individuals and the medium-ability individuals. However, we do see that low-ability individuals are significantly likely to draw a disability pension at age 35 if they faced a high UR16. In particular, I find that the likelihood of entering the disability pension program increases by as much as 20 percent for the

Table 5: Employment, Disability Pension and High Earnings

	(1) Employed		(2) Ft employment		(3) DP		(4) Earnings> 6 ba		(5) Earnings> 8 ba	
	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE
UR16	-0.0014	(0.0018)	-0.0027	(0.0023)	0.0010+	(0.0005)	-0.0005	(0.0036)	-0.0005	(0.0033)
UR19	-0.0006	(0.0017)	-0.0013	(0.0019)	0.0005	(0.0005)	-0.0043	(0.0028)	-0.0056**	(0.0020)
UR35	-0.0030	(0.0022)	-0.0036	(0.0027)	0.0010	(0.0007)	-0.0116*	(0.0045)	-0.0148**	(0.0035)
Low ability×UR16	-0.0262**	(0.0063)	-0.0188*	(0.0090)	0.0132**	(0.0036)	-0.0148+	(0.0078)	-0.0047	(0.0050)
Low ability×UR19	-0.0020	(0.0050)	-0.0034	(0.0055)	0.0047	(0.0038)	0.0029	(0.0067)	0.0003	(0.0041)
Low ability×UR35	-0.0136	(0.0090)	-0.0113	(0.0107)	-0.0007	(0.0050)	-0.0056	(0.0107)	0.0111	(0.0076)
Medium ability×UR16	-0.0006	(0.0035)	-0.0005	(0.0039)	0.0001	(0.0016)	0.0017	(0.0046)	0.0049	(0.0041)
Medium ability×UR19	-0.0033	(0.0022)	-0.0067*	(0.0033)	-0.0001	(0.0013)	-0.0101*	(0.0043)	-0.0029	(0.0028)
Medium ability×UR35	-0.0037	(0.0039)	-0.0059	(0.0049)	-0.0014	(0.0020)	-0.0008	(0.0070)	0.0098*	(0.0044)
Mean of the dependent variable for:										
Low	0.813		0.691		0.0708		0.275		0.0663	
Median	0.881		0.788		0.0274		0.408		0.129	
High	0.908		0.843		0.0113		0.575		0.281	
Observations	427,407		427,407		427,407		427,407		427,407	

Notes: OLS regressions, with robust standard errors clustered by region in parentheses (+$p < 0.10$, *$p < 0.05$, **$p < 0.01$). The dependent variables in columns 1 and 2, employment and full-time employment, are indicator variables based on thresholds of earnings defined in Section 4. In column 3 the dependent variable is an indicator variable for drawing disability pension at age 35, and in columns 4 and 5 the dependent variable indicates earnings at particularly high levels (recall from Section 4 that one basic amount (1 ba) corresponds to 70,006 NOK (approximately 13,017 USD) measured in fixed 2009 prices). All the models are identical to the preferred model in Table 2 column 3, but with different outcome variables.

low-ability youth if the UR16 increases by 1 percentage point.[49]

It is worth noting that if the unemployment rates at age 16 and 19 affect labor market attachment at age 35, then the negative effect on earnings at age 35 (detected in Table 2) could stem entirely from the reduction in employment or the increase in disability utilization, and not from a reduction in wages. The plausibility of this could be examined by re-estimating the preferred model from Table 2 using different sample restrictions based on labor market attachment at age 35. However, this line of sample restriction may be problematic since it is, as demonstrated in Table 5, endogenous to the local unemployment rates youth face at ages 16 and 19.[50] In columns 4 and 5 I implement an alternate strategy for exploring whether reduced employment is the mechanism of primary importance for explaining the negative effect on earnings observed in Table 2. That is, I present the estimated effects on alternative earnings thresholds of the local unemployment rates at ages 16 and 19. If the entire earnings effect observed in Table 2 is explained by an effect on labor market attachment, then we should not expect any effects of UR16 and UR19 on the likelihood of having particularly high earnings. In columns 4 and 5, two indicator variables for high earnings are defined for earning above six and eight times the “basic amount” defined in Section 4.

Column 4 reveals that those of high ability are less likely to earn more than six times the “basic amount” if they faced a high UR19, but this is insignificant. The interaction between low- (medium-) ability type and UR16 (UR19) is negative, large in magnitude, and statistically significant. This suggests that for low- (medium-) ability individuals, compared to those with high abilities, UR16 (UR19) is more likely to reduce the probability of having high earnings during adulthood. Nonetheless, high-ability individuals are significantly less likely to end up with particularly high earnings (defined by earning more than eight times the “basic amount”, see column 5). This also applies for the low- and medium-ability types, as the interaction terms between ability type and UR19 are negative, small in magnitude, and insignificant. In general, the results suggest that the effects on labor market attachment observed in columns 1 and 2 are not the only important mechanisms explaining the effect of UR16 and UR19 on long-term earnings. Moreover, comparing the estimated effect for the high-ability individuals in column 1 to that in column 5, we also see that the effect on earnings observed for these individuals (in Table 2 column 3) appears to be mainly driven by a

[49] Notably, poor labor market entry conditions might affect disability participation through a health effect. In particular, Tella et al. (2003) shows that recessions lead to a considerable loss in national well-being. Moreover, in the epidemiological literature, youth unemployment experiences have been linked to depression through loss of self-esteem or mental stress (McKee-Ryan et al., 2005). Moreover, there is evidence of health effects, including effects on mortality, of being exposed to plant downsizing(Rege et al., 2009; Sullivan and von Wachter, 2009).

[50] However, the endogeneity of such a sample will probably lead to a downward bias because of negative selection. This type of negative selection aligns with the theory stating that if all else is equal, then the most productive worker has a higher likelihood of being employed. If these workers were employed, they would most likely be low earners. Hence, with this restriction, we would probably exclude more of the predicted low earners who faced a high unemployment rate at ages 16 or 19.

reduction in the likelihood of ending up with particularly high earnings.

In Section 2.2, I address how admission standards in high schools and colleges might increase during recessions due to an increase in the number of applicants. I thus expect a larger effect of the unemployment rate at ages 16 and 19 on education for individuals of the high-ability type than for the low-ability type. If so, the long-term effects on earnings for the high-ability type mirror both a negative effect on earnings for those who actually enter the labor market, and a mitigating positive effect on earnings for those who undertake higher education. Table 6 explores potentially heterogeneous effects on educational attainment of UR16 and UR19.

Column 1 shows that the effect of the local unemployment rates at ages 16 and 19 on completing high school is close to zero and statistically insignificant. Meanwhile, in column 2, which explores the estimated effect of low- and medium-ability types interacted with the local unemployment rates at ages 16 and 19, reveals that the low- and medium-ability types are less likely (than the high-ability type) to complete high school if they faced a high unemployment rate at their expected time of graduation, although the differences are small in magnitude and statistically insignificant.

In column 3 I investigate whether the local unemployment rates affect the likelihood of undertaking higher education. Not surprisingly, the coefficient of UR16 is negative, small in magnitude, and insignificant: at this age, youth are still in secondary education and the unemployment rate at this age is not likely to affect their decision to go on to higher education. The coefficient of UR19 is, however, positive but also small in magnitude and insignificant. This echoes the findings of Raaum and Røed (2006), who find no effect of UR16 and UR19 on educational attainment.

Column 4 includes the interaction between ability type and UR16 and UR19 to investigate whether there is a differential effect on the likelihood of undertaking higher education. Interestingly, the estimated effect for the high-ability type demonstrates that they are significantly more likely to undertake higher education if they face a high unemployment rate at age 19. For example, the coefficient of 0.0059 implies that an increase by 1 percentage point in the local unemployment rate at age 19 raises the likelihood of undertaking higher education by about 2 percent for the high-ability individuals. The estimate on the interaction between low- (medium-) ability type and UR16 (UR19) is negative but only statistically significant for the medium-ability type. The estimates in column 4 indicate that the effect on educational attainment is close to zero and insignificant for the low- and medium-ability types. In general, the results support the assertion that it is the high-ability individuals who undertake higher education when unemployment is high.[51]

[51] The increase in educational attainment could simply be explained through an increase in the supply side, where more attractive study places are available. However, recall from Section 5 that the empirical model includes year fixed effects. With this inclusion,

Table 6: Educational Attainment

	(1)		(2)		(3)		(4)	
	Completed high school		Completed high school		Higher education		Higher education	
	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE
UR16	0.0039	(0.0066)	0.0051	(0.0063)	-0.0014	(0.0022)	-0.0023	(0.0034)
UR19	-0.0010	(0.0033)	-0.0005	(0.0035)	0.0034	(0.0021)	0.0059*	(0.0028)
UR35	0.0031	(0.0042)	0.0003	(0.0044)	0.0012	(0.0029)	0.0011	(0.0041)
Low ability×UR16			-0.0096	(0.0103)			-0.0010	(0.0048)
Low ability×UR19			0.0035	(0.0080)			-0.0050	(0.0035)
Low ability×UR35			0.0101	(0.0111)			0.0042	(0.0056)
Medium ability×UR16			-0.0032	(0.0046)			0.0036	(0.0038)
Medium ability×UR19			-0.0063	(0.0045)			-0.0078**	(0.0028)
Medium ability×UR35			0.0058	(0.0060)			-0.0019	(0.0045)
Mean of the dependent variable for:								
Low ability			0.275				0.00916	
Medium ability			0.526				0.0610	
High ability			0.803				0.350	
Observations	427,407		427,407		427,407		427,407	

Notes: OLS regressions, with robust standard errors clustered by region in parentheses (+$p < 0.10$, *$p < 0.05$, **$p < 0.01$). Dependent variable is based on years of education at age 34, where “completed high school” indicates more than 12 years of education and “higher education” indicates more than 14 years of education. The models in columns 1 and 3 are identical to column 2 in Table 2. In columns 2 and 4 the models are identical to the preferred model in Table 2 column 3.

It is worth underlining that the estimated effects shown in this table, comparing columns 3 and 4, suggest that the mean effect on educational attainment of the unemployment rate at graduation could be small in magnitude or close to zero, as this effect potentially masks offsetting heterogeneous effects. As such, this could explain the lacking (or small) effect of labor market conditions on educational attainment detected in some other studies (see e.g. Raaum and Røed, 2006; Kahn, 2010). Although the estimated effect for the high-ability individuals is not very large, it is supportive of the hypothesis suggesting that the differential effects across ability type on long-term earnings of the local unemployment rates at ages 16 and 19 (detected in Table 2) are explained through an indirect effect on the likelihood of high-ability individuals' undertaking higher education.

7 Conclusion

This paper investigates how the local unemployment rates faced by males at ages 16 and 19 have long-term effects on their labor market outcomes. The empirical model focuses on the unemployment rates at ages 16 and 19 because, in Norway, the first is the expected graduation age for compulsory school (16) and the second, for high school (19), and thus also the ages of typical labor market entry for low-skilled workers. The results suggest that young men facing a high unemployment rate at ages 16 or 19 are subject to a long-lasting reduction in labor market outcomes.

There is a large literature showing that low-skilled youth are predicted to suffer most in terms of unemployment or job quality during recessions (see e.g. Hines Jr. et al., 2002; Elsby et al., 2010; Hoynes et al., 2012), but the existing literature that has investigated the long-term effects on labor market outcomes for less advantaged or low-skilled youth is somewhat mixed. The analysis of the present paper applied a direct measure of ability that is available for every Norwegian man (IQ). Employing this measure shows that the low-ability individuals who experienced poor labor market conditions at their expected time of labor market entry suffer from a persistent reduction in earnings and a substantially higher disability rate at age 35.

The empirical results demonstrate that low-ability males, versus those with high ability, suffer larger earnings reductions, have a weaker adult labor market attachment, and are more likely to receive a disability pension at age 35. Moreover, youth who faced poor labor market conditions at age 16 or at age 19 are less

the yearly increase in the number of study places is controlled for. Notably, the estimated effect could still reflect an increase (decrease) in the supply of study places, rather than increased (decreased) demand, if the regional supply of study places is correlated with the regional unemployment rate(See e.g Reiling and Strøm, 2015, for a discussion of this). Unemployment rates could also affect students' decisions to enter (or remain in) higher education. While high unemployment could induce high-ability individuals to undertake more education, it may reduce the low-ability individuals' expected payoffs from further education if they fear that they will not be able to obtain work regardless of educational level, or if they are not admitted since the high-ability students occupy more study places. This could thus induce low-ability individuals to undertake less education if unemployment is high.

likely to have particularly high earnings in adulthood, suggesting that an effect on labor market attachment is not the only mechanism explaining the long-lasting reduction in earnings. Indeed, the paper also finds that high-ability youth, but not youth in general, are more likely to undertake higher education if unemployment rates are high at the time of their graduation from high school.

This paper is relevant to the current policy discussion on the youth that could be "left behind" because of the financial crises. If the timing of labor market entry is particularly important for a youth's long-run labor market outcome, then governments might want to intervene with job training programs or programs that improve the transition from school to work for young labor market entrants. Moreover, if there exist effects that depend on ability, then we might want to target the particularly less advantaged individuals, not only to help them enter and remain in the labor force, but also to avoid future public costs in terms of disability expenses.

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Appendices

Appendix A: Subsample Analysis Broken Down by Predicted Years of Education

The results in Appendix Table A.1 are provided to explore the dependence on different measures of ability type of the effect on long term earnings. Following Raaum and Røed (2006), I have estimated a model predicting years of education at age 34 based on several exogenous parental and individual characteristics, all included in Equation 1. The individual score function obtained from this model was subsequently used to construct three subsamples by dividing the sample by the deciles of the individual score function: the two lowest deciles, deciles 2–4, and deciles 5–10. The number of individuals in each category for this model is essentially the same as in the three ability categories used in column 3 of Table 6.1. Appendix Table A.1 presents the results from subsamples broken down by deciles of predicted years of education. In column 2 of Appendix Table A.1, we see that the estimated effects of UR16 and UR19 on earnings for the subsamples produced by this model are negative and suggest that low-ability youth are more vulnerable to the local unemployment rate at age 16, but the coefficient is statistically insignificant. This echoes the statistically insignificant heterogeneity in the effects on long-term employment and non-employment of UR16 and UR19 that Raaum and Røed (2006) report.

Table A.1: Subsample Analysis Broken Down by Predicted Years of Education

	(1)	(2)	(3)
UR16	-0.0029	-0.0030	-0.0003
	(0.0042)	(0.0037)	(0.0042)
UR19	-0.0054+	-0.0057+	-0.0065*
	(0.0029)	(0.0029)	(0.0028)
UR35	-0.0173**	-0.0134**	-0.0154**
	(0.0040)	(0.0044)	(0.0046)
Low ability×UR16	-0.0338**	-0.0107	-0.0301**
	(0.0105)	(0.0084)	(0.0089)
Low ability×UR19	-0.0036	-0.0103	-0.0172*
	(0.0081)	(0.0074)	(0.0067)
Low ability×UR35	-0.0133	-0.0136	-0.0198
	(0.0158)	(0.0107)	(0.0123)
Medium ability×UR16	0.0006	0.0041	0.0013
	(0.0061)	(0.0061)	(0.0053)
Medium ability×UR19	-0.0086+	-0.0054	-0.0003
	(0.0045)	(0.0047)	(0.0047)
Medium ability×UR35	-0.0000	-0.0036	0.0028
	(0.0070)	(0.0077)	(0.0071)
Ability type based on	IQ	Family	Family and IQ
Observations	427,407	427,407	427,407

Notes: OLS regressions, with robust standard errors in parentheses corrected for clusters across regions (+$p < 0.10$, *$p < 0.05$, **$p < 0.01$). Dependent variable is log earnings at age 35. All models include region and birth cohort fixed effects; Mother's and father's education; years of education (<10, 10–11, 12–15, ≥16 and missing) in 5x2 categories; indicators for birth order and family size (representing 1,2,3,4,5,6+); linear and quadratic terms for mother's age at child's birth and paternal earnings (log of paternal mean earnings from the period when the child is aged 8–10).The ability type in column (1) is based on IQ and divided into the three groups according to <3, 3–4, and ≥5, this model replicates column 3 of Table 2. Ability types in Column (2) and (3) are based on a individual score function obtained from a model where I predict years of education at age 34 based on several exogenous parental and individual characteristics all included in Equation 1 (IQ is not included in Column (2)). The individual score function obtained from this model is further used to construct three subsamples by dividing the sample by deciles of the individual score function: those in the lowest deciles, those in deciles 2–4, and those in deciles 5–10.

Table A.2: Decomposing the Sample, Effects on Earnings at Age 35

	(1)	(2)	(3)
ur16	-0.0029	0.0106	-0.0055
	(0.0042)	(0.0113)	(0.0041)
ur19	-0.0054+	0.0006	-0.0035
	(0.0029)	(0.0066)	(0.0035)
ur35	-0.0173**	-0.0160+	-0.0169**
	(0.0040)	(0.0083)	(0.0054)
Low ability×ur16	-0.0338**	-0.0375	-0.0256*
	(0.0105)	(0.0385)	(0.0122)
Low ability×ur19	-0.0036	-0.0021	-0.0025
	(0.0081)	(0.0205)	(0.0110)
Low ability×ur35	-0.0133	-0.0341	-0.0073
	(0.0158)	(0.0258)	(0.0225)
Medium ability×ur16	0.0006	-0.0179	0.0112*
	(0.0061)	(0.0191)	(0.0054)
Medium ability×ur19	-0.0086+	-0.0216*	-0.0080
	(0.0045)	(0.0103)	(0.0053)
Medium ability×ur35	-0.0000	-0.0259	0.0164
	(0.0070)	(0.0173)	(0.0100)
Sample restriction:			
Education years	All	All	All
Birth cohort	1959–1973	1959–1964	1965–1973
Observations	427,407	162,549	264,858

Notes: OLS regressions, with robust standard errors clustered by region in parentheses (+$p < 0.10$, *$p < 0.05$, **$p < 0.01$). Dependent variable is log earnings at age 35. All models are identical to the preferred model in Table 2 column 3, but with different sample restrictions.

Table A.3: Decomposing Sample, Effect on Education

	(1)	(2)	(3)	(4)	(5)	(6)
	Completed high school			Higher education		
ur16	0.0051	0.0082	0.0011	-0.0023	-0.0020	-0.0014
	(0.0063)	(0.0081)	(0.0031)	(0.0034)	(0.0079)	(0.0038)
ur19	-0.0005	0.0128+	0.0025	0.0059*	0.0141**	0.0079**
	(0.0035)	(0.0069)	(0.0032)	(0.0028)	(0.0053)	(0.0029)
ur35	0.0003	0.0006	0.0007	0.0011	0.0057	0.0076
	(0.0044)	(0.0072)	(0.0051)	(0.0041)	(0.0060)	(0.0059)
Low ability×ur16	-0.0096	0.0390	-0.0083	-0.0010	0.0063	-0.0009
	(0.0103)	(0.0355)	(0.0107)	(0.0048)	(0.0095)	(0.0049)
Low ability×ur19	0.0035	0.0069	0.0035	-0.0050	-0.0144*	-0.0052
	(0.0080)	(0.0112)	(0.0103)	(0.0035)	(0.0064)	(0.0039)
Low ability×ur35	0.0101	0.0252	0.0081	0.0042	0.0013	-0.0003
	(0.0111)	(0.0232)	(0.0177)	(0.0056)	(0.0072)	(0.0092)
Medium ability×ur16	-0.0032	0.0238	-0.0061	0.0036	0.0093	0.0038
	(0.0046)	(0.0163)	(0.0059)	(0.0038)	(0.0086)	(0.0050)
Medium ability×ur19	-0.0063	-0.0044	-0.0047	-0.0078**	-0.0164**	-0.0089*
	(0.0045)	(0.0095)	(0.0054)	(0.0028)	(0.0056)	(0.0035)
Medium ability×ur35	0.0058	-0.0045	0.0124	-0.0019	-0.0077	-0.0064
	(0.0060)	(0.0102)	(0.0094)	(0.0045)	(0.0065)	(0.0065)
Sample restriction:						
Birth cohort	1959–1973	1959–1964	1965–1973	1959–1973	1959–1964	1965–1973
Observations	427,407	162,549	264,858	427,407	162,549	264,858

Notes: OLS regressions, with robust standard errors clustered by region in parentheses (+$p < 0.10$, *$p < 0.05$, **$p < 0.01$). The dependent variable is an indicator for high school completion (column 1–3) but in indicator for higher education (column 4–6). All models are identical to the preferred model in Table 2 column 3, but with different outcome variables and sample restrictions.

Table A.4: Analysis of Critical Ages—Using Unemployment Rate at Alternative Ages

	(1)		(2)		(3)		(4)	
	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE
ur12							-0.0022	(0.0033)
ur16	-0.0006	(0.0041)			-0.0060	(0.0040)		
ur17	-0.0041	(0.0045)	-0.0049	(0.0043)				
ur19	-0.0018	(0.0034)			-0.0037	(0.0031)		
ur20	-0.0035	(0.0035)	-0.0046	(0.0029)				
ur23							-0.0018	(0.0034)
ur35	-0.0176**	(0.0039)	-0.0174**	(0.0039)	-0.0196**	(0.0050)	-0.0171**	(0.0053)
Low ability × UR12							-0.0113	(0.0137)
Low ability × UR16	-0.0378**	(0.0114)			-0.0319**	(0.0106)		
Low ability × UR17	0.0048	(0.0101)	-0.0163+	(0.0090)				
Low ability × UR19	0.0026	(0.0095)			-0.0015	(0.0093)		
Low ability × UR20	-0.0102	(0.0086)	-0.0061	(0.0081)				
Low ability × UR23							0.0063	(0.0099)
Low ability × UR35	-0.0120	(0.0162)	-0.0058	(0.0171)	-0.0049	(0.0195)	0.0040	(0.0196)
Medium ability × UR12							0.0064	(0.0057)
Medium ability × UR16	-0.0032	(0.0062)			0.0081	(0.0055)		
Medium ability × UR17	0.0065	(0.0055)	0.0016	(0.0054)				
Medium ability × UR19	-0.0126+	(0.0064)			-0.0094+	(0.0051)		
Medium ability × UR20	0.0035	(0.0061)	-0.0042	(0.0044)				
Medium ability × UR23							-0.0012	(0.0058)
Medium ability × UR35	0.0004	(0.0070)	0.0014	(0.0072)	0.0119	(0.0090)	0.0103	(0.0088)
Sample restriction:								
Birth cohorts	1959–1973		1959–1973		1963–1973		1963–1973	
Observations	427407		427407		322189		322189	

Notes: OLS regressions, with robust standard errors in parentheses corrected for clusters across regions (+$p < 0.10$, *$p < 0.05$, **$p < 0.01$). Dependent variable is log earnings at age 35. The model in column 1 is identical to the preferred model in column 3 Table 2 but with the inclusion of the unemployment rates at ages 17 and 20. Column 2 is identical to column 1 but with the exclusion of the unemployment rates at ages 16 and 19. In column 3 the model is identical to column 3 in Table 2 but with different sample restrictions. Column 4 is identical to column 3 but with the exclusion of the unemployment rates at ages 16 and 19, and including the unemployment rates at ages 12 and 23.

Table A.5: Sample Restriction

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Var.	Earnings	Earnings	Earnings	Earnings	Mortality	Migration
UR16	-0.0006	-0.0007	-0.0029	-0.0036	0.0003	0.0003
	(0.0036)	(0.0040)	(0.0042)	(0.0043)	(0.0007)	(0.0008)
UR19	-0.0079**	-0.0079**	-0.0054+	-0.0059*	-0.0001	-0.0005
	(0.0027)	(0.0027)	(0.0029)	(0.0027)	(0.0005)	(0.0007)
UR35	-0.0177**	-0.0176**	-0.0173**	-0.0198**	0.0001	-0.0015+
	(0.0037)	(0.0038)	(0.0040)	(0.0041)	(0.0008)	(0.0009)
Low ability×UR16			-0.0338**	-0.0315**	0.0011	0.0016
			(0.0105)	(0.0091)	(0.0027)	(0.0020)
Low ability×UR19			-0.0036	-0.0098	-0.0012	-0.0009
			(0.0081)	(0.0076)	(0.0022)	(0.0015)
Low ability×UR35			-0.0133	-0.0201	-0.0044	0.0010
			(0.0158)	(0.0141)	(0.0036)	(0.0022)
Medium ability×UR16			0.0006	0.0019	0.0002	-0.0003
			(0.0061)	(0.0050)	(0.0013)	(0.0013)
Medium ability×UR19			-0.0086+	-0.0091*	0.0001	0.0004
			(0.0045)	(0.0039)	(0.0010)	(0.0010)
Medium ability×UR35			-0.0000	0.0042	0.0024+	0.0012
			(0.0070)	(0.0074)	(0.0014)	(0.0013)
Sample restricted to:						
Non missing		x	x	x	x	x
Not migrated or dead				x		
Mean of the dependent variable for:						
Low					0.0289	0.0116
Median					0.0193	0.0127
High					0.0131	0.0246
N	464,026	427,407	427,407	407,532	427,407	427,407

Notes: OLS regressions, with robust standard errors clustered by region in parentheses (+ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$). Dependent variable is log earnings at age 35 in columns 1–4, died before the age of 36 in column 5, and migrated out of the country before 2009 in column 6. The model in columns 1 and 2 is identical to column 2 in Table 2. In columns 3–6 the models are identical to the preferred model in Table 2 column 3. "Non-missing" indicates no missing observation for IQ, education or both parents. The data do not contain information about the year of migration; hence I use migration status in 2009 instead of the status at a specific age.

Table A.6: Specification Analyses, Exploring Zero Earnings.

	(1)	(2)	(3)	(4)	(5)	(6)
ur16	-992	-0.0017	-0.0212	-0.0036	-0.0029	-0.0025
	(1774)	(0.0046)	(0.0159)	(0.0045)	(0.0042)	(0.0040)
ur19	-2860*	-0.0051	-0.0063	-0.0055+	-0.0054+	-0.0053*
	(1108)	(0.0034)	(0.0157)	(0.0032)	(0.0029)	(0.0026)
ur35	-8673**	-0.0169**	-0.0449+	-0.0184**	-0.0173**	-0.0166**
	(1661)	(0.0049)	(0.0232)	(0.0044)	(0.0040)	(0.0037)
L ability×ur16	-10467**	-0.0363**	-0.2293**	-0.0415**	-0.0338**	-0.0283**
	(3599)	(0.0123)	(0.0791)	(0.0123)	(0.0105)	(0.0092)
L ability×ur19	-373	-0.0008	-0.0172	-0.0041	-0.0036	-0.0028
	(2838)	(0.0109)	(0.0607)	(0.0093)	(0.0081)	(0.0072)
L ability×ur35	-961	-0.0282	-0.0585	-0.0158	-0.0133	-0.0110
	(5506)	(0.0195)	(0.0949)	(0.0181)	(0.0158)	(0.0141)
M ability×ur16	601	0.0069	-0.0070	0.0007	0.0006	0.0005
	(2400)	(0.0059)	(0.0348)	(0.0070)	(0.0061)	(0.0055)
M ability×ur19	-2129	-0.0109*	-0.0280	-0.0094+	-0.0086+	-0.0080+
	(1650)	(0.0047)	(0.0212)	(0.0050)	(0.0045)	(0.0041)
M ability×ur35	2271	0.0045	-0.0169	-0.0009	-0.0000	0.0009
	(2634)	(0.0081)	(0.0423)	(0.0079)	(0.0070)	(0.0064)
Mean of the dependent variable for:						
Low	332,734	12.64	11.34	12.56	12.61	12.65
Median	394,228	12.82	11.98	12.75	12.78	12.81
High	475,155	13.00	12.30	12.93	12.95	12.97
Observations	427,407	401,529	427,407	427,407	427,407	427,407

Notes: OLS regressions, with robust standard errors clustered by region in parentheses (+$p < 0.10$, *$p < 0.05$, **$p < 0.01$). All models are identical to the preferred model in Table 2 column 3, but with different outcome variables, and the sample in column 2 is restricted to individuals with earnings above zero. The dependent variable is earnings at age 35 in column 1, log of earning at age 35 in column 2 and log of (earning + 1) in column 3. In columns 4–6 the dependent variable is log of earning at age 35, but to keep the zero earners, earnings below one basic amount (basic amount is defined in Section 4) are replaced by the basic amount (column 4), by 100,000 (column 5) and by the 10th percentile of earnings (column 6). Low- and medium-ability types are denoted by L and M.

Table A.7: Specification Analyses, Exploring Zero Earnings and Mean Earnings at Age 30-35.

	(1)	(2)	(3)	(4)	(5)	(6)
ur16	-1668	-0.0075+	-0.0098	-0.0047	-0.0040	-0.0016
	(1372)	(0.0045)	(0.0110)	(0.0036)	(0.0034)	(0.0035)
ur19	-2460*	-0.0070	-0.0014	-0.0059+	-0.0062*	-0.0046+
	(1034)	(0.0045)	(0.0107)	(0.0033)	(0.0030)	(0.0024)
ur30	-506	-0.0050	0.0292*	0.0002	-0.0007	0.0045
	(1532)	(0.0051)	(0.0121)	(0.0044)	(0.0041)	(0.0031)
ur35	-3132*	-0.0095+	-0.0019	-0.0063	-0.0061	-0.0152**
	(1544)	(0.0054)	(0.0157)	(0.0044)	(0.0041)	(0.0034)
L ability$\times$ur16	-7216*	-0.0413*	-0.1625**	-0.0333**	-0.0258*	-0.0217**
	(3127)	(0.0180)	(0.0545)	(0.0119)	(0.0100)	(0.0078)
L ability$\times$ur19	112	-0.0071	0.0103	-0.0025	-0.0020	-0.0022
	(2528)	(0.0139)	(0.0350)	(0.0088)	(0.0079)	(0.0061)
L ability$\times$ur30	-2770	0.0007	-0.0238	-0.0032	-0.0039	0.0003
	(2718)	(0.0145)	(0.0404)	(0.0098)	(0.0087)	(0.0066)
L ability$\times$ur35	932	0.0037	-0.0527	-0.0042	-0.0023	-0.0073
	(4128)	(0.0182)	(0.0685)	(0.0150)	(0.0129)	(0.0122)
M ability$\times$ur16	-272	0.0000	-0.0304	-0.0036	-0.0029	0.0003
	(2037)	(0.0081)	(0.0309)	(0.0069)	(0.0060)	(0.0046)
M ability$\times$ur19	-2463+	-0.0102+	-0.0069	-0.0106*	-0.0099*	-0.0073*
	(1390)	(0.0055)	(0.0158)	(0.0044)	(0.0040)	(0.0036)
M ability$\times$ur30	-1671	-0.0012	-0.0182	-0.0030	-0.0032	-0.0019
	(2190)	(0.0091)	(0.0260)	(0.0074)	(0.0064)	(0.0051)
M ability$\times$ur35	2279	0.0062	-0.0206	-0.0006	0.0006	0.0017
	(2244)	(0.0126)	(0.0277)	(0.0079)	(0.0068)	(0.0058)
Mean of the dependent variable for:						
Low	324,302	12.51	11.88	12.55	12.59	12.70
Median	379,574	12.73	12.34	12.73	12.76	12.84
High	448,697	12.91	12.58	12.90	12.91	13.00
Observations	427,407	415,022	427,407	427,407	427,407	427,407

Notes: OLS regressions, with robust standard errors clustered by region in parentheses (+$p < 0.10$, *$p < 0.05$, **$p < 0.01$). All models are identical to the preferred model in Table 2 column 3, but with different outcome variables, and the sample in column 2 is restricted to individuals with earnings above zero. Dependent variable is mean earnings from 30–35 in column 1, log of mean earning from 30–35 in column 2 and log of (earnings + 1) in column 3. In columns 4–6 the dependent variable is log of mean earnings at ages 30–35, but to keep the zero earners, earnings below one basic amount in earnings (basic amount is defined in Section 4) are replaced by the basic amount (column 4), by 100,000 (column 5) and by the 10th percentile of earnings (column 6). Low- and medium-ability types are denoted by L and M.

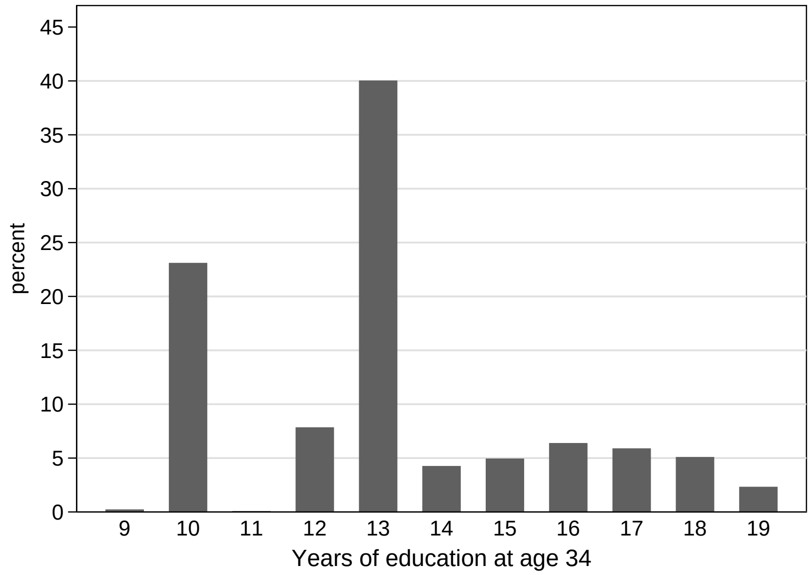
In Appendix A.8, panel A, I explore the effects on earnings of UR in a model where I only include UR16, UR19, UR25 and UR35. The estimated effects from this model (columns 1 and 2) echo those in Table 3. Panel B uses a model where I take the average of the unemployment rates experienced over a four-year period. From panel B columns 1 and 3, we see that for high-ability youth, there is a persisting negative effect of the unemployment rate they experience from 22–25 on their long-term earnings. Meanwhile, the estimated interaction between low- (medium-) ability type and UR22–25 is positive and large in magnitude but only statistically significant for medium-ability individuals. This could suggest that the UR22-25 is not important for long-term earnings for the low- and medium-ability types.

Table A.8: Effect of Subsequent Unemployment Rate on Earnings, Exploring Alternative Specifications

	(1)		(2)	
Panel A				
UR16	-0.0051	(0.0041)	-0.0018	(0.0045)
UR19	-0.0057+	(0.0029)	-0.0087*	(0.0035)
UR25	-0.0068*	(0.0030)	-0.0084*	(0.0032)
Low ability×UR16	-0.0317**	(0.0104)	-0.0311**	(0.0103)
Low ability×UR19	-0.0033	(0.0082)	-0.0016	(0.0082)
Low ability×UR25	0.0063	(0.0100)	0.0075	(0.0099)
Medium ability×UR16	0.0040	(0.0052)	0.0023	(0.0059)
Medium ability×UR19	-0.0080+	(0.0045)	-0.0064	(0.0048)
Medium ability×UR25	0.0113+	(0.0058)	0.0135*	(0.0052)
Panel B				
UR16–19	-0.0122*	(0.0060)	-0.0102+	(0.0056)
UR22–25	-0.0116**	(0.0036)	-0.0143**	(0.0045)
UR28–31	-0.0022	(0.0051)	0.0033	(0.0059)
Low ability×UR16–19	-0.0273+	(0.0138)	-0.0295*	(0.0138)
Low ability×UR22–25	0.0118	(0.0161)	0.0119	(0.0156)
Low ability×UR28–31	0.0100	(0.0139)	0.0014	(0.0127)
Medium ability×UR16–19	-0.0060	(0.0080)	-0.0100	(0.0079)
Medium ability×UR22–25	0.0161+	(0.0092)	0.0179*	(0.0087)
Medium ability×UR28–31	-0.0010	(0.0098)	-0.0064	(0.0097)
Observations	427407		304308	

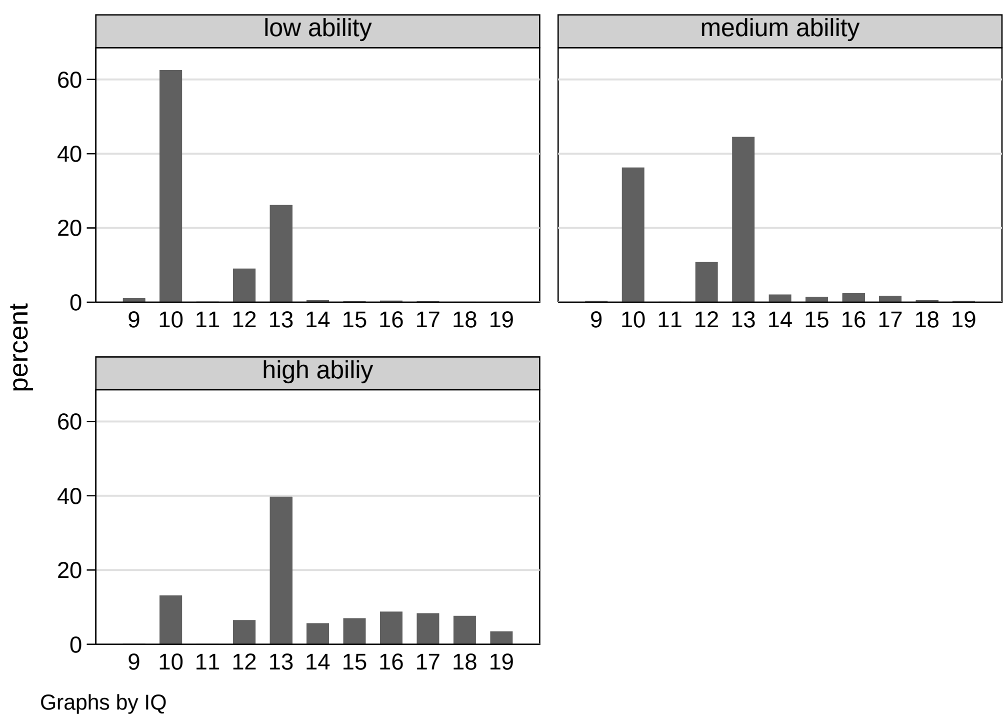
Notes: OLS regressions, with robust standard errors clustered by region in parentheses (+$p < 0.10$, *$p < 0.05$, **$p < 0.01$). Dependent variable is log earnings at age 35. The model in panel A, columns 1 and 2 is essentially the same as the preferred model in Table 2 column 3, but it also includes interaction of ability type and the local unemployment rate at age 25. In panel B, UR16–19, UR22–25 and UR28–31 refer to the mean of the local unemployment rate that the youth faced at the time they were 16 to 19, 22 to 25 and 28 to 31 years old, respectively. All models in the table also include the current unemployment rate. The sample in column 2 is restricted to individuals with less than 14 years of education at age 34.

Figure B.1: Distribution in Educational Attainment Measured as Years of Schooling



Notes: There is no clear spike in education years above 13 years. A large educational reform in 2003 introduced master and bachelor degrees to the Norwegian higher educational system. Before this, the years of education qualifying for different degrees was more dispersed. The cohort in my sample are predicted to graduate from college before 2003. Thus predicting the age at labor market entry for the high ability individuals that undertake higher education is challenging.

Figure B.2: Distribution in Educational Attainment Measured as Years of Schooling Across Ability Type



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