The Effect of Labor Market Conditions at Entry on Workers' Long-Term Skills*

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Abstract

This paper studies the impact of labor market conditions during the education-to-work transition on workers' long-term skill development. Using representative survey data on measures of work-relevant cognitive skills for adults from 19 countries, I document four main findings: i) cohorts of workers who faced higher unemployment rates at ages 18–25 have lower skills at ages 36–59; ii) unemployment rates faced at later ages (26–35) do not have such an effect; iii) the former findings hold even though, on average, people get more formal education as a response to higher unemployment in their late teens and early twenties; iv) skill inequality is affected: workers whose parents were less educated bear most of the negative effects. These findings can be rationalized by on-the-job learning during the early twenties being an important factor of skill-development, and such learning being negatively impacted by bad macroeconomic conditions. Using German panel data on skills, I show that young workers at large firms experience higher skill growth than those at small firms. This finding suggests firm heterogeneity in human capital provision to young workers as a potential mechanism since, in bad economic times, young workers disproportionately match with small firms.

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1 Introduction

The initial steps young people take in the labor market are key for their long-term career prospects. A growing body of literature shows how graduating and entering the labor market during bad macroeconomic times leads to sizable earnings losses that are persistent in time (e.g. Kahn, 2010; Oreopoulos et al., 2012).[1] Furthermore, even controlling for initial macroeconomic conditions, the type of firm where a young person starts out can impact lifetime earnings (Arellano-Bover, 2020). In spite of this mounting evidence, our understanding of *why* initial conditions are key is much more limited.

There are two broad groups of potential explanations behind the relevance of early conditions. The first group relates to labor market frictions. Even holding constant workers' productive capacity, it could be that search frictions, mobility costs, or imperfect information result in those entering in bad times being stuck in bad jobs, thrown to the bottom rungs of a hard-to-climb job ladder, or penalized for "thin" résumés. The second group of explanations relates instead to human capital. If on-the-job skill accumulation is an important source of wage growth, a negative shock to the foundations of that process—i.e., early experiences—could put workers on a different, worse human-capital accumulation path, with effects that persist in time.

Building a better understanding of why initial conditions matter is important for two reasons. First, it would improve our understanding of how labor markets operate in a key period of workers' careers. Second, each set of explanations—frictions vs. human capital—has different implications for aggregate efficiency. A new cohort of young workers is an input in the aggregate economy, and persistent wage losses stemming from bad entry conditions would provide different lessons depending on the mechanisms at play. A frictions explanation would imply that macroeconomic shocks amplify inefficiencies in how we *combine* inputs (i.e., the matching of workers with capital, firms, jobs). A human-capital explanation would instead imply that macroeconomic shocks persistently hurt the underlying *quality* of these inputs.

This paper provides a new test for the importance of these explanations, by investigating the relevance of human capital in explaining the lifetime impact of initial labor market conditions. Using individual-level survey data from 19 countries (the OECD PIAAC Survey of Adult Skills) on direct measures of adults' work-relevant cognitive skills, I study the effects of labor market entry conditions on workers' skills at ages 36–59. My approach, using direct measures of skills, stands in contrast to the standard way of inferring human capital from data on wages or employment. A direct measurement of skills is key to disentangle a human capital channel from frictions-based channels since the classic metric of human-capital development—wage growth—is potentially impacted by both types of channels.

My analysis starts with a conceptual framework linking labor market conditions at entry to formal education decisions, skill investments on- and off-the-job, and lifetime skill accumulation. Two main predictions arise from this framework on the relationship between

[1] Additional examples include Oyer (2006); Brunner and Kuhn (2014); Altonji et al. (2016); Fernández-Kranz and Rodríguez-Planas (2018); Schwandt and Von Wachter (2019).

entry conditions, educational investments, and skills. First, in bad economic times formal education investments are more likely to occur. Second, the relationship between conditions at entry and long-term skill accumulation is ambiguous: On one side, bad economic conditions lead to worse skill investments *in the labor market*. On the other side, bad economic conditions increase the likelihood that people postpone entering the labor market and acquire additional skills through formal education.

Next, I test the predictions of the conceptual framework using data from 19 PIAAC Survey participant countries, combined with information on national-level unemployment series. I focus on experienced prime-age workers (ages 36–59), and I leverage variation across countries in the unemployment conditions that different birth cohorts faced at different ages. In line with the conceptual framework and with existing literature (e.g. Card and Lemieux, 2001), I first show that higher unemployment rates in the late teens and early twenties lead to a higher probability of completing post-secondary education. Second, I show that, in spite of the increase in formal education, workers who faced higher unemployment rates at ages 18–25 have lower skills at ages 36–59: a one-standard deviation increase in the unemployment rates encountered at ages 18–25 leads to a decrease in numeracy skills of 10 to 14% of a standard deviation.[2]

My results also indicate that a cohort's exposure to bad initial conditions not only lowers average skills, but it also increases skill inequality. The PIAAC survey includes information on respondents' parental education, which allows me to re-estimate the previous effects separately for workers whose parents were more or less educated. In principle, if young people with less educated parents are more liquidity-constrained, their optimal responses to a macroeconomic shock could be hindered (for example, they might find extending their formal education unfeasible, or be more willing to accept any job no matter how poor its skill-development prospects). Accordingly, I find that the negative effects of bad initial conditions on long-term skills are mostly driven by workers with the least educated parents.

The set of results above hold when controlling for unemployment rates workers faced at ages 26–30 and 31–35. Importantly, unemployment rates at 26–30 and 31–35 have a much more muted and statistically insignificant impact on later skills. These results are consistent with the *initial* steps a young person takes in the labor market (as opposed to future periods) being relevant for human capital accumulation, and they suggest that labor-market-entry years (late teens and early twenties) are a sensitive skill-acquisition period.

Finally, I test a mechanism that could underlie countercyclical skill investments in the labor market: the notion that firms are heterogeneous in the skill-development opportunities they offer—an idea going back at least to Rosen (1972)—and that in bad economic times young people are more likely to match with firms that are worse along this dimension. I test this mechanism using German data and focusing on skill-development at firms of different sizes. While the PIAAC data is a single cross-section for most countries, Germany followed up their respondents and assessed their cognitive skills once again three years after the

[2] As it is common in the literature on entry conditions, I assume that there are no unobserved cohort-level characteristics that impact skill-accumulation and are correlated with the unemployment rates a cohort encounters at ages 18–25. This assumption conveys a causal interpretation to my findings.

initial survey. Using panel data on skills for German workers, I find that young people employed in large firms experienced higher skill *growth* than those employed in small firms. Since young entrants are less likely to match with large firms in bad economic times,[3] this finding could explain part of the negative relationship between unemployment conditions at entry and later skills.

A large literature exists on the negative effects of entering the labor market during a recession. Examples include Oyer (2006); Kahn (2010); Oreopoulos et al. (2012); Brunner and Kuhn (2014); Altonji et al. (2016); Fernández-Kranz and Rodríguez-Planas (2018) and Schwandt and Von Wachter (2019).[4] This paper is, to the best of my knowledge, the first to estimate the long-term effects of economic conditions during the education-work transition on workers' cognitive skills. By doing so, I provide direct evidence on mechanisms underlying the original findings in this literature, and a clear test for the human capital channel.[5]

This paper also contributes to an heterogeneous set of previous work on the relevance of early experiences in the labor market, not directly related to macroeconomic conditions. Some examples include theoretical (e.g. Jovanovic and Nyarko, 1997; Gibbons and Waldman, 2006) and empirical contributions (e.g. von Wachter and Bender, 2006; Müller and Neubaeumer, 2018; Arellano-Bover, 2020). This paper shows how early-career is a sensitive period for skill-building using actual data on cognitive skills. This is in line with what the theoretical findings in this literature, as well as with empirical results obtained using data on employment and wages.

Lastly, this paper adds to a vast literature that examines the sources of wage growth (see Rubinstein and Weiss, 2006, for a summary), by demonstrating that early shocks can persistently impact the development of skills in the long run. Rosen (1972) argued theoretically that firms can vary in the skill opportunities they provide to their workers.[6] I find supporting empirical evidence of this source of firm heterogeneity by examining firms of different sizes. Finally, while the literature on early skill-formation focuses on young children (see Cunha et al., 2006), similar forces—complementarity of skill investments, existence of sensitive periods—could be at play for young adults developing on-the-job skills. This paper's findings on the heterogeneous impacts of macroeconomic shocks at different ages are suggestive of this type of skill production function, and of the importance of early-career human capital accumulation.

[3]See Oreopoulos et al. (2012) for evidence from Canada, Brunner and Kuhn (2014) for Austria, and Arellano-Bover (2020) for Spain.

[4]In unpublished work, Wee (2016) uses a macro model to argue that entering during a recession hinders learning about comparative advantage and occupation-specific human capital accumulation. Giuliano and Spilimbergo (2013) examine the impacts of bad entry conditions on attitudes such as preferences for redistribution.

[5]Leist et al. (2014) use the Survey of Health, Ageing and Retirement in Europe to document that the cognitive functions of those aged 50–74 are worse if they experienced recessions between ages 25–49. The main differences with this paper is that i) I focus on younger and employed people (36–59), ii) specifically study unemployment conditions during the education-work transition (18–25), and iii) that the PIAAC Survey is designed to measure *skills* that are general, learnable, and useful in the workplace. Leist et al. (2014) study cognitive functions associated with old age decline (memory, orientation, simple arithmetic tasks).

[6]See Arellano-Bover (2020) and Gregory (2019) for recent empirical evidence.

The rest of this paper is organized as follows. Section 2 lays out the conceptual framework and derives the predictions that I take to the data. Section 3 describes the data sources, measurement, and outlines some stylized facts. Section 4 describes the empirical approach, and Section 5 presents the main results. Section 6 analyzes the role of firm heterogeneity using German panel data on skills. Section 7 concludes.

2 Conceptual Framework

This section presents a stylized framework relating unemployment conditions during labor-market-entry years, formal education decisions, skill investments on- and off-the-job, and skill levels later in life. Using this framework, I derive a set of predictions which I take to the data.

2.1 Setup

There are two periods, indexed by t, and one skill. A person's skill level S_t after period t depends on investments I_t and past skills S_{t-1}:

$$S_1 = f_1(I_1, S_0) \equiv S_1(I_1)$$
$$S_2 = f_2(I_2, S_1(I_1)) \equiv S_2(I_2, I_1)$$

Initial skill level S_0 is constant across people. The production function f_t is indexed by t to indicate the possibility that, for equal amounts of investment and current skills, some periods can be better suited than others to develop skills.

Each period is characterized by labor market conditions (tight/slack, boom/bust), indexed by u_t. A higher u_t indicates worse labor market conditions (the empirical analogue of u_t are unemployment rates). Investments in period 1, I_1, can be realized through either formal education, E, or through employment in the labor market, $J(u_1)$. These investments are mutually exclusive. That is, $I_1 \in \{E, J(u_1)\}$. While skill investments on-the-job vary as a function of u_t, the level of investments in formal education, E, is constant across states of the economy.

In period 2, skill investments are realized exclusively on the job. Thus, $I_2 = J(u_2)$ for all persons. Investments on the job during good and bad economic times are such that $J'(u_t) < 0$. Larger skill investments on the job during good economic times could be driven by a combination of i) matching with employers that provide better skill-development opportunities (Rosen, 1972; Oreopoulos et al., 2012; Arellano-Bover, 2020), and ii) more intense learning-by-doing during busy economic times or experiencing less gaps in employment (Gibbons and Waldman, 2006; Edin and Gustavsson, 2008).

For simplicity, I will start by assuming that $E > J(u_t)$ for any value of u_t: skill investments through formal education are always larger than those carried out on the job. This is not a key assumption and later on it will become clear what role the relationship between E and $J(u_t)$ plays.

2.2 Formal Education Choice

Assume that u_1 and u_2 are orthogonal and, thus, the choice of I_1 is independent of the expected labor market state in period 2.[7] Each person i chooses investment type in period 1, $I_1 \in \{E, J(u_1)\}$, so as to maximize:

$$V(S_{2i}) - \mathbf{1}\{I_{1i} = E\} \cdot c_i.$$

Where $\mathbf{1}\{\cdot\}$ is the indicator function, and $c_i \geq 0$ captures the heterogeneous cost of investing in formal education. This cost is distributed according to the distribution function $F(c)$ and corresponding density function $f(c)$. Heterogeneous education costs could arise from liquidity constraints, access to education financing, or information frictions. People value the amount of skills at the end of period 2, S_2, through an increasing function $V(\cdot)$. This could represent intrinsic preferences for higher skills or for their expected wage returns.

Denoting $V(I_1) \equiv V(S_2(I_2, I_1))$, the optimal decision I_{1i}^* is given by:

$$I_{1i}^* = \begin{cases} E & \text{if } c_i \leq V(E) - V(J(u_1)), \\ J(u_1) & \text{if } c_i > V(E) - V(J(u_1)). \end{cases}$$

For notational simplicity let $u \equiv u_1$, and define the cutoff value $c(u) \equiv V(E) - V(J(u))$. The fraction of young people choosing formal education is given by

$$Pr\big(I_1 = E \big| u\big) = F\big(c(u)\big).$$

Following the fact that $c'(u) > 0$, the first prediction of the model is:

$$\frac{\partial Pr\big(I_1 = E \big| u\big)}{\partial u} = \frac{\partial F\big(c(u)\big)}{\partial u} = f\big(c(u)\big) \cdot c'(u) > 0. \tag{1}$$

Prediction (1) indicates that, during bad economic times, entering the labor market early is less attractive due to diminished skill investment opportunities.[8] Thus, a positive relationship exists between unemployment rates and the fraction of people choosing formal education.

2.3 Average Skills as a Function of Initial Labor Market Conditions

The average $t = 2$ skill level as a function of initial macroeconomic conditions u is the weighted average of skills developed by those who chose $I_1 = E$ and those who chose

[7]This assumption will be more or less plausible depending on the time frequency of periods t. In any case, in the empirical analysis I explicitly hold constant future unemployment conditions.

[8]This countercyclical education response is in line with existing empirical evidence (e.g. Card and Lemieux, 2001; Petrongolo and San Segundo, 2002; Sievertsen, 2016; Atkin, 2016).

$I_1 = J(u)$:

$$\begin{aligned}\mathbf{E}\big(S_2\big|u\big) &= Pr\big(I_1 = E\big|u\big)\cdot\mathbf{E}\big(S_2\big|I_1 = E, u\big) + Pr\big(I_1 = J(u)\big|u\big)\cdot\mathbf{E}\big(S_2\big|I_1 = J(u), u\big)\\ &= F\big(c(u)\big)\cdot S_2\big(E\big) + \Big[1 - F\big(c(u)\big)\Big]\cdot S_2\big(J(u)\big).\end{aligned}$$

Where for simplicity, and given that $I_2 = J(u_2)$ for all, I have denoted $S_2(I_1) \equiv S_2(I_2, I_1)$.

The gradient between average long-term skills and initial macroeconomic conditions u is given by:

$$\frac{\partial\mathbf{E}\big(S_2\big|u\big)}{\partial u} = \underbrace{f\big(c(u)\big)c'(u)}_{\substack{\text{amount of J-to-E}\\ \text{switching}\\ >0}}\cdot\underbrace{\Big[S_2\big(E\big) - S_2\big(J(u)\big)\Big]}_{\substack{\text{skill differential}\\ \text{E vs. J}\\ >0}} + \underbrace{\Big[1 - F\big(c(u)\big)\Big]}_{\substack{\text{amount}\\ \text{choosing J}\\ >0}}\cdot\underbrace{\frac{\partial S_2\big(J(u)\big)}{\partial u}}_{\substack{\text{effect of } u \text{ on}\\ \text{J skill investment}\\ <0}} \tag{2}$$

In equation (2), the first summand is positive: it combines the skill differential that E provides with respect to $J(u)$, with the amount of people who, due to worse macroeconomic conditions, switch from choosing on-the-job investments, $J(u)$, to choosing formal education investments, E.

The second summand of (2) is negative: it combines the negative effect of unemployment conditions on on-the-job skill development, $\frac{\partial S_2(J(u))}{\partial u}$, with the fraction of people who choose this type of skill investment.

As a consequence, the relationship between early macroeconomic conditions and long-term skills is ambiguous:

$$\frac{\partial\mathbf{E}\big(S_2\big|u\big)}{\partial u} \gtreqless 0. \tag{3}$$

This ambiguity arises because, during bad economic times, on-the-job investments are lower but some people avoid them by switching to formal education. The sign in (3) will be positive if formal education provides far more skills than learning on the job, $E >> J(u)$, and enough people switch to formal education in response to higher unemployment rates. On the other hand, the sign in (3) will be negative if heterogeneity of on-the-job learning across macroeconomic conditions is sufficiently large, $\frac{\partial S_2(J(u))}{\partial u} << 0$, and the fraction of people choosing this type of skill investment is also large.

Assessing the sign and magnitude of (3) is an empirical question that I address in this paper. Note that I will be estimating $\frac{\partial\mathbf{E}(S_2|u)}{\partial u}$, the effect of early unemployment conditions on cohorts' average skills in the long run. To the extent that $\frac{\partial S_2(J(u))}{\partial u}$, the effect of early unemployment conditions on on-the-job skill learning, is an object of interest in its own right, the estimate of $\frac{\partial\mathbf{E}(S_2|u)}{\partial u}$ will be a lower bound of the negative effect $\frac{\partial S_2(J(u))}{\partial u}$.[9]

[9]This claim is based on the signs assigned in equation (2) and the fact that, rearranging:

$$\frac{\partial S_2(J(u))}{\partial u} = \frac{1}{1 - F\big(c(u)\big)}\cdot\Big[\frac{\partial\mathbf{E}(S_2|u)}{\partial u} - f(c(u))c'(u)\cdot\big[S_2(E) - S_2\big(J(u)\big)\big]\Big]$$

2.4 Heterogeneity across Education Costs

The framework indicates that the two opposing forces present in equation (2) have a differential impact across the distribution of formal education costs, c_i. Consider a rise in initial unemployment conditions u and the resulting effects on average skills for groups of people with different levels of c_i. Those with the lowest costs, who would always choose formal education ("always-takers"), would be unaffected. Those with the highest costs, who would always choose to enter the labor market ("never-takers"), would *only* be affected by the negative impact of $\frac{\partial S_2(J(u))}{\partial u}$. Those around the marginal values of c_i would experience the negative impacts of $\frac{\partial S_2(J(u))}{\partial u}$ but would also be cushioned (as a group) by the people who switch to formal education and experience the skills boost implied by $\left[S_2(E) - S_2(J(u))\right]$.

This discussion suggests that negative shocks to macroeconomic conditions at entry, u, have the largest negative impacts on the skill-development of those with higher costs of entering formal education. I will test this prediction using parental education as a proxy for costs, c_i. This test builds upon the notion that costs such as liquidity constraints, access to finance, or information frictions are more prevalent for young people from more disadvantaged backgrounds.

3 Data and Measurement

The empirical analysis combines two types of data: the PIAAC Survey on Adult Skills, and national unemployment time series for 19 countries drawn from various sources.

3.1 PIAAC Survey on Adult Skills

This survey, carried out by the OECD in different member and non-member countries, is aimed at measuring information-processing competencies of the target population: non-institutionalized 16-65 year-olds residing in each country at the time of data collection. The survey is designed to measure cognitive skills that are useful, general, learnable, and relevant for the workplace. Sample sizes vary across countries but are typically in the range of 5,000–6,000 people. While the survey is planned to have more rounds in the future, this paper uses cross-sections from participating countries of the first two rounds, which took place in 2011-2012 and 2014-2015.[10]

Survey respondents were interviewed at home and filled out a questionnaire which includes information on their demographics, education, and labor market outcomes. Respondents also completed an assessment that measures three types of skills using item response theory: numeracy, literacy, and problem-solving in technology-rich environments. Since some countries did not measure problem-solving skills, I focus on numeracy and literacy skills.

[10] Round 1 (2011-12) participating countries were Australia, Austria, Belgium (Flanders), Canada, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Ireland, Italy, Japan, Korea, Netherlands, Norway, Poland, Russian Federation, Slovak Republic, Spain, Sweden, United Kingdom (England and Northern Ireland), and USA. Round 2 (2014-15) participating countries were Chile, Greece, Israel, Lithuania, New Zealand, Singapore, Slovenia, and Turkey. I use data for 19 out of these 33 countries for reasons I explain below.

What do PIAAC skills measure?

The PIAAC survey is designed to measure "*key information-processing skills*", i.e., those "*necessary for fully integrating and participating in the labour market, education and training, and social and civic life; [...] highly transferable, in that they are relevant to many social contexts and work situations; and "learnable" and, therefore subject to the influence of policy*" (OECD, 2013). These measures intend to capture cognitive skills that are general, learnable, and work-relevant.

The two skill measures I study in this paper are categorized as numeracy and literacy skills. The definition provided by OECD (2013) for numeracy skills is "*the ability to access, use, interpret and communicate mathematical information and ideas.*". The definition of literacy skills is the "*ability to understand, evaluate, use and engage with written texts.*"

Skills are measured through item response theory, with an adaptive assessment carried out either in a computer or by hand. Some of the practice questions relate to real life work situations. For instance, in the numeracy assessment these situations might include "*completing purchase orders; totalling receipts; calculating change; managing schedules, budgets and project resources; using spreadsheets; organising and packing goods of different shapes; completing and interpreting control charts; making and recording measurements; reading blueprints; tracking expenditures; predicting costs; and applying formulas*" (OECD, 2013). Appendix Figure A1 shows an example question of the numeracy assessment.

In addition to the stated goals of the assessment, there is independent evidence showing that skills measured by PIAAC are highly relevant for work and the labor market. Hanushek et al. (2015) show that skills measured by PIAAC are strongly correlated with wages, even when keeping constant years of schooling. In addition, the observed age profile of skills resembles the typical "hump" shape observed in wage age profiles. Figure 1 shows the age profile for numeracy skills, with skills peaking in the mid thirties.[11] If instead of work-relevant skills PIAAC were capturing general knowledge learned at school, one would have expected to see a different shape (for instance, a monotone function with negative slope).

Sample Selection

The analysis focuses on a subset of PIAAC-participating countries. Two reasons drive inclusion into the sample. The first is data availability: several countries' microdata is either not publicly available, or its public-use version does not include respondents' age, critical for my analysis.[12] Countries excluded for this reason are Austria, Australia, Canada, New Zealand, Singapore, and USA. Second, I exclude former socialist states since no unemployment data exists for these countries prior to the 1990s, and my analysis uses data going significantly further back in time.[13] Countries excluded for this reason are the Czech Republic,

[11] Since I use a single cross-section, the patterns of Figure 1 might combine age and cohort effects. Appendix Figure A2 shows a similar pattern for literacy skills.

[12] Rather than providing age, these countries report age brackets.

[13] Unemployment in these communist states factually and/or officially did not exist.

Estonia, Lithuania, Poland, Russia, Slovakia, and Slovenia. My final sample is composed of survey respondents from 19 countries: Belgium, Chile, Cyprus, Denmark, Finland, France, Germany, Greece, Ireland, Israel, Italy, Japan, Korea, Netherlands, Norway, Spain, Sweden, Turkey, and UK.[14]

Among the respondents of these 19 countries, my empirical analysis focuses on employed workers aged 36 to 59.[15] I focus on those over age 35 since i) I can observe the macroeconomic conditions they faced at different stages of their working life (18-25, 26-30, 31-35), and ii) it is plausible that the most important skill-development phase is over by age 36 (Salthouse, 2009). I do not include workers aged over 59 because retirement starts to be prevalent, and because few countries have unemployment time series going sufficiently back in time to observe economic conditions at the beginning of the working life of these cohorts.

I further exclude from the sample non-natives who moved to their country of residence after age 18 (for those born abroad, the survey reports age of migration). These excluded workers were exposed to different labor market conditions, and generally I do not observe their country of birth, which prevents me from assigning them to their relevant initial labor market.

A potential concern related to sample composition arises if high unemployment rates at ages 18–25 lead young people to migrate internationally, and do so differentially by skill level. This would affect my estimates if such international migrants are "missing" from my sample. However, it would pose no problem if people migrate when young for a few years while macroeconomic conditions are bad, and then return to their country of origin in time to show up in the PIAAC survey by ages 36–59. These concerns should be less worrying once we take into account that international migration is a rare event (much more infrequent than within-country migration), and that among the small number of young people who migrate internationally many return to their countries of origin after a few years. This last point might apply especially for those who leave *because of* bad macroeconomic conditions. In Section 5, I formally test for and find no relationship between unemployment rates faced at 18–25 and cohort size in my sample.

Table 1 shows summary statistics for my analysis sample, a total of 37,160 respondents from 19 countries and 24 different ages. For workers in my sample the average age is 46.5, 43% are women, 62% are private sector workers, 21% are public sector workers, and 18% are self-employed.

Panel PIAAC data for Germany

Germany is the only PIAAC country which followed up their respondents over time, providing a unique opportunity to use panel data in this setting. The baseline PIAAC sur-

[14] In Belgium, only Flandes participated in the survey. In the UK, only England and Northern Ireland participated. My sample does not include survey respondents from East Germany.

[15] I later show that results are robust to focusing on employed and unemployed persons. I also show that the "treatment" of interest—unemployment rates experienced at ages 18–25, 26–30, 31–35—does not impact labor force participation at the time of the survey. This allays potential concerns of endogenous sample selection.

vey was carried out in Germany between 2011 and 2012. Follow-up waves were carried out in 2014, 2015, and 2016, with the skills assessment carried out for a second time only in the 2015 follow-up. This provides a two-period panel on individuals' skills in Germany. I use these data to measure skill *growth* and study mechanisms in Section 6.

3.2 National Unemployment Time Series

I measure labor market conditions using unemployment rates at the national level. In order to observe the labor market conditions that workers aged 36-59 in 2011-2015 faced during their labor-market-entry years, I need time series that go back in time to the late 1960s–early 1970s. I gathered these time series from various sources, listed in Table 2.

Table 2 also lists, for each country, the beginning and end year of the time series. The criteria for how many years to include in the unemployment series is i) to go forward up until the year in which the respective PIAAC survey began (listed in Table 2), and ii) go back just far enough to compute the unemployment rate that the oldest workers in my sample faced at age 18. For Chile and Greece the data do not go back far enough; I go as far back as the data allow, and the sample excludes the oldest cohorts in these two countries.

Measurement and Descriptives

I use data from 19 countries with different labor market characteristics and institutions. In such a setting, the same unemployment rate level can represent very different labor market conditions in different countries: an unemployment rate of 8% can represent good economic times in Spain and bad times in Japan.

I normalize the unemployment time series in a way that makes its units comparable across countries. I do this by separately standardizing each country's time series, so that the unemployment rate in a given country and year is expressed in terms of country-specific standard deviations.[16] For the remainder of the paper "unemployment rate" refers to the standardized measure, unless stated otherwise. Figure 2 shows the unemployment time series of each country.[17]

My empirical approach relies on the existence of sufficient variation across countries in the timing of good and bad labor market conditions. While this variation is already visible in Figure 2, Figure 3 makes it more explicit. Panel (a) combines all the separate time series in the same figure: it is visually apparent that for each year some countries are doing well while others are not. Panel (b) condenses this information by showing, year by year, the 75th, 50th, and 25th percentiles of the unemployment distribution. The interquartile range oscillates between 0.5 and 1.75 standard deviations.

[16] That is, let u_{ct} be the unemployment rate in country c and year t. The standardized measure is given by $\tilde{u}_{ct} = \frac{u_{ct} - \bar{u}_c}{\sigma_c^u}$, where $\bar{u}_c$ is the average unemployment rate in country c (averaged over the years listed in Table 2), and σ_c^u is the standard deviation of the unemployment rate in country c (over the years listed in Table 2).

[17] Appendix Figure A3 shows the time series in levels. As a robustness test, I later show that results are comparable when using (i) unemployment rates without standardization, or (ii) when measuring standardized unemployment rates as deviations from a country-specific linear time trend. This last measure implies not using within-country variation in unemployment rates that can be explained by a secular trend.

The variation in countries' unemployment time series translates into variation in the unemployment rates that different cohorts in different countries faced during their labor-market-entry years. Figure 4 shows the average level of unemployment that each cohort in each country faced between the ages of 18-25 (the main variable of interest in the empirical analysis). The figure summarizes the variation used in the analysis: for different countries, different cohorts faced good or bad economic conditions between ages 18-25, and the time (cohort) trends are different across countries.

I focus on ages 18–25, an age range in which the majority of people from different countries and different education levels make the education-to-work transition and spend their first few years in the labor market. Previous work on the impact of recessions while young has also focused on this age range (e.g. Giuliano and Spilimbergo, 2013).

4 Empirical Approach

Using the sample of 36–59 year-olds and leveraging variation across countries in the labor market conditions faced by different cohorts at different ages, I estimate the following model via OLS:

$$y_{ic} = \beta u_{a(i)c}^{18-25} + \delta_c + \delta_{a(i)} + \delta_c a(i) + \delta_c a(i)^2 + X_i'\gamma + \varepsilon_{ic}. \quad (4)$$

Where i indexes people, c countries, and a ages. The outcome y_{ic} is person i's skill level (numeracy or literacy), and $u_{a(i)c}^{18-25}$ is the average unemployment rate that i faced in her country of residence between ages 18-25. Country fixed effects δ_c control for any cross-country differences in skill levels that are common across cohorts. Age fixed effects $\delta_{a(i)}$ flexibly allow for any age effects on cognitive skills that are common across countries. Country-specific quadratic age trends $\delta_c a(i) + \delta_c a(i)^2$ control for any country-specific secular patterns in the skill-age profile that could be driven, for instance, by chances in education institutions. Lastly, X_i is a set of predetermined controls (gender, parents' education, and birthplace).

The parameter of interest is β, which captures deviations from country-specific quadratic age trends in country- and age-demeaned skill levels that are associated with country-age-specific variation in unemployment rates faced between ages 18-25. Since u^{18-25} is measured in terms of country-specific standard deviations, β measures the effect on skill levels of a one-standard deviation increase in the average unemployment rate people faced in their country of residence between ages 18–25.

Note that β captures the effect of experiencing higher unemployment between ages 18–25, *given the typical subsequent evolution* of unemployment rates. An alternative is to explicitly control for the subsequent evolution of economic conditions:

$$y_{ic} = \beta_1 u_{a(i)c}^{18-25} + \beta_2 u_{a(i)c}^{26-30} + \beta_3 u_{a(i)c}^{31-35} + \delta_c + \delta_{a(i)} + \delta_c a(i) + \delta_c a(i)^2 + X_i'\gamma + \varepsilon_{ic}. \quad (5)$$

In this specification, β_1 captures the effect of higher unemployment between ages 18–25, *keeping constant* unemployment experienced between ages 26–35. Estimating β_1, β_2, and β_3

is also informative for understanding which periods are more sensitive for skill development. If skill investments in the late-teens and early-twenties are more relevant than those in the late-twenties and early-thirties, we would expect β_1 to be larger in magnitude than β_2 and β_3.

I estimate equations (4) and (5) through OLS using survey weights and clustering standard errors at the country-age level (Abadie et al., 2017). Standard errors are further adjusted to take into account that skills are measured through multiple plausible values (following the procedure from OECD, 2013).

Measurement error might bias estimates towards zero since I infer the country in which someone lived at ages 18–25 (and 26–30) from country of birth, and country of residence at the time of the survey (ages 36-59). If a person was born in country A, migrated when young to country B, and then returned to country A before the survey date, I would misclassify the labor market conditions she faced when young. Excluding non-natives who migrated after age 18 diminishes this concern, but misclassification is still possible for those who migrated more than once in the past.

5 Results

5.1 Education Responses

I begin by testing the first prediction of the conceptual framework in Section 2: in bad economic times, young people on the education-work transition years will be more likely to get additional formal education.

Table 3 shows estimates of β in equation (4) using as outcome dummy variables for the completion of two incremental levels of education: post-secondary education and college education. Table 1 shows that 39% of sample respondents have completed post-secondary education while 24% have completed a college education (those with a college education are a subset of those with a post-secondary education). Different columns of the two panels in Table 3 show results when using as explanatory variable unemployment experienced at different ages: 16, 17, 18, and the 18–25 average.[18]

A one-standard deviation increase in unemployment rates faced at ages 16 and 17 has a positive impact on the probability of post-secondary education completion, with estimates equal to 0.027 and 0.025 (6–7% of the sample mean). A one-standard deviation increase in unemployment rates at age 18 has a positive impact on both post-secondary and college completion, with estimates equal to 0.013 and 0.010 respectively (3% and 4% of the respective sample means). When averaging unemployment rates between ages 18–25 point estimates are still positive (0.008 and 0.013) but imprecisely estimated.

[18] Sample sizes are reduced when going back before age 18 due to lack of data on unemployment experienced by the oldest cohorts at ages 16 and 17.

Heterogeneity by Parental Education

In Table 4 I re-estimate the above parameters, allowing them to vary across three categories of parental education.[19] The education choices of people with parents with the highest education level are more responsive to unemployment conditions, especially at ages 18 and above. The college education responses to unemployment are exclusively driven by workers whose parents were in the highest education group. As the framework in Section 2 argues, this heterogeneity could come from heterogeneous costs of accessing education. Young people from all socioeconomic backgrounds might realize there is a lower opportunity cost of higher education in bad economic times, but only those from better-off families might have the means or access to credit to invest in additional education and cushion the blow.

Overall, the data align with the prediction that cohorts of young people who face worse labor market prospects during their late teens and early twenties will be more likely to invest in additional education. This holds on average, it is equally spread across socioeconomic groups for post-secondary education during ages 16–17, and it is disproportionately driven by young people with higher socioeconomic status for ages 18 and above for college investments.

5.2 Numeracy Skills at Ages 36–59

Next, I test for the sign and magnitude of the second prediction in the conceptual framework, the gradient between average later skills and initial conditions. Table 5 shows results from estimating equation (4), using numeracy skills as outcome variable (left panel). The first column does not include any controls, while the second column controls for respondents' gender, parents' education, and native-born status.

The estimates of β in these two columns are negative, equal to -4.63 and -5.40 respectively. These estimates correspond to around 2% of the numeracy skills sample mean, and 9–10% of its standard deviation.

The third and fourth columns of Table 5 show estimates of equation (5). The estimates of β_1 (capturing the effect of unemployment at ages 18–25) are also negative and larger in magnitude than when not controlling for subsequent unemployment rates. They are equal to -6.16 and -7.29 (2.3%–2.7% of the sample mean, 11.8%–14% of the standard deviation), without and with controls, respectively.

Interestingly, the estimates of β_2 (unemployment through ages 26–30) and β_3 (unemployment through ages 31–35) are quite smaller in magnitude, and none of them are statistically different from zero. Estimates of β_2 are equal to -0.87 and -1.29. Estimates of β_3 are equal to -2.14 and -1.89.

[19] PIAAC reports respondents' parental education in three categories using ISCED97 (1997 International Standard Classification of Education). Low parental education corresponds to ISCED 1, 2, and 3C short. Medium corresponds to ISCED 3C short, and 4. High corresponds to ISCED 5 and 6. I assign each respondent the maximum level of education among her two parents. Table 1 shows that 49% of the sample had parents in the low education category, 33% in the medium category, and 18% in the high category.

Overall, the left panel of Table 5 indicates that those workers who face higher unemployment rates when aged 18–25, even if they are more likely to get post-secondary education, have lower skill levels when aged 36–59. These negative effects are moderately sized: 2% of the sample mean and 10–14% of the standard deviation. Going back to the conceptual framework, these negative effects are consistent with significant heterogeneity of on-the-job skill investments across good and bad macroeconomic times (i.e., $\frac{\partial S_2(J(u))}{\partial u} << 0$).

Table 5 also documents more muted impacts of unemployment faced between ages 26-35, with estimated effects that are between 4 and 8 times smaller in magnitude than the effect of unemployment at ages 18–25. This finding is consistent with a skill-formation model in which human capital investments at different periods complement each other, and the early years in the labor market are a sensitive period of skill acquisition.

5.3 Literacy Skills at Ages 36–59

The right panel of Table 5 shows estimation results for equations (4) and (5) using literacy skills as an outcome variable. The pattern that arises is similar to the one in numerical skills, but point estimates are smaller in magnitude and estimates of β or β_1 are only statistically significant at the 10% level (with controls). We still see negative effects of unemployment at ages 18–25 (point estimates between -3.42 and -5.41; 1.3%–2% of the sample mean, or 7.3%–11.5% of the standard deviation), and much more muted effects for ages 26–30 and 31–35 (point estimates equal to -0.88 and -1.06, and equal to -1.23 and -1.11, respectively).[20]

5.4 Skills Inequality: Heterogeneity by Parental Education

To better understand how skill losses are distributed, I re-estimate equations (4) and (5) letting the parameters β, β_1, β_2, and β_3 vary across survey respondents based on the level of education of their parents. The conceptual framework from Section 2 suggests that those with higher education costs (which are plausibly related to lower parental education) should bear disproportionately negative effects. Following the categorization in PIAAC data, I use three categories of parental education, which I denote as low, medium, and high.[21] Table 1 shows that 49% of respondents had parents with low level of education, 33% with medium, and 18% with high.

Table 6 shows results for the parameters of interest interacted with parental education. The effects of initial unemployment rates on skills in the long run are not evenly distributed. Workers whose parents were the least educated are the most affected, with point estimates that are 26–36% higher in absolute value than those from the pooled sample (for both numerical and literacy skills). Estimates for the lowest parental education group are also the only ones that remain statistically significant. The fact that young people from less advantaged backgrounds are most negatively impacted suggests that cohorts exposed to an

[20] Interestingly, more muted effects in literacy test scores with respect to numeracy test scores is a common result in the economics of education literature (children's test scores) across a wide variety of treatments, policies, or interventions (see, for instance, Chetty et al., 2014).

[21] See footnote 19.

unemployment shock during the education-to-work transition end up not only with lower average skills, but also with higher skills inequality.

Liquidity constraints are a potential reason why young people from more disadvantaged backgrounds have higher skills losses. In the face of bad macroeconomic conditions at labor-market-entry years, liquidity constraints might make people less able to respond by obtaining more formal education. The evidence from Table 4 is consistent with this mechanism. Further, family liquidity constraints might influence the choice of the first job (Coffman et al., 2019), making disadvantaged young people more willing to accept any job regardless of potentially poor skill-development prospects.

5.5 Robustness Tests

I perform a variety of robustness tests for the results of Tables 5 (main results) and 6 (heterogeneity by parental education). I also show that the "treatment" of interest does not seem to move people in or out of the sample (through contemporaneous employment or labor force participation).

Alternative unemployment measure: Deviations from country-specific linear trend

I use an alternative measure of macroeconomic conditions to address the potential concern that, in the same way that unemployment levels across countries might not be comparable (which justifies the standardization), the same might happen within a country across distant periods of time. I thus measure (standardized) unemployment in deviations from a country-specific linear trend. That is, I ignore any variation in a country's unemployment that is explained by a secular linear trajectory. Appendix Tables A1 and A2 show estimates analogous to those of Tables 5 and 6, obtained using this alternative measure of unemployment. The results are very similar to baseline, reflecting the fact that the empirical model already does a good job controlling for country-specific trends and such trends are not driving my results.

Alternative unemployment measure: No standardization

Section 3 points out the rationale for standardizing unemployment rates. In any case, it might be reassuring to see that similar results hold when using measures of "raw" unemployment levels. Appendix Tables A3 and A4 show results equivalent to those of Tables 5 and 6 obtained using non-standardized unemployment rates (shown in Appendix Figure A3). Although without standardization the magnitudes have a less clear interpretation, the qualitative patterns remain the same (although estimated with less precision): negative effects of unemployment at ages 18–25, more muted impacts from unemployment at ages 26–30 and 31–35, and a gradient based on parental education where those with the least educated parents experience the larger skill losses.

Alternative sample: All active persons

The baseline sample focuses on employed workers. Unemployed workers, especially the long-term unemployed, might have experienced skill losses that make their skill assessment not comparable to employed workers. In any case, Appendix Tables A5 and A6 show that results are very similar when including unemployed workers in the sample. Point estimates are very similar to baseline although estimated less precisely. The main qualitative patterns (early vs. late conditions) and heterogeneous results by parents' education remain unchanged.

Potential effects on labor force participation

Sample composition could be endogenously determined if unemployment conditions at labor-market entry impact labor force participation at ages 36–59. I test formally for this possibility by estimating models equivalent to those in equations (4) and (5), where the outcome variable is a dummy for labor force participation (using the sample of all persons). Given differences across genders in labor force participation, I show results for all persons and separately for men and women. Appendix Table A7 shows results for this test. The estimated effects are very close to zero, both for men and women, and we cannot reject that they are zero at conventional significance levels. This suggests that the variation in unemployment conditions at entry that I use in my main analysis is not determinant for whether someone will be part of the labor force or not in the long run.

Test for endogenous sample selection due to migration

Lastly, I test for the possibility that unemployment rates when young lead to international migration. In principle, differential migration by high-skilled people as a response to high unemployment could lead to part of the main results being driven by sample composition effects. In such a scenario, we would expect a negative relationship between the unemployment conditions a cohort faces when young and its size at the time of the survey. I perform this test estimating specifications (4) and (5) at the cohort level (i.e., the interaction of country and age), where the outcome variable is survey-weighted cohort size.

Appendix Table A8 shows results for this test. For two cohort size definitions (those employed, or those in the labor force) and for both specifications (4) and (5), estimates of β, β_1, β_2, and β_3 are small and statistically insignificant. I perform tests of the null of β, β_1, β_2, and β_3 being jointly equal to zero and, across specifications, the p-values range between 0.42–0.79. Overall, the data fail to reject a zero relationship between cohort size and unemployment conditions when young.

6 A Mechanism: Differential Skill Growth by Firm Size

In this section I provide evidence consistent with some of the mechanisms discussed in Section 2. In the model, on-the-job human capital accumulation is heterogeneous across bad and good states of the economy. This differential could be due to bad economic times being associated with working less intensively and/or matching with employers that provide worse skill-development opportunities.

While the relationship between employment gaps and human capital accumulation is present in many models of the labor market and has been tested empirically (e.g. Edin and Gustavsson, 2008), we know very little about whether and how on-the-job skill accumulation differs across heterogeneous firms.[22] For a given worker, different firms could provide very different opportunities for skill development due to differences in firm productivity, technology, training policies, or coworkers.

Using the panel PIAAC data for Germany, I test whether skill *growth* differs across workers who are employed at firms of different sizes, where size is measured as number of employees. Why focus on firm size? First, evidence from a variety of contexts shows that in good economic times young workers are more likely to find their first job at large firms (Oreopoulos et al., 2012; Brunner and Kuhn, 2014; Arellano-Bover, 2020). The cyclicality of large- vs. small-firm hiring of young workers makes firm size a candidate mechanism in explaining the long-term skill results. Second, firm-size differentials have long been studied in the literature and the evidence indicates that firm size is positively associated with worker training, productivity, managerial quality, or technology adoption. Arellano-Bover (2020) shows evidence consistent with young workers having better on-the-job skill development at large firms (using data on wages, not skills).

6.1 Descriptive Motivation

Figure 5, panel (a) uses 2012 PIAAC data to plot the average numeracy skills in Germany by age group and firm size. We can see that higher-skilled workers are selected into the largest firms. Interestingly, the skill-size gradient is more pronounced for older workers (36–59) compared to younger ones (18–35). To the extent that this pattern is (at least in part) driven by age effects, it suggests two things: (i) as time in the labor market increases, more skilled workers sort into larger firms (Haltiwanger et al., 2018); and/or (ii) workers experience higher skill growth when employed in large firms. I formally test the latter hypothesis using panel data on the skills of German workers.

6.2 Estimating Skill Growth Differentials by Firm Size

The German panel PIAAC data allows me to observe two different skill assessments for each person—one in 2012 and another one in 2015. I also observe (in intervals) the size of the firm where the worker was employed in 2012. Using private-sector workers of all ages, I estimate the following regression (where firms with 1–10 employees are the omitted category):

$$y_{it} = \delta^{11-50}_{J(i,t-1)} + \delta^{51-250}_{J(i,t-1)} + \delta^{251-1000}_{J(i,t-1)} + \delta^{>1000}_{J(i,t-1)} + \theta y_{i,t-1} + X'_{i,t-1}\gamma + \varepsilon_{it}. \tag{6}$$

[22] This is an idea put forward theoretically by Rosen (1972). See Arellano-Bover (2020) and Gregory (2019) for recent empirical evidence.

Where y_{it} is the (numeracy or literacy) skill level of worker i in 2015. $J(i,t-1)$ indexes the firm where i was employed in 2012, and $\delta^k_{J(i,t-1)} \equiv \delta^k \cdot \mathbf{1}\{size_{J(i,t-1)} \in k\}$ for $k \in \{$11–50, 51–250, 251–1000, $>$1000$\}$. $y_{i,t-1}$ represents skill on 2012, and $X_{i,t-1}$ are covariates including gender, age, and industry of firm $J(i,t-1)$.

Given the specification in equation (6), the δ parameters have the following interpretation (omitting covariates $X_{i,t-1}$ for simplicity):

$$\delta^k = E\left(y_{it}|size_{J(i,t-1)} \in k, y_{i,t-1}\right) - E\left(y_{it}|size_{J(i,t-1)} \in [1-10], y_{i,t-1}\right)$$

That is, keeping constant skill level in 2012, δ^k captures the differential skill increase in 2015 associated with being employed in a firm of size category k, relative to being employed in a firm of the smallest size category.

To allow for the fact that human capital accumulation is likely more relevant for young people, I augment (6) to let the firm-size differentials in skill growth vary across workers' age (normalized with respect to age 18):

$$y_{it} = \sum_k \left[\delta^k_{J(i,t-1)} + \phi^k_{J(i,t-1)} \cdot (age_{i,t-1} - 18)\right] + \theta y_{i,t-1} + X'_{i,t-1}\gamma + \varepsilon_{it}. \quad (7)$$

I now have the following age-varying differentials, with δ^k capturing the differential for those who are age 18, and ϕ^k capturing the (linear) age gradient of these differentials:

$$\delta^k + (a-18)\cdot\phi^k =$$
$$E\left(y_{it}|size_{J(i,t-1)} \in k, y_{i,t-1}, age_{i,t-1} = a\right) - E\left(y_{it}|size_{J(i,t-1)} \in [1-10], y_{i,t-1}, age_{i,t-1} = a\right)$$

6.3 Skill Growth Differentials by Firm Size: Results

Table 7 shows estimation results of equations (6) and (7) for numeracy skills. Estimates of equation (6), which imposes a common firm-size differential for workers of all ages, are small and not statistically different from zero. The results are quite different, however, for equation (7) which allows the differential to vary with age. In columns 3 and 4 (with and without industry fixed effects) we can see positive and sizable point estimates (21.89 and 20.95) for the largest firms ($>$1,000 workers) for 18 year old workers, and a declining effect of age (-0.89 and -0.87). This suggests that numeracy skill growth is more pronounced at large firms, in a way that varies across workers' age. As expected, younger workers are most impacted by the type of firm in which they find themselves. The similarity of the estimates in columns 3 and 4 imply that controlling for seven broad industry categories does not impact the main conclusion.

Differential growth across firm size is not as pronounced for literacy skills. Appendix Table A9 shows estimation results of equations (6) and (7) for literacy skills. Point estimates for young workers at the largest firm categories (251–1000 and $>$1,000) are positive but smaller in magnitude and not statistically significant (9.25 and 6.12 without industry fixed effects). This goes in line with the more muted impacts on literacy skills in Section 5, and it could be due to the numeracy skills assessment being more heavy on work-related tasks than the literacy one.

Figure 5 panel (b) uses the estimates from Table 7 to show the estimated differentials in skill growth by firm size and worker age, for workers in their early-career experiences (ages 18–25). The differential skill growth of between 15–20 units, relative to that occurring in the smallest firms (1–10 employees) is quite sizable, equal to 5% to 6% of the average skill of young workers in large firms (see Figure 5 panel (a)).[23]

These result suggest that young workers enjoy better skill-development opportunities at large firms. This result is consistent with previous evidence on wages and employment (von Wachter and Bender, 2006; Müller and Neubaeumer, 2018; Arellano-Bover, 2020).

6.4 Skill Growth Differentials: Robustness

Restricting the sample to "stayers"

The previous estimates are obtained assigning workers the size of their employer in 2012, irrespectively of whether they change jobs or not between 2012 and 2015. Appendix Table A10 shows estimates restricting the sample to those who do not change jobs between 2012 and 2015 ("stayers"). Results are very similar to those from baseline in Table 7, but slightly larger in magnitude. Larger estimates for stayers are consistent with the interpretation of better skill development opportunities at large firms, since stayers have had a longer time spent at a large firm between survey waves.

Skill Changes as Outcome Variable

An alternative to equation (6) is the following:

$$\Delta y_{it} = \delta^{11-50}_{J(i,t-1)} + \delta^{51-250}_{J(i,t-1)} + \delta^{251-1000}_{J(i,t-1)} + \delta^{>1000}_{J(i,t-1)} + X'_{i,t-1}\gamma + \varepsilon_{it}. \tag{8}$$

An alternative to equation (7) is the following:

$$\Delta y_{it} = \sum_k \left[\delta^k_{J(i,t-1)} + \phi^k_{J(i,t-1)} \cdot (age_{i,t-1} - 18)\right] + X'_{i,t-1}\gamma + \varepsilon_{it}, \tag{9}$$

where Δy_{it} is a change in levels ($\Delta y_{it} = y_{it} - y_{i,t-1}$) or in percentage terms ($\Delta y_{it} = 100 \cdot (y_{it} - y_{i,t-1})/y_{i,t-1}$). Appendix Tables A11 and A12 show numeracy skills estimation results for equations (8) and (9) using changes in level and percentage terms respectively. The interpretation of the results is very similar in this case. When measuring Δy_{it} in levels, results in Appendix Table A11 are very similar in magnitude to baseline ones in Table 7. When measuring Δy_{it} as a percentage increase, we see a similar qualitative pattern. In terms of magnitudes, Appendix Table A12 estimates indicate that young workers (age 18) at the largest set of firms experience numeracy skills growth that is around 7 percentage points higher than those at the smallest firms.

[23] Appendix Figure A5 plots the >1,000 differential together with confidence intervals.

7 Conclusion

A growing body of evidence suggests that, from a lifetime perspective, the early years in the labor market can be critical for young people. The literature has shown that entering in bad or good macroeconomic times, or in one type of firm or another, can have long-lasting impacts for young workers. While a human capital explanation has been suggested as a potential channel, no previous work has tested for a link between early labor market circumstances and later measures of workers' skills. This paper aims to fill this gap in the literature.

Using international data from the PIAAC Survey of Adult Skills, I have documented how experienced workers who faced worse economic conditions during their education-to-work transition do systematically worse in terms of cognitive skills assessments. Interestingly, this effect arises even though these groups of workers were more likely to obtain post-secondary education in response to bad economic conditions. Further, the impacts of unemployment conditions at the beginning of the working life (18–25), are much more important than impacts of unemployment conditions at later ages (26–35). Finally, these long-term negative effects are most felt by workers whose parents were less educated. This suggests that, whenever a cohort experiences a high-unemployment shock during labor-market entry, the decrease in the cohort's long-run average skill level is accompanied by an increase in within-cohort skill inequality.

A simple conceptual framework rationalizes these findings by a combination of i) on-the-job skill investments being quantitatively important and sufficiently heterogeneous across good and bad economic times; and ii) *early*-career investments being key either through dynamic complementarities, and/or the early twenties being a critical period to develop on-the-job skills. Evidence from German panel data examining differential skill growth across firms of different sizes is consistent with these explanations. This evidence suggests that firm heterogeneity in skill-development opportunities together with worker-firm matches that vary across the business cycle play a role in explaining the long-term skill effects.

Overall, by showing direct evidence of an underlying human capital channel, this paper shows how labor market frictions do not fully explain the long-term wage losses arising from entry in bad labor market conditions. We might want any policies that are designed to support young people exposed to negative shocks in their entry years to be designed keeping these skill losses in mind and trying to remedy them.

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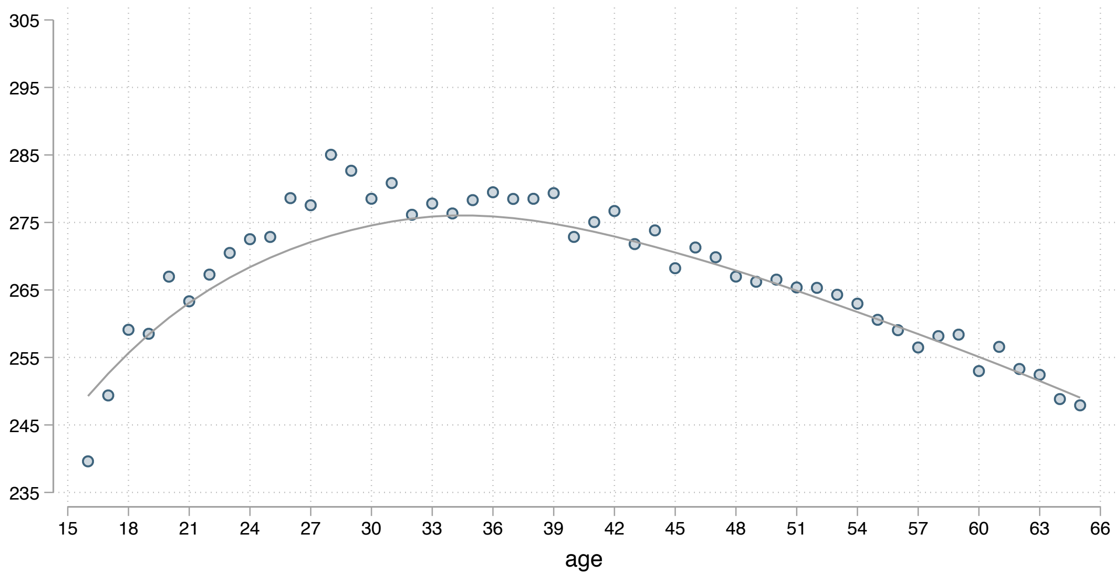
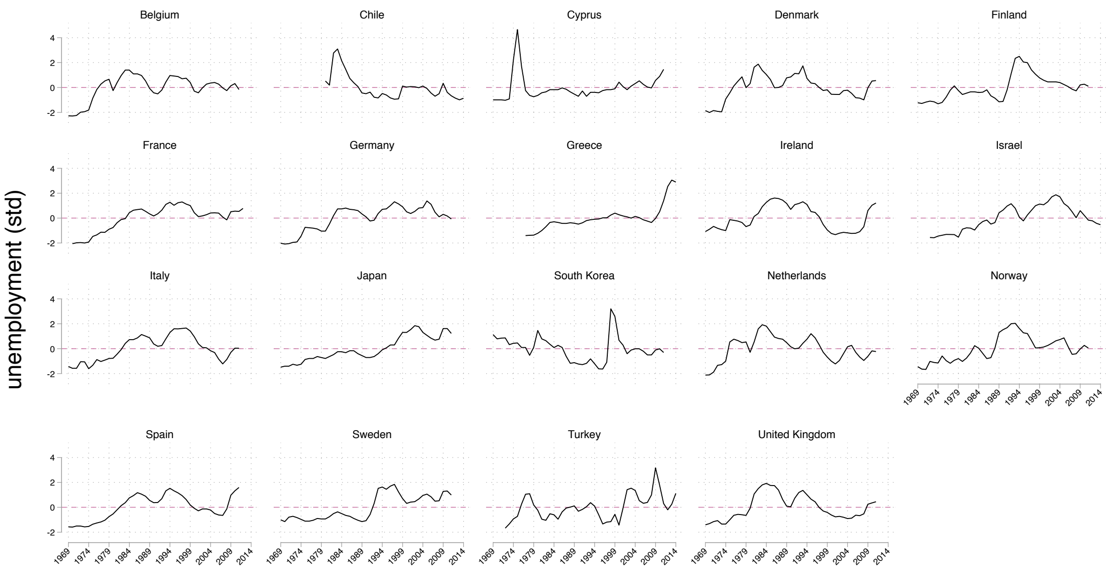
Figures and Tables

Figure 1: Average Numeracy Skills by Age



Notes: Average numeracy skills by age, and local linear regression smoother. Employed workers who were born in their country of residence or migrated there before age 18. PIAAC respondents from countries listed in Table 1. Appendix Figure A2 shows a similar figure for literacy skills.

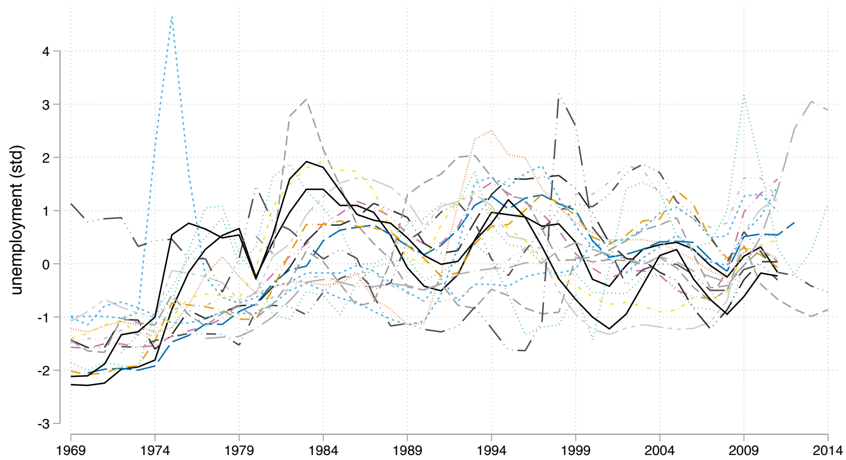
Figure 2: National Standardized Unemployment Time Series By Country



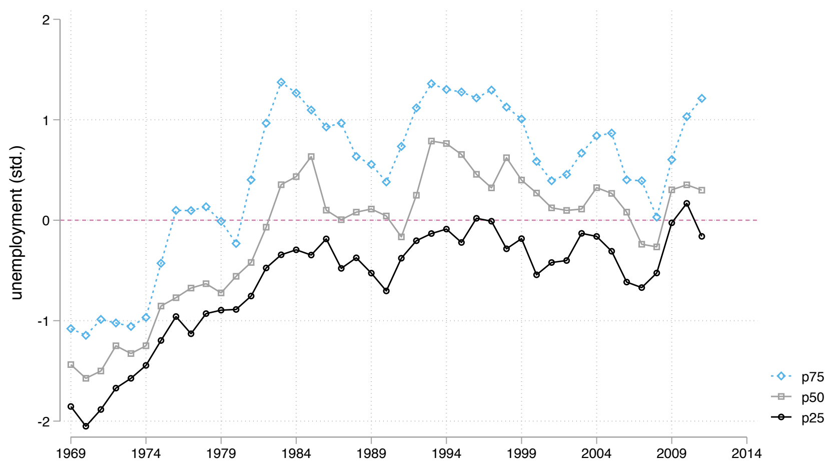
Notes: Unemployment time series for each country in the sample. Units are country-specific standard deviations. Table 2 lists the source for each country. Appendix Figure A3 shows the same figure in levels.

Figure 3: Cross-Country Variation in Unemployment Time Series

(a) All countries

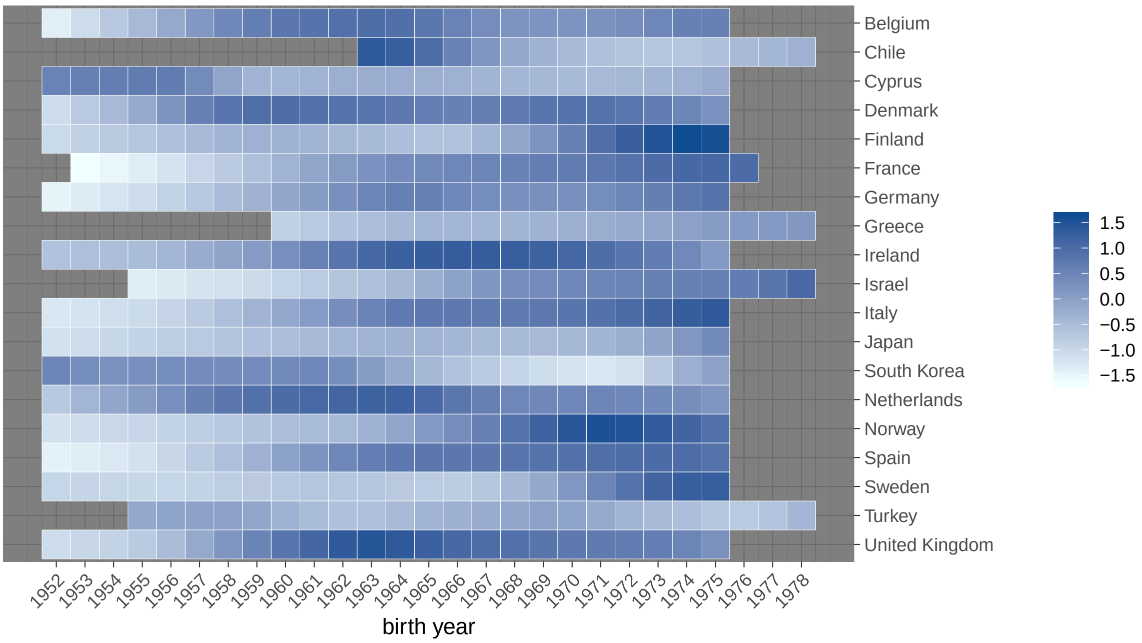


(b) Year-by-year percentiles



Notes: Panel (a) plots the time series of standardized unemployment rates for each of the 19 countries in the sample. Panel (b) plots, for each year, the 75th, 50th, and 25th percentiles of the country-level distribution.

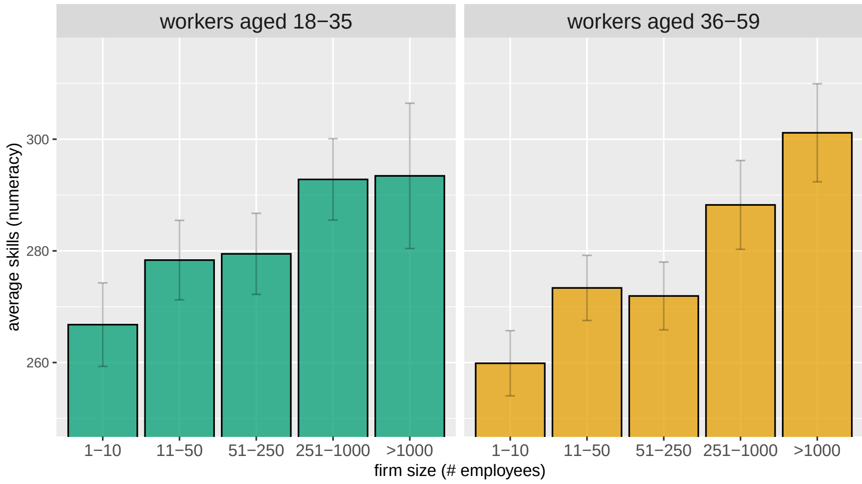
Figure 4: Unemployment Between Ages 18-25: Across Countries and Cohorts



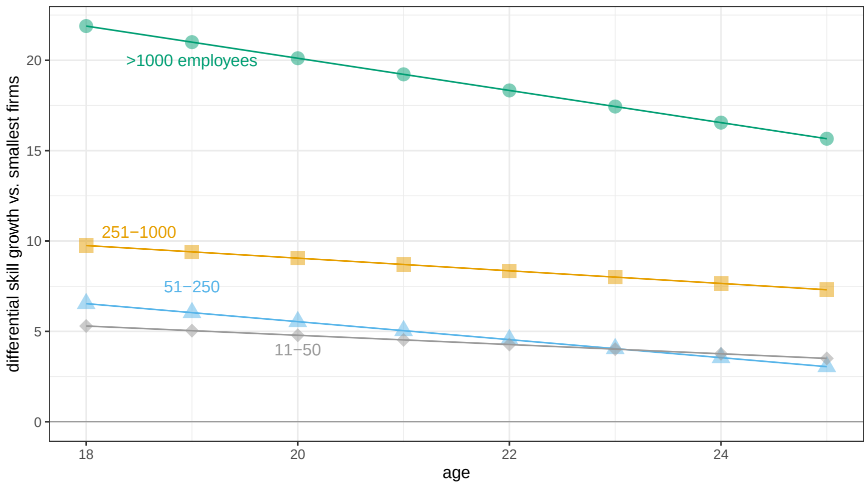
Notes: Heatmap displaying the average standardized unemployment rate faced between ages 18-25 by each country-cohort; sample summarized in Table 1.

Figure 5: Firm Size and Skills in Germany

(a) Average numeracy skills by firm size and age group



(b) Firm size and skill growth: Estimated differentials wrt. size 1–10 by age



Notes: Panel (a): Mean numeracy skills in 2012 Germany PIAAC respondents, by age group and firm size. Sample of private-sector workers of all ages. Spikes represent 95% confidence intervals. Survey weights are used. Standard errors take into account survey and assessment design. Panel (b): Estimated differentials in skill growth by firm size group and age. Uses estimates from equation (7) found in Table 7.

Table 1: PIAAC Survey Summary Statistics

	N	Mean	SD.
Age	37160	46.541	6.589
Female	37159	0.430	0.495
Native-born	37136	0.974	0.160
Post-secondary education	37153	0.382	0.486
College education	37153	0.231	0.422
Parents' education = low	36467	0.493	0.500
Parents' education = medium	36467	0.330	0.470
Parents' education = high	36467	0.177	0.382
Belgium*	37160	0.011	0.106
Chile	37160	0.021	0.144
Cyprus	37160	0.001	0.032
Denmark	37160	0.010	0.099
Finland	37160	0.009	0.096
France	37160	0.100	0.301
Germany†	37160	0.127	0.333
Greece	37160	0.012	0.111
Ireland	37160	0.006	0.075
Israel	37160	0.009	0.094
Italy	37160	0.090	0.286
Japan	37160	0.224	0.417
Korea	37160	0.099	0.299
Netherlands	37160	0.030	0.170
Norway	37160	0.009	0.092
Spain	37160	0.070	0.254
Sweden	37160	0.015	0.123
Turkey	37160	0.069	0.254
United Kingdom‡	37160	0.086	0.280
Private sector worker	36504	0.616	0.486
Public sector worker	36504	0.207	0.405
Self-employed	36504	0.177	0.382
Numeracy skills	37160	270.243	52.242
Literacy skills	37160	272.510	47.366

Notes: Summary statistics for employed PIAAC respondents between the ages of 36–59 who reside in the countries listed in the table. Sample excludes non-natives who migrated to the country at age 18 or later. Means and standard deviations computed using survey weights. Parents' education is the maximum among a respondent's two parents: low = ISCED 1, 2, and 3C short; medium = ISCED 3 (excl 3C short) and 4; high = ISCED 5 and 6. Numeracy and literacy test scores statistics computed using plausible values and they range from 0–500.

* PIAAC was only carried out in Flanders.

† PIAAC respondents from West Germany.

‡ PIAAC was only carried out in England and Northern Ireland.

Table 2: List of Countries, Unemployment Series Information, and Year of PIAAC Survey

	Country	Start	End	Source	PIAAC Survey
1	Belgium*	1969	2011	OECD	2011-12
2	Chile	1980	2014	IMF	2014-15
3	Cyprus	1969	2011	Statistical Service of Cyprus	2011-12
4	Denmark	1969	2011	OECD	2011-12
5	Finland	1969	2011	OECD	2011-12
6	France	1970	2012	OECD	2012
7	Germany†	1969	2011	Federal Employment Agency, Nürnberg	2011-12
8	Greece	1977	2014	OECD	2014-15
9	Ireland	1969	2011	OECD	2011-12
10	Israel	1972	2014	IMF and ILO	2014-15
11	Italy	1969	2011	Italian National Institute of Statistics	2011-12
12	Japan	1969	2011	OECD	2011-12
13	Korea	1969	2011	ILO	2011-12
14	Netherlands	1969	2011	OECD	2011-12
15	Norway	1969	2011	OECD	2011-12
16	Spain	1969	2011	OECD	2011-12
17	Sweden	1969	2011	OECD	2011-12
18	Turkey	1972	2014	OECD	2014-15
19	United Kingdom‡	1969	2011	Bank of England	2011-12

Notes: List of PIAAC countries included in the sample; begin date, end date, and source of the national unemployment series; dates in which PIAAC data was collected.
* PIAAC was only carried out in Flanders. Unemployment series is that of all Belgium.
† Unemployment series is that of West Germany.
‡ PIAAC was only carried out in England and Northern Ireland. Unemployment series is that of all the UK.

Table 3: Countercyclical Education Responses

	=1 IF POST-SECONDARY EDUCATION				=1 IF COLLEGE EDUCATION			
u(16)	0.027***				0.007			
	(0.010)				(0.007)			
u(17)		0.025***				0.008		
		(0.009)				(0.007)		
u(18)			0.013*				0.010*	
			(0.007)				(0.006)	
u(18-25)				0.008				0.013
				(0.017)				(0.014)
mean(Y)	.393	.391	.388	.388	.238	.237	.235	.235
SE Clusters	406	425	443	443	406	425	443	443
N	34066	35317	36460	36460	34066	35317	36460	36460

Notes: OLS estimates of regressions at the worker level, using survey weights. Sample consists of employed, experienced (ages 36-59) workers residing in the 19 countries listed in Table 1, who are natives or migrated to the country before age 18. Dependent variable in left panel is a dummy that equals one if the worker has completed any post-secondary education. Dependent variable in right panel is a dummy that equals one if the worker has completed any college education. Unemployment is measured in country-specific standard deviations and averaged across the ages in parentheses. All regressions include age fixed effects, country fixed effects, country-specific quadratic age trends, a gender dummy, parents' education (maximum education over mother and father in the form of dummies for three educational levels), and a native-born dummy. Standard errors in parentheses are clustered at the level of country×age. * 0.10 ** 0.05 *** 0.01.

Table 4: Countercyclical Education Responses: Heterogeneity by Parents' Education

	=1 IF POST-SECONDARY EDUCATION				=1 IF COLLEGE EDUCATION			
u(16) ×								
parents' education = low	0.023**				0.003			
	(0.011)				(0.008)			
parents' education = middle	0.029**				0.008			
	(0.011)				(0.009)			
parents' education = high	0.039**				0.018			
	(0.015)				(0.012)			
u(17) ×								
parents' education = low		0.024**				0.006		
		(0.009)				(0.007)		
parents' education = medium		0.023**				0.004		
		(0.011)				(0.009)		
parents' education = high		0.034**				0.021*		
		(0.014)				(0.012)		
u(18) ×								
parents' education = low			0.012				0.007	
			(0.008)				(0.007)	
parents' education = medium			0.011				0.005	
			(0.010)				(0.008)	
parents' education = high			0.024*				0.032***	
			(0.013)				(0.011)	
u(18-25) ×								
parents' education = low				0.009				0.010
				(0.017)				(0.014)
parents' education = medium				-0.006				0.004
				(0.020)				(0.016)
parents' education = high				0.030				0.041**
				(0.022)				(0.019)
mean(Y)	.393	.391	.388	.388	.238	.237	.235	.235
SE Clusters	406	425	443	443	406	425	443	443
N	34066	35317	36460	36460	34066	35317	36460	36460

Notes: OLS estimates of regressions at the worker level, using survey weights. Sample consists of employed, experienced (ages 36-59) workers residing in the 19 countries listed in Table 1, who are natives or migrated to the country before age 18. Dependent variable in left panel is a dummy that equals one if the worker has completed any post-secondary education. Dependent variable in right panel is a dummy that equals one if the worker has completed any college education. Unemployment is measured in country-specific standard deviations and averaged across the ages in parentheses. All regressions include age fixed effects, country fixed effects, country-specific quadratic age trends, a gender dummy, parents' education (maximum education over mother and father in the form of dummies for three educational levels), and a native-born dummy. Parents' education is the maximum among a respondent's two parents: low = ISCED 1, 2, and 3C short; medium = ISCED 3 (excl 3C short) and 4; high = ISCED 5 and 6. Standard errors in parentheses are clustered at the level of country×age. * 0.10 ** 0.05 *** 0.01.

Table 5: Early-Career Labor Market Conditions and Skills

	NUMERICAL SKILLS				LITERACY SKILLS			
u(18-25)	-4.63	-5.40**	-6.16*	-7.29**	-3.42	-3.98*	-4.69	-5.41*
	(2.82)	(2.73)	(3.66)	(3.62)	(2.26)	(2.23)	(3.21)	(3.19)
u(26-30)			-0.87	-1.29			-0.88	-1.06
			(2.03)	(2.12)			(1.90)	(1.93)
u(31-35)			-2.14	-1.89			-1.23	-1.11
			(1.47)	(1.52)			(1.37)	(1.35)
Controls	no	yes	no	yes	no	yes	no	yes
mean(Y)	270	271	270	271	273	273	273	273
SD(Y)	52	52	52	52	47	47	47	47
SE Clusters	443	443	443	443	443	443	443	443
N	37160	36465	37160	36465	37160	36465	37160	36465

Notes: OLS estimates of regressions at the worker level, using survey weights. Sample consists of employed, experienced (ages 36-59) workers residing in the 19 countries listed in Table 1, who are natives or migrated to the country before age 18. Dependent variable is a worker's level of numeracy or literacy skills. Unemployment is measured in country-specific standard deviations and averaged across the ages in parentheses. All regressions include age fixed effects, country fixed effects, and country-specific quadratic age trends. "Controls" include a gender dummy, parents' education (maximum education over mother and father in the form of dummies for three educational levels), and a native-born dummy. Standard errors in parentheses are clustered at the level of country×age and take into account that skills are measured through multiple plausible values. * 0.10 ** 0.05 *** 0.01.

Table 6: Early-Career Labor Market Conditions and Skills: Heterogeneity by Parents' Education

	NUMERICAL SKILLS		LITERACY SKILLS	
u(18-25) ×				
parents' education = low	-7.15***	-9.17**	-5.44**	-6.96**
	(2.76)	(3.60)	(2.30)	(3.19)
parents' education = medium	-4.11	-5.71	-3.67	-5.21
	(2.86)	(3.70)	(2.35)	(3.27)
parents' education = high	-1.84	-3.61	0.28	-1.25
	(3.05)	(4.01)	(2.48)	(3.45)
u(26-30) ×				
parents' education = low		-1.01		-1.36
		(2.33)		(2.09)
parents' education = medium		-1.80		-0.70
		(2.22)		(2.11)
parents' education = high		-1.74		-0.98
		(2.45)		(2.26)
u(31-35) ×				
parents' education = low		-2.66		-1.67
		(1.78)		(1.50)
parents' education = medium		-0.06		0.26
		(1.77)		(1.62)
parents' education = high		-1.98		-0.98
		(2.08)		(1.84)
Controls	yes	yes	yes	yes
mean(Y)	271	271	273	273
SD(Y)	52	52	47	47
SE Clusters	443	443	443	443
N	36465	36465	36465	36465

Notes: OLS estimates of regressions at the worker level, using survey weights. Sample consists of employed, experienced (ages 36-59) workers residing in the 19 countries listed in Table 1, who are natives or migrated to the country before age 18. Dependent variable is a worker's level of numeracy or literacy skills. Unemployment is measured in country-specific standard deviations and averaged across the ages in parentheses. All regressions include age fixed effects, country fixed effects, and country-specific quadratic age trends. "Controls" include a gender dummy, parents' education (maximum education over mother and father in the form of dummies for three educational levels), and a native-born dummy. Parents' education is the maximum among a respondent's two parents: low = ISCED 1, 2, and 3C short; medium = ISCED 3 (excl 3C short) and 4; high = ISCED 5 and 6. Standard errors in parentheses are clustered at the level of country×age and take into account that skills are measured through multiple plausible values. * 0.10 ** 0.05 *** 0.01.

Table 7: German PIAAC Panel: Numeracy Skills Growth By Firm Size and Age

	NUMERACY SKILLS$_{2015}$			
firm size =				
11-50	-0.32	-0.88	5.30	4.64
	(3.43)	(3.47)	(8.12)	(8.06)
51-250	-4.45	-4.92	6.54	6.24
	(4.48)	(4.46)	(8.13)	(8.17)
251-1000	2.12	1.89	9.75	9.64
	(4.09)	(4.52)	(8.67)	(8.98)
$>$1000	2.38	1.73	21.89**	20.95*
	(4.56)	(4.59)	(10.40)	(11.05)
(age-18) $\times$ firm size =				
11-50			-0.26	-0.25
			(0.33)	(0.34)
51-250			-0.50	-0.50
			(0.35)	(0.36)
251-1000			-0.35	-0.35
			(0.36)	(0.36)
$>$1000			-0.89**	-0.87*
			(0.43)	(0.45)
skills$_{2012}$	0.82***	0.81***	0.82***	0.81***
	(0.03)	(0.04)	(0.03)	(0.04)
Industry FE	no	yes	no	yes
N	1321	1316	1321	1316

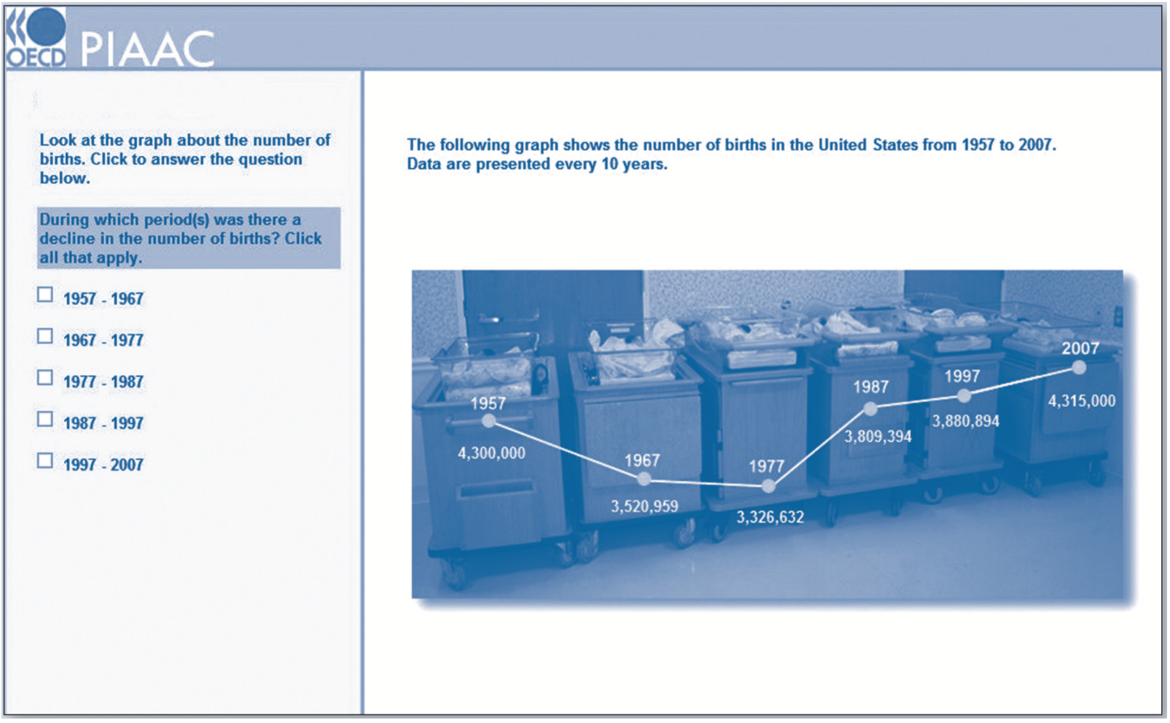
Notes: OLS estimates of different specifications of equations (6) and (7) in the text. Regressions at the worker level, using survey weights. Sample is a panel of salary workers who were employed in Germany in 2012 and 2015, and who were private-sector workers in 2012 between the ages of 18–59. Firm size categories refer to the size of the firm where a worker was employed in 2012. Omitted category is firm size 1–10. Outcome is the level of numerical skills in 2015. All regressions control for numerical skills in 2012, a quadratic in age and gender. Specifications labeled "Industry FE" further control for 7 categories of industry fixed effects. Robust standard errors in parentheses take into account PIAAC survey and assessment design. * 0.10 ** 0.05 *** 0.01.

- SUPPLEMENTARY APPENDICES -

A Additional Figures and Tables

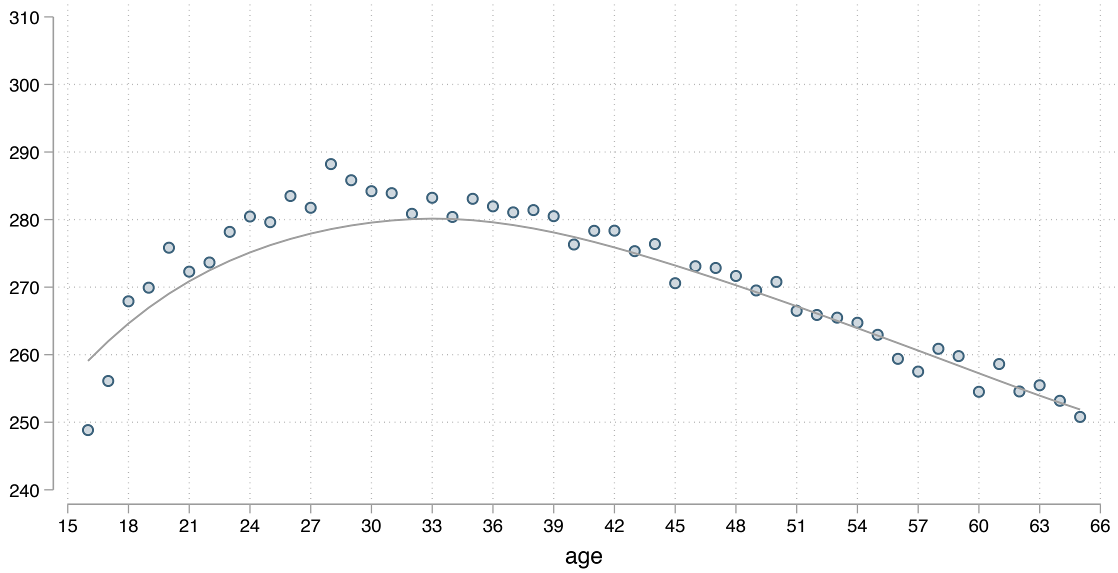
Appendix Figures

Figure A1: Example question, PIAAC numeracy assessment



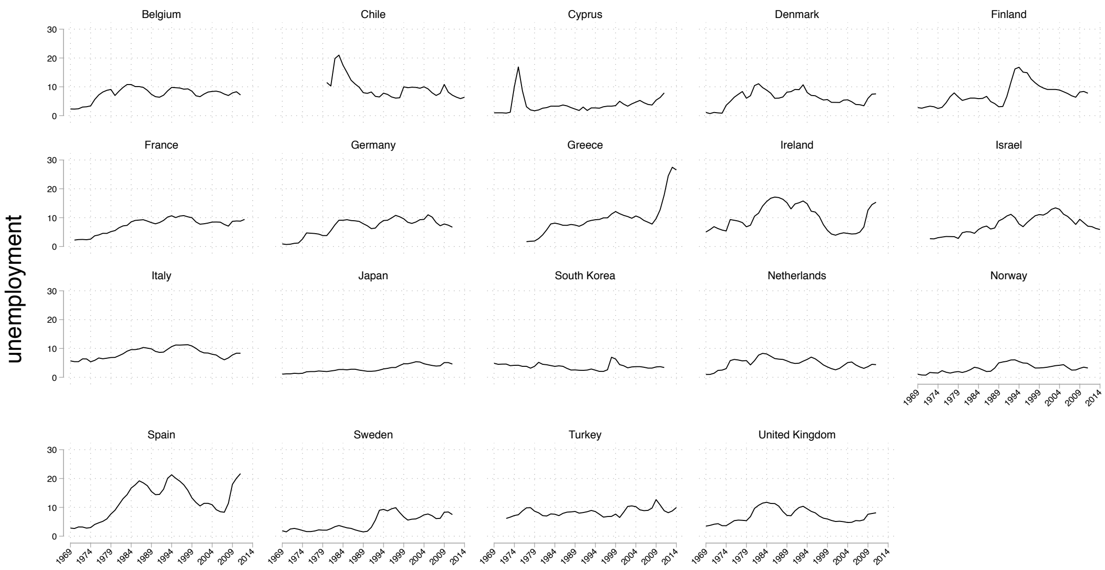
Source: OECD (2013).

Figure A2: Average Literacy Skills by Age



Notes: Average literacy skills by age, and local linear regression smoother. Employed workers who were born in their country of residence or migrated there before age 18. PIAAC respondents from countries listed in Table 1.

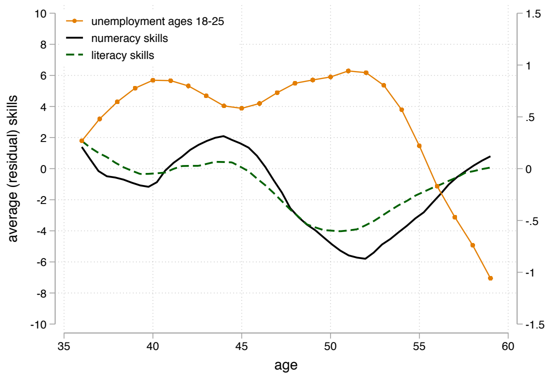
Figure A3: National Unemployment Time Series By Country



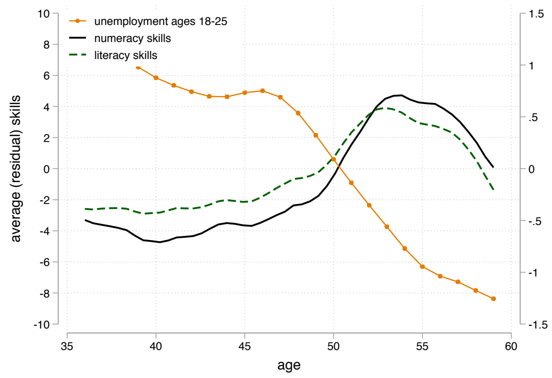
Notes: Unemployment time series for each country in the sample. Table 2 lists the source for each country.

Figure A4: Visual Relationship between 18-25 Unemployment and Skills, for Select Countries

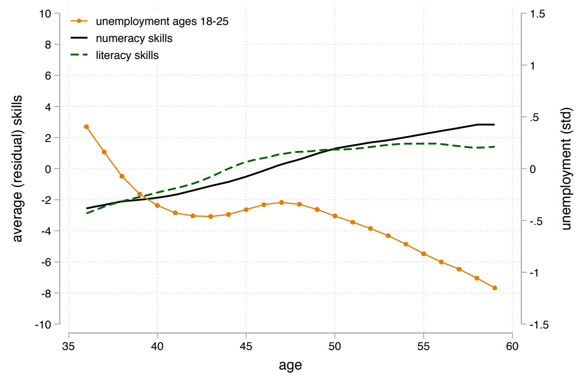
(a) Denmark



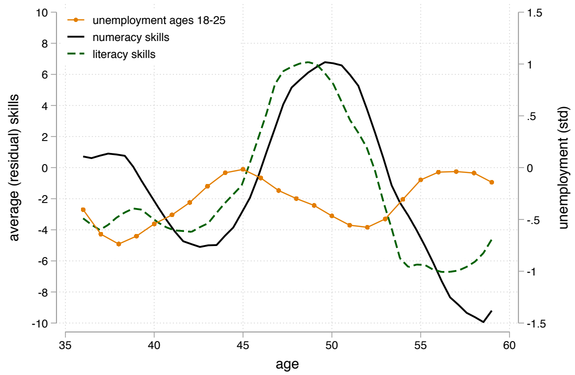
(b) Italy



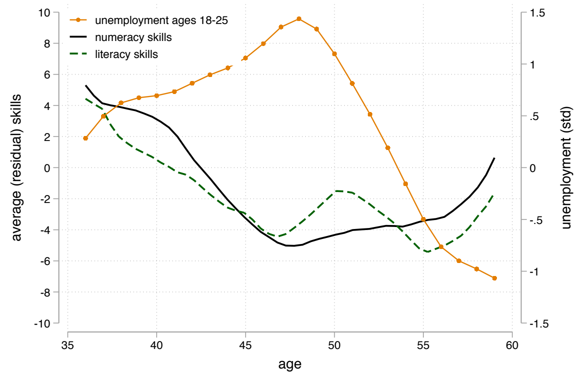
(c) Japan



(d) Turkey

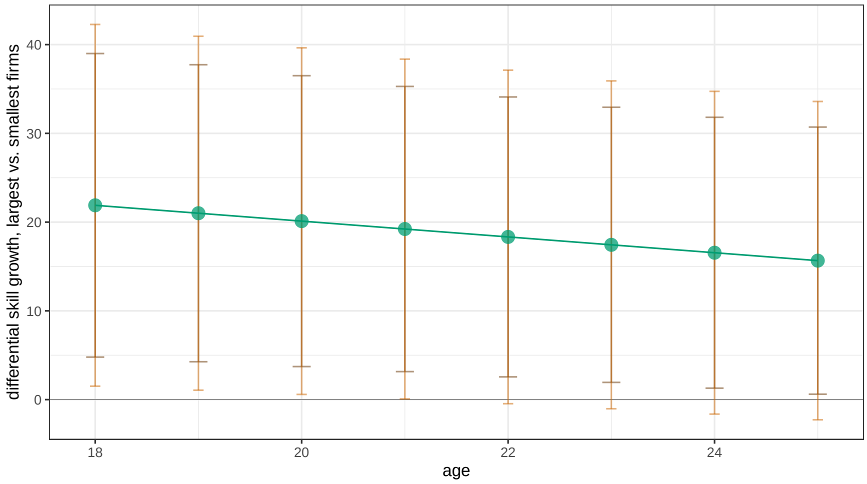


(e) United Kingdom



Notes: For select countries and each cohort in the sample this figure shows residualized and smoothed average skills (left axis) together with the average unemployment rate faced between ages 18–25. Residualized skills are net of a quadratic of age, gender, parents' education, and native-born status. The skills residuals–age gradient is smoothed using a kernel-weighted local polynomial regression. Average unemployment faced between ages 18–25 is measured in country-specific standard deviations. In the United Kingdom PIAAC was only carried out in England and Northern Ireland.

Figure A5: Firm size and skill growth: Estimated differential of size >1000 wrt. size 1–10, by age



Notes: Estimated differentials in skill growth by age for workers in firms of size >1000 relative to workers in firms of size 1–10. Uses estimates from equation (7) found in Table 7. Spikes represent 90% and 95% confidence intervals.

Appendix Tables

Table A1: Robustness, deviations from linear trend in standardized unemployment rates; Early-Career Labor Market Conditions and Skills

	NUMERICAL SKILLS				LITERACY SKILLS			
u(18-25)	-4.69*	-5.45**	-6.42*	-7.51**	-3.52	-4.06*	-5.06	-5.72*
	(2.82)	(2.73)	(3.62)	(3.61)	(2.26)	(2.24)	(3.19)	(3.20)
u(26-30)			-1.01	-1.41			-1.09	-1.23
			(2.02)	(2.11)			(1.88)	(1.91)
u(31-35)			-2.21	-1.94			-1.34	-1.20
			(1.46)	(1.51)			(1.36)	(1.35)
Controls	no	yes	no	yes	no	yes	no	yes
mean(Y)	270	271	270	271	273	273	273	273
SD(Y)	52	52	52	52	47	47	47	47
SE Clusters	443	443	443	443	443	443	443	443
N	37160	36465	37160	36465	37160	36465	37160	36465

Notes: OLS estimates of regressions at the worker level, using survey weights. Sample consists of employed, experienced (ages 36-59) workers residing in the 19 countries listed in Table 1, who are natives or migrated to the country before age 18. Dependent variable is a worker's level of numeracy or literacy skills. As opposed to the main specification, unemployment is measured as deviations from a country-specific linear time trend. All regressions include age fixed effects, country fixed effects, and country-specific quadratic age trends. "Controls" include a gender dummy, parents' education (maximum education over mother and father in the form of dummies for three educational levels), and a native-born dummy. Standard errors in parentheses are clustered at the level of country$\times$age and take into account that skills are measured through multiple plausible values. * 0.10 ** 0.05 *** 0.01.

Table A2: Robustness, deviations from linear trend in standardized unemployment rates; Early-Career Labor Market Conditions and Skills: Heterogeneity by Parents' Education

	NUMERICAL SKILLS		LITERACY SKILLS	
u(18-25) $\times$				
parents' education = low	-8.00***	-10.70***	-6.13***	-8.38***
	(2.80)	(3.58)	(2.34)	(3.18)
parents' education = medium	-3.63	-4.71	-3.61	-4.67
	(2.93)	(3.82)	(2.47)	(3.45)
parents' education = high	-0.09	-1.76	2.11	0.74
	(3.14)	(4.05)	(2.52)	(3.42)
u(26-30) $\times$				
parents' education = low		-1.52		-1.84
		(2.29)		(2.05)
parents' education = medium		-1.53		-0.65
		(2.24)		(2.12)
parents' education = high		-1.28		-0.45
		(2.49)		(2.19)
u(31-35) $\times$				
parents' education = low		-3.49**		-2.37
		(1.73)		(1.47)
parents' education = medium		1.07		1.12
		(1.82)		(1.74)
parents' education = high		-0.73		0.08
		(2.18)		(1.84)
Controls	yes	yes	yes	yes
mean(Y)	271	271	273	273
SD(Y)	52	52	47	47
SE Clusters	443	443	443	443
N	36465	36465	36465	36465

Notes: OLS estimates of regressions at the worker level, using survey weights. Sample consists of employed, experienced (ages 36-59) workers residing in the 19 countries listed in Table 1, who are natives or migrated to the country before age 18. Dependent variable is a worker's level of numeracy or literacy skills. As opposed to the main specification, unemployment is measured as deviations from a country-specific linear time trend. All regressions include age fixed effects, country fixed effects, and country-specific quadratic age trends. "Controls" include a gender dummy, parents' education (maximum education over mother and father in the form of dummies for three educational levels), and a native-born dummy. Parents' education is the maximum among a respondent's two parents: low = ISCED 1, 2, and 3C short; medium = ISCED 3 (excl 3C short) and 4; high = ISCED 5 and 6. Standard errors in parentheses are clustered at the level of country$\times$age and take into account that skills are measured through multiple plausible values. * 0.10 ** 0.05 *** 0.01.

Table A3: Robustness, no standardization of unemployment rates; Early-Career Labor Market Conditions and Skills

	NUMERICAL SKILLS				LITERACY SKILLS			
u(18-25)	-1.52	-1.64	-2.18*	-2.43*	-1.23	-1.38	-1.77	-1.88
	(1.15)	(1.12)	(1.31)	(1.31)	(0.95)	(0.91)	(1.18)	(1.17)
u(26-30)			-0.67	-0.78			-0.46	-0.42
			(0.78)	(0.80)			(0.75)	(0.76)
u(31-35)			-0.08	-0.06			0.31	0.29
			(0.45)	(0.47)			(0.46)	(0.46)
Controls	no	yes	no	yes	no	yes	no	yes
mean(Y)	270	271	270	271	273	273	273	273
SD(Y)	52	52	52	52	47	47	47	47
SE Clusters	443	443	443	443	443	443	443	443
N	37160	36465	37160	36465	37160	36465	37160	36465

Notes: OLS estimates of regressions at the worker level, using survey weights. Sample consists of employed, experienced (ages 36-59) workers residing in the 19 countries listed in Table 1, who are natives or migrated to the country before age 18. Dependent variable is a worker's level of numeracy or literacy skills. As opposed to the main specification, unemployment is measured as percentage points (no standardization). All regressions include age fixed effects, country fixed effects, and country-specific quadratic age trends. "Controls" include a gender dummy, parents' education (maximum education over mother and father in the form of dummies for three educational levels), and a native-born dummy. Standard errors in parentheses are clustered at the level of country$\times$age and take into account that skills are measured through multiple plausible values. * 0.10 ** 0.05 *** 0.01.

Table A4: Robustness, no standardization of unemployment rates; Early-Career Labor Market Conditions and Skills: Heterogeneity by Parents' Education

	NUMERICAL SKILLS		LITERACY SKILLS	
u(18-25) $\times$				
parents' education = low	-2.21**	-2.73**	-1.85**	-2.05*
	(1.12)	(1.33)	(0.92)	(1.17)
parents' education = medium	-1.16	-2.09	-1.15	-1.93
	(1.14)	(1.33)	(0.93)	(1.19)
parents' education = high	-0.76	-1.54	-0.31	-1.00
	(1.15)	(1.45)	(0.95)	(1.27)
u(26-30) $\times$				
parents' education = low		-0.45		-0.42
		(0.91)		(0.82)
parents' education = medium		-0.97		-0.31
		(0.83)		(0.84)
parents' education = high		-1.11		-0.48
		(0.95)		(0.89)
u(31-35) $\times$				
parents' education = low		-0.58		-0.05
		(0.53)		(0.47)
parents' education = medium		0.70		0.71
		(0.61)		(0.60)
parents' education = high		0.62		0.79
		(0.72)		(0.69)
Controls	yes	yes	yes	yes
mean(Y)	271	271	273	273
SD(Y)	52	52	47	47
SE Clusters	443	443	443	443
N	36465	36465	36465	36465

Notes: OLS estimates of regressions at the worker level, using survey weights. Sample consists of employed, experienced (ages 36-59) workers residing in the 19 countries listed in Table 1, who are natives or migrated to the country before age 18. Dependent variable is a worker's level of numeracy or literacy skills. As opposed to the main specification, unemployment is measured as percentage points (no standardization). All regressions include age fixed effects, country fixed effects, and country-specific quadratic age trends. "Controls" include a gender dummy, parents' education (maximum education over mother and father in the form of dummies for three educational levels), and a native-born dummy. Parents' education is the maximum among a respondent's two parents: low = ISCED 1, 2, and 3C short; medium = ISCED 3 (excl 3C short) and 4; high = ISCED 5 and 6. Standard errors in parentheses are clustered at the level of country$\times$age and take into account that skills are measured through multiple plausible values. * 0.10 ** 0.05 *** 0.01.

Table A5: Alternative sample, active persons; Early-Career Labor Market Conditions and Skills

	NUMERICAL SKILLS				LITERACY SKILLS			
u(18-25)	-4.04	-4.77*	-4.82	-5.89*	-3.06	-3.60	-4.45	-4.98
	(2.73)	(2.63)	(3.60)	(3.54)	(2.22)	(2.19)	(3.15)	(3.12)
u(26-30)			-0.32	-0.71			-1.08	-1.13
			(2.06)	(2.12)			(1.87)	(1.89)
u(31-35)			-1.51	-1.28			-0.91	-0.72
			(1.47)	(1.50)			(1.34)	(1.33)
Controls	no	yes	no	yes	no	yes	no	yes
mean(Y)	269	270	269	271	271	272	271	272
SD(Y)	53	52	53	52	48	48	48	48
SE Clusters	443	443	443	443	443	443	443	443
N	39157	38400	39157	38400	39157	38400	39157	38400

Notes: OLS estimates of regressions at the worker level, using survey weights. Sample consists of employed and unemployed, experienced (ages 36-59) workers residing in the 19 countries listed in Table 1, who are natives or migrated to the country before age 18. Dependent variable is a worker's level of numeracy or literacy skills. Unemployment is measured in country-specific standard deviations and averaged across the ages in parentheses. All regressions include age fixed effects, country fixed effects, and country-specific quadratic age trends. "Controls" include a gender dummy, parents' education (maximum education over mother and father in the form of dummies for three educational levels), and a native-born dummy. Standard errors in parentheses are clustered at the level of country×age and take into account that skills are measured through multiple plausible values. * 0.10 ** 0.05 *** 0.01.

Table A6: Alternative sample, active persons; Early-Career Labor Market Conditions and Skills: Heterogeneity by Parents' Education

	NUMERICAL SKILLS		LITERACY SKILLS	
u(18-25) ×				
parents' education = low	-6.60**	-7.82**	-5.00**	-6.46**
	(2.67)	(3.51)	(2.27)	(3.12)
parents' education = medium	-3.53	-4.40	-3.31	-4.88
	(2.74)	(3.61)	(2.29)	(3.20)
parents' education = high	-0.85	-1.87	0.50	-0.92
	(2.96)	(3.95)	(2.45)	(3.38)
u(26-30) ×				
parents' education = low		-0.54		-1.50
		(2.34)		(2.05)
parents' education = medium		-1.01		-0.50
		(2.24)		(2.06)
parents' education = high		-1.08		-1.25
		(2.47)		(2.26)
u(31-35) ×				
parents' education = low		-1.98		-1.24
		(1.74)		(1.46)
parents' education = medium		0.59		0.58
		(1.77)		(1.61)
parents' education = high		-1.46		-0.54
		(2.09)		(1.81)
Controls	yes	yes	yes	yes
mean(Y)	270	270	272	272
SD(Y)	52	52	48	48
SE Clusters	443	443	443	443
N	38400	38400	38400	38400

Notes: OLS estimates of regressions at the worker level, using survey weights. Sample consists of employed and unemployed, experienced (ages 36-59) workers residing in the 19 countries listed in Table 1, who are natives or migrated to the country before age 18. Dependent variable is a worker's level of numeracy or literacy skills. Unemployment is measured in country-specific standard deviations and averaged across the ages in parentheses. All regressions include age fixed effects, country fixed effects, and country-specific quadratic age trends. "Controls" include a gender dummy, parents' education (maximum education over mother and father in the form of dummies for three educational levels), and a native-born dummy. Parents' education is the maximum among a respondent's two parents: low = ISCED 1, 2, and 3C short; medium = ISCED 3 (excl 3C short) and 4; high = ISCED 5 and 6. Standard errors in parentheses are clustered at the level of country×age and take into account that skills are measured through multiple plausible values. * 0.10 ** 0.05 *** 0.01.

Table A7: Early-Career Labor Market Conditions and Labor Force Participation

	=1 IF ACTIVE (EMPLOYED OR UNEMPLOYED)					
u(18-25)	0.019	0.015	0.015	-0.000	0.021	0.025
	(0.016)	(0.021)	(0.016)	(0.022)	(0.026)	(0.034)
u(26-30)		-0.004		-0.013		0.003
		(0.013)		(0.013)		(0.022)
u(31-35)		0.003		-0.004		0.005
		(0.009)		(0.010)		(0.013)
Controls	yes	yes	yes	yes	yes	yes
Sample	all	all	men	men	women	women
mean(Y)	.79	.79	.9	.9	.681	.681
SE Clusters	443	443	443	443	443	443
N	46962	46962	22494	22494	24468	24468

Notes: OLS estimates of regressions at the worker level, using survey weights. Sample consists of persons between the ages 36-59 residing in the 19 countries listed in Table 1, who are natives or migrated to the country before age 18. Dependent variable is a dummy variable equal to one if person is in the labor force (employed or unemployed). Unemployment is measured in country-specific standard deviations and averaged across the ages in parentheses. All regressions include age fixed effects, country fixed effects, and country-specific quadratic age trends. "Controls" include a gender dummy, parents' education (maximum education over mother and father in the form of dummies for three educational levels), and a native-born dummy. Standard errors in parentheses are clustered at the level of country$\times$age and take into account that skills are measured through multiple plausible values. * 0.10 ** 0.05 *** 0.01.

Table A8: No Unemployment-Induced International Migration

	Outcome: LOG NUMBER OF PEOPLE IN COHORT			
u(18-25)	0.0205	0.0018	0.0088	0.0054
	(0.0345)	(0.0464)	(0.0331)	(0.0450)
u(26-30)		-0.0142		-0.0000
		(0.0303)		(0.0292)
u(31-35)		-0.0367		-0.0264
		(0.0248)		(0.0238)
Cohort includes	employed	employed	labor force	labor force
p-value	.552	.419	.789	.566
N	443	443	443	443

Notes: OLS estimates of specifications (4) and (5) in the text at the cohort (country$\times$age) level. Sample consists of persons between the ages 36-59 residing in the 19 countries listed in Table 1, who are natives or migrated to the country before age 18. Dependent variable is log cohort size (computed using survey weights). Unemployment is measured in country-specific standard deviations and averaged across the ages in parentheses. All regressions include age fixed effects, country fixed effects, country-specific quadratic age trends, and controls for cohort composition: gender, parents' education, and native/foreign-born. Robust standard errors in parentheses. * 0.10 ** 0.05 *** 0.01. p-value in each column refers to a test where the null is all coefficients (one coefficient in odd columns, three coefficients in even columns) being equal to zero.

Table A9: German PIAAC Panel: Literacy Skills Growth By Firm Size and Age

	LITERACY SKILLS$_{2015}$			
firm size =				
11-50	2.57	2.04	0.72	0.55
	(3.42)	(3.47)	(6.41)	(6.34)
51-250	-5.22	-6.11*	-5.86	-5.60
	(3.74)	(3.71)	(7.02)	(7.03)
251-1000	2.72	1.40	9.25	8.58
	(3.60)	(4.00)	(6.91)	(7.28)
$>$1000	4.04	2.57	6.12	5.63
	(4.12)	(4.29)	(8.30)	(8.66)
(age-18) $\times$ firm size =				
11-50			0.08	0.07
			(0.26)	(0.26)
51-250			0.03	-0.02
			(0.32)	(0.32)
251-1000			-0.30	-0.33
			(0.29)	(0.29)
$>$1000			-0.10	-0.14
			(0.34)	(0.34)
skills$_{2012}$	0.80***	0.78***	0.80***	0.78***
	(0.03)	(0.03)	(0.03)	(0.03)
Industry FE	no	yes	no	yes
N	1321	1316	1321	1316

Notes: OLS estimates of different specifications of equations (6) and (7) in the text. Regressions at the worker level, using survey weights. Sample is a panel of salary workers who were employed in Germany in 2012 and 2015, and who were private-sector workers in 2012 between the ages of 18–59. Firm size categories refer to the size of the firm where a worker was employed in 2012. Omitted category is firm size 1–10. Outcome is the level of numerical skills in 2015. All regressions control for numerical skills in 2012, a quadratic in age and gender. Specifications labeled "Industry FE" further control for 7 categories of industry fixed effects. Robust standard errors in parentheses take into account PIAAC survey and assessment design. * 0.10 ** 0.05 *** 0.01.

Table A10: German PIAAC Panel: Numerical Skills Growth By Firm Size and Age; Sample of Stayers

	NUMERACY SKILLS$_{2015}$			
firm size =				
11-50	-2.49	-3.21	5.37	4.38
	(4.31)	(4.49)	(12.71)	(12.70)
51-250	-4.27	-5.48	3.38	1.85
	(4.61)	(4.96)	(11.30)	(11.57)
251-1000	1.29	-0.00	11.49	10.14
	(4.95)	(5.61)	(12.82)	(13.22)
$>$1000	1.13	-0.15	24.22*	22.71*
	(5.10)	(5.33)	(13.44)	(13.48)
(age-18) $\times$ firm size =				
11-50			-0.33	-0.31
			(0.48)	(0.49)
51-250			-0.32	-0.30
			(0.46)	(0.47)
251-1000			-0.43	-0.43
			(0.48)	(0.48)
$>$1000			-0.99*	-0.98*
			(0.54)	(0.54)
skills$_{2012}$	0.81***	0.80***	0.82***	0.81***
	(0.04)	(0.04)	(0.04)	(0.04)
Industry FE	no	yes	no	yes
N	988	986	988	986

Notes: OLS estimates of different specifications of equations (6) and (7) in the text. Regressions at the worker level, using survey weights. Sample is a panel of salary workers who were employed in Germany in 2012 and 2015, and who were private-sector workers in 2012 between the ages of 18–59. Sample further restricted to workers who in 2015 were in the same job as in 2012. Firm size categories refer to the size of the firm where a worker was employed in 2012. Omitted category is firm size 1–10. Outcome is the level of numerical skills in 2015. All regressions control for numerical skills in 2012, a quadratic in age and gender. Specifications labeled "Industry FE" further control for 7 categories of industry fixed effects. Robust standard errors in parentheses take into account PIAAC survey and assessment design. * 0.10 ** 0.05 *** 0.01.

Table A11: German PIAAC Panel: Numerical Skills Growth By Firm Size and Age; Skill change as outcome

	ΔNUMERICAL SKILLS			
firm size =				
11-50	-2.93	-3.24	3.02	2.62
	(3.52)	(3.61)	(8.20)	(8.16)
51-250	-5.93	-6.02	4.35	3.90
	(4.46)	(4.50)	(8.39)	(8.46)
251-1000	-2.20	-1.79	4.61	4.97
	(4.19)	(4.62)	(8.68)	(8.94)
>1000	-3.46	-3.36	21.11**	20.13*
	(4.49)	(4.60)	(10.43)	(11.08)
(age-18) × firm size =				
11-50			-0.27	-0.26
			(0.34)	(0.34)
51-250			-0.47	-0.44
			(0.37)	(0.37)
251-1000			-0.31	-0.30
			(0.36)	(0.36)
>1000			-1.11**	-1.06**
			(0.43)	(0.45)
Industry FE	no	yes	no	yes
N	1321	1316	1321	1316

Notes: OLS estimates of different specifications of equations (8) and (9) in the text. Regressions at the worker level, using survey weights. Sample is a panel of salary workers who were employed in Germany in 2012 and 2015, and who were private-sector workers in 2012 between the ages of 18–59. Firm size categories refer to the size of the firm where a worker was employed in 2012. Omitted category is firm size 1–10. Outcome is the change in numerical skills between 2012 and 2015. All regressions control for a quadratic in age and gender. Specifications labeled "Industry FE" further control for 7 categories of industry fixed effects. Robust standard errors in parentheses take into account PIAAC survey and assessment design. * 0.10 ** 0.05 *** 0.01.

Table A12: German PIAAC Panel: Numerical Skills Growth By Firm Size and Age; Skill percentage change as outcome

	%ΔNUMERACY SKILLS			
firm size =				
11-50	-1.09	-1.23	1.00	0.81
	(1.42)	(1.46)	(3.23)	(3.21)
51-250	-2.33	-2.36	1.54	1.30
	(1.86)	(1.86)	(3.43)	(3.43)
251-1000	-1.31	-1.11	1.01	1.13
	(1.63)	(1.81)	(3.35)	(3.47)
>1000	-1.61	-1.52	7.58*	7.15
	(1.67)	(1.73)	(4.11)	(4.38)
(age-18) × firm size =				
11-50			-0.09	-0.09
			(0.13)	(0.14)
51-250			-0.17	-0.16
			(0.15)	(0.15)
251-1000			-0.10	-0.10
			(0.14)	(0.14)
>1000			-0.42**	-0.39**
			(0.17)	(0.18)
Industry FE	no	yes	no	yes
N	1321	1316	1321	1316

Notes: OLS estimates of different specifications of equations (8) and (9) in the text. Regressions at the worker level, using survey weights. Sample is a panel of salary workers who were employed in Germany in 2012 and 2015, and who were private-sector workers in 2012 between the ages of 18–59. Firm size categories refer to the size of the firm where a worker was employed in 2012. Omitted category is firm size 1–10. Outcome is the percentage change in numerical skills between 2012 and 2015. All regressions control for a quadratic in age and gender. Specifications labeled "Industry FE" further control for 7 categories of industry fixed effects. Robust standard errors in parentheses take into account PIAAC survey and assessment design. * 0.10 ** 0.05 *** 0.01.