THE EFFECT OF LABOR MARKET CONDITIONS AT ENTRY ON WORKERS' LONG-TERM SKILLS

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Abstract—Using data on adults' cognitive skills from nineteen countries, this paper shows that labor market conditions during the education-to-work transition affected workers' long-term skill development. Workers who faced higher unemployment rates at ages 18 to 25 have lower skills at ages 36 to 59. Unemployment rates at ages 26 to 35 do not have such an effect. Skill inequality is affected: those with less educated parents experience most of the negative effects. Using German panel data on skills, I document a mechanism related to heterogeneous skill development across firms: young workers at large firms experience higher skill growth than those at small firms.

I. Introduction

THE initial steps young people take in the labor market are key to their long-term career prospects. A growing literature shows how entering the labor market during bad macroeconomic times leads to sizable and persistent earnings losses (Kahn, 2010; Oreopoulos, von Wachter, & Heisz, 2012). Furthermore, even controlling for initial macroeconomic conditions, the type of firm where a young person starts out can have an impact on 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, search frictions, mobility costs, or imperfect information could 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 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—early experiences—could put workers on a worse human-capital accumulation path, with effects that persist in time.

Building a better understanding of why initial conditions matter is important for at least 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 versus 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 impacts on human capital of initial labor market conditions. Using individual-level survey data from nineteen 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 to 59. 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 disentangling a human capital channel from frictions-based channels since the classic metric of human-capital development—wage growth—is potentially affected 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. 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 development 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 nineteen PIAAC Survey participant countries, combined with information on national-level unemployment series. I focus on experienced prime-age workers (ages 36 to 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, I first show that facing higher unemployment rates in the late teens and early twenties leads to a higher probability of completing postsecondary education.[1] Second, I show that in spite of the increase in formal education, workers who faced higher unemployment rates at ages 18 to 25 have lower skills at ages 36 to 59: a 1 standard deviation increase in the unemployment rates encountered at ages 18 to 25 leads to a

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[1] This result aligns with existing literature (Card & Lemieux, 2001).

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decrease in numeracy skills of 10% to 14% of a standard deviation.[2]

A cohort's exposure to bad initial conditions not only lowers average skills; it also increases skill inequality. The PIAAC survey includes information on respondents' parental education, which allows me to reestimate 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 (e.g., they might find extending their 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 skills are mostly driven by those with the least educated parents.

The results above hold when controlling for unemployment rates faced at ages 26 to 30 and 31 to 35. Importantly, unemployment rates at 26 to 35 have a more muted impact on later skills than those at 18 to 25 and are statistically insignificant. These results are consistent with the initial steps a young person takes in the labor market (as opposed to future periods) being key 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 procyclical 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. Germany followed up on their respondents and assessed their cognitive skills once again three years after the initial survey, which allows constructing a panel on German workers' skills. Using these data, 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 relationship between entry conditions 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, Kahn, and Speer (2016), Fernández-Kranz and Rodríguez-Planas (2018), and Schwandt and von Wachter (2019).[4] This paper is the first to estimate the long-term effects of economic conditions during the education-work transition on workers' long-term cognitive skills. I provide direct evidence on mechanisms underlying the findings in this literature and a clear test for the human capital channel.[5]

A heterogeneous set of previous work studies the relevance of early labor market experiences, not directly focusing on macroeconomic conditions. Examples include theoretical (Jovanovic & Nyarko, 1997; Gibbons & Waldman, 2006) and empirical ones (von Wachter & Bender, 2006; Müller & Neubaeumer, 2018; Arellano-Bover, 2020). This paper adds to this literature by showing how early career is a sensitive period for skill building using data on cognitive skills. My findings are consistent with empirical results that use earnings data.

Finally, this paper adds to a vast literature on the sources of wage growth (see Rubinstein & Weiss, 2006) by demonstrating that early shocks can persistently affect skills development. Rosen (1972) argued theoretically that firms can vary in the skill opportunities they provide to their workers, for which I find supporting evidence.[6] 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 learning on the job. My findings on the heterogeneous impacts of shocks at different ages are suggestive of this type of skill production function and of the importance of early-career human capital accumulation.

The rest of this paper is organized as follows. Section II lays out the conceptual framework and derives the predictions that I take to the data. Section III describes the data sources and measurement and outlines some stylized facts. Section IV describes the empirical approach, and section V presents the main results. Section VI analyzes the role of firm heterogeneity using German panel data on skills. Section VII concludes. The online appendix includes additional figures and tables.

II. 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. A set of testable predictions arises from the framework.

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

[3]See Oreopoulos et al. (2012), Brunner and Kuhn (2014), and Arellano-Bover (2020).

[4]Wee (2016) uses a macroeconomic model to argue that entering during a recession hinders learning about comparative advantage and occupation-specific skills.

[5]Leist, Hessel, and Avendano (2014) document that the cognitive functions of those aged 50 and 74 are worse if they experienced recessions between ages 25 to 49. The main differences with this paper is that (a) I focus on younger and employed people (36–59), (b) specifically study unemployment conditions during the education-work transition (18–25), and (c) 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 (2020) for recent related evidence.

A. 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 might be better suited than others to develop skills.

Each period is characterized by labor market conditions indexed by u_t. A higher u_t indicates worse labor market conditions (the empirical analogues of u_t are unemployment rates). Investments in period 1, I_1, can be realized through formal education, E, or employment in the labor market, $J(u_1)$. These investments are mutually exclusive. That is, $I_1 \in \{E, J(u_1)\}$. Skill investments on-the-job vary as a function of u_t, while 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) matching with employers that provide better learning opportunities (Rosen, 1972; Oreopoulos et al., 2012; Arellano-Bover, 2020), (b) more intense learning by doing during busy economic times (Gibbons & Waldman, 2006), or (c) lower probability of experiencing unemployment (Edin & Gustavsson, 2008).

For simplicity, I assume that $E > J(u_t)$ for all values of u_t: skill investments through formal education are always greater than those carried out on the job. This is not a key assumption; it will become clear in this section what role the relationship between E and $J(u_t)$ plays.

B. 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

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

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 skills at the end of period 2, S_2, through an increasing function $V(\cdot)$. This could represent 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 as a function of macroeconomic conditions 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

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

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.

C. Average Skills and Initial Labor Market Conditions

Average $t = 2$ skills as a function of initial conditions u is the weighted average of skills developed by those who chose $I_1 = E$ and those who chose $I_1 = J(u)$:

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

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 conditions u is given by

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

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

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

In equation (2), the first summand is positive: it combines the skill differential that E provides with respect to $J(u)$ with the number 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 equation (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 sign of the relationship between early macroeconomic conditions and long-term skills is ambiguous: $\frac{\partial \mathbf{E}(S_2|u)}{\partial u}$ could be positive or negative.

This ambiguity arises because on-the-job investments are lower during bad economic times, but some people avoid them by switching to formal education. The sign in equation (2) will be positive if formal education provides far more skills than learning on the job, $E \gg J(u)$ and enough people switch to formal education in response to higher unemployment rates. On the other hand, the sign in equation (2) will be negative if the heterogeneity of on-the-job learning across macroeconomic conditions is sufficiently large, $\frac{\partial S_2(J(u))}{\partial u} \ll 0$, and the fraction of people choosing this type of skill investment is also large.

Assessing the sign and magnitude of equation (2) 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]

D. *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 the labor market ("never takers"), would be affected only 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 $S_2\big(E\big) - S_2\big(J(u)\big)$.

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

III. Data and Measurement

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

A. *PIAAC Survey on Adult Skills*

This survey, carried out by the OECD in different member and nonmember countries, is aimed at measuring information-processing competencies of the target population: noninstitutionalized 16 to 65-year-olds residing in each country at the time of data collection. It 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 to 6,000 people. 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 with 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 (PS-TRE). Most respondents completed an adaptive assessment using a computer; a minority instead used paper and pencil.[11]

This paper focuses on numeracy and literacy skills for two reasons. First, PS-TRE measure the intersection of computer skills and cognitive skills required to solve problems. Computer skills are thus a necessary condition to perform well on PS-TRE (OECD, 2013a), and paper-and-pencil PIAAC respondents did not carry out the PS-TRE assessment.[12] The second reason is that out of the nineteen countries in my

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

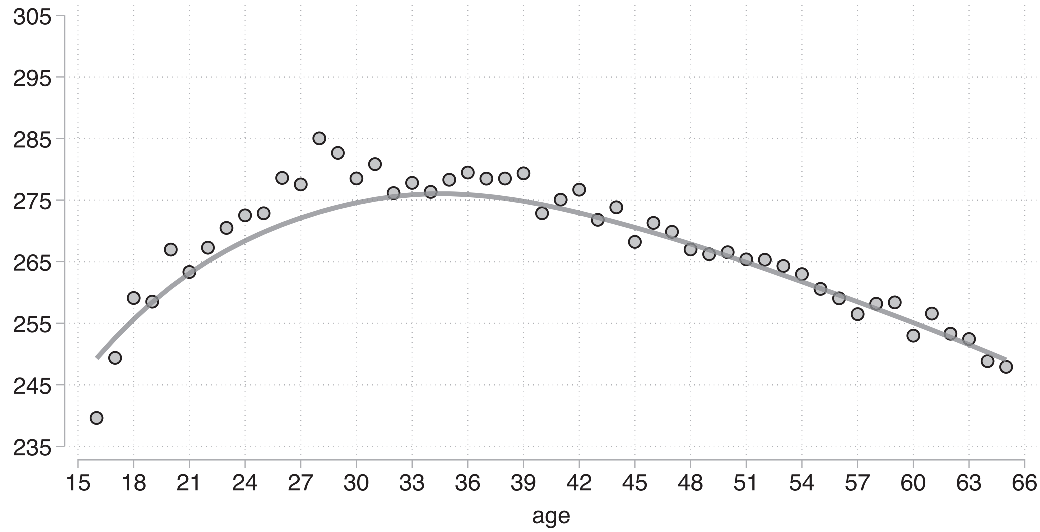
$$\frac{\partial S_2(J(u))}{\partial u} = \frac{1}{1 - F(c(u))} \times \left[\frac{\partial \mathbf{E}(S_2|u)}{\partial u} - f(c(u))c'(u) \times [S_2(E) - S_2(J(u))] \right].$$

[10]The survey is planned to have more rounds in the future. Round 1 (2011–2012) 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 the United States. Round 2 (2014–2015) 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.

[11]About 80% of respondents completed the assessment using a computer and 20% using paper and pencil (OECD, 2013a). Numeracy and literacy skill assessments were explicitly designed so that they would be comparable across both modes of delivery (OECD, 2013b).

[12]Further, computer skills are arguably less general than numeracy and literacy, especially so during the time period in which workers in my sample were ages 18 to 25 (most of my sample was 18 in the 1970s and 1980s).

FIGURE 1.—AVERAGE NUMERACY SKILLS BY AGE



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.

sample, a significant fraction of them did not assess PS-TRE (France, Italy, Spain, and Cyprus). This restriction, coupled with the loss of paper-and-pencil respondents, would diminish the sample with PS-TRE substantially, reducing the number of respondents by 37%.

What do PIAAC skills measure? The PIAAC survey is designed to measure "key information-processing skills," 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, 2013b). These measures intend to capture cognitive skills that are general, learnable, and work relevant. The definition provided by OECD (2013b) 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."

Some of the assessment 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, 2013b). Appendix figure A1 shows an example question of the numeracy assessment.

In addition to PIAAC's stated goals, other evidence shows 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 age profile of skills resembles the typical hump shape observed in wage age profiles. Figure 1 displays the age profile for numeracy skills, showing that skills peak in the mid-thirties.[13] If instead of work-relevant skills, PIAAC were capturing general knowledge learned at school, one would expect to see a different shape (e.g., 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 are either not publicly available, or their public use version does not include respondents' age, which is critical for my analysis. Countries excluded for this reason are Austria, Australia, Canada, New Zealand, Singapore, and the United States. Second, I exclude former socialist states since no unemployment data exist for these countries prior to the 1990s, and my analysis uses data going significantly further back in time. Countries excluded for this reason are the Czech Republic, Estonia, Lithuania, Poland, Russia, Slovakia, and Slovenia. My final sample is composed of survey respondents from nineteen countries: Belgium, Chile, Cyprus, Denmark, Finland, France, Germany, Greece, Ireland, Israel, Italy, Japan, Korea, Netherlands, Norway, Spain, Sweden, Turkey, and the United Kingdom.[14]

While the seminal studies on the effects of entering the labor market during bad times were carried out with U.S. (Kahn, 2010) and Canadian (Oreopoulos et al., 2012) data, subsequent literature has shown that these effects are a

[13] Since I use a single cross-section, figure 1 might combine age and cohort effects. Appendix figure A2 shows a similar pattern for literacy skills.

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

pervasive phenomenon, taking place in many countries. Countries for which an existing study has documented the *graduating-in-a-recession* effect include Austria (Brunner & Kuhn, 2014), Belgium (Cockx & Ghirelli, 2016), Britain (Taylor, 2013), Finland (Päällysaho, 2017), Japan (Genda, Kondo, & Ohta, 2010), Korea (Han, 2018), Netherlands (van den Berge, 2018), Norway (Liu et al., 2014), and Spain (Fernández-Kranz & Rodríguez-Planas, 2018). Except for Austria, all of the countries in this list are in my sample.

Among the respondents of the nineteen countries in my sample, my empirical analysis focuses on employed workers aged 36 to 59.[15] I focus on those over age 35 since I can observe the macroeconomic conditions they faced at different stages of their working life (18–25, 26–30, 31–35), and it is plausible that the most important skill development phase is over by age 36 (Salthouse, 2009). I do not include workers older than 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 nonnatives who moved to their country of residence after age 18. These 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.

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

Table 1.—PIAAC Survey Summary Statistics

	N	Mean	SD
Age	37,160	46.541	6.589
Female	37,159	0.430	0.495
Native-born	37,136	0.974	0.160
Postsecondary education	37,153	0.382	0.486
College education	37,153	0.231	0.422
Parents' education = low	36,467	0.493	0.500
Parents' education = medium	36,467	0.330	0.470
Parents' education = high	36,467	0.177	0.382
Belgium[a]	37,160	0.011	0.106
Chile	37,160	0.021	0.144
Cyprus	37,160	0.001	0.032
Denmark	37,160	0.010	0.099
Finland	37,160	0.009	0.096
France	37,160	0.100	0.301
Germany[b]	37,160	0.127	0.333
Greece	37,160	0.012	0.111
Ireland	37,160	0.006	0.075
Israel	37,160	0.009	0.094
Italy	37,160	0.090	0.286
Japan	37,160	0.224	0.417
Korea	37,160	0.099	0.299
Netherlands	37,160	0.030	0.170
Norway	37,160	0.009	0.092
Spain	37,160	0.070	0.254
Sweden	37,160	0.015	0.123
Turkey	37,160	0.069	0.254
United Kingdom[c]	37,160	0.086	0.280
Private sector worker	36,504	0.616	0.486
Public sector worker	36,504	0.207	0.405
Self-employed	36,504	0.177	0.382
Numeracy skills	37,160	270.243	52.242
Literacy skills	37,160	272.510	47.366

Summary statistics for employed PIAAC respondents between the ages of 36 and 59 who reside in the countries listed in the table. Sample excludes nonnatives 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 to 500.

[a]PIAAC was carried out only in Flanders.

[b]PIAAC respondents from West Germany.

[c]PIAAC was carried out only in England and Northern Ireland.

Potential sample attrition? Migration and mortality. A potential concern related to sample composition arises if high unemployment rates at ages 18 to 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 to 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 V, I formally test for and find no relationship between unemployment rates faced at ages 18 to 25 and cohort size in my sample.

Mortality is a second potential source of sample attrition that would, in any case, likely work against the negative effects on skills that I find. Schwandt and von Wachter (2020) show that in the United States, cohorts entering the labor market in bad times experienced higher mortality in middle age, mostly driven by diseases tied to harmful health behaviors such as liver disease and drug poisoning. To the extent that those suffering these excess deaths have relatively lower skills, such differential mortality would bias true negative effects toward zero.

Panel PIAAC data for Germany. Germany followed up its PIAAC respondents over time and assessed their numeracy and literacy skills a second time.[16] The baseline PIAAC survey 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 a second time only in

[15]The reasons for focusing on the employed are comparability to the main results of the literature on entry during bad times, typically expressed in terms of wage losses, and existing work showing meaningful skill depreciation from time spent unemployed (Edin & Gustavsson, 2008). I later show that results are robust to including the unemployed and that the "treatment" of interest does not have an impact on labor force participation at the time of the survey.

[16]Other countries have followed up their PIAAC respondents but not reassessed their skills.

TABLE 2.—LIST OF COUNTRIES, UNEMPLOYMENT SERIES INFORMATION, AND YEAR OF PIAAC SURVEY

	Country	Start	End	Source	PIAAC Survey
1	Belgium[a]	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[b]	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[c]	1969	2011	Bank of England	2011–12

List of PIAAC countries included in the sample; begin date, end date, and source of the national unemployment series; dates when PIAAC data were collected.
[a]PIAAC was carried out only in Flanders. Unemployment series is that of all Belgium.
[b]Unemployment series is that of West Germany.
[c]PIAAC was carried out only in England and Northern Ireland. Unemployment series is that of all the United Kingdom.

the 2015 follow-up. The same methodology and assessment PIAAC instrument were used in 2015, since the goal of the reassessment was to be able to allow researchers to measure how PIAAC skills change over time (German PIAAC-Longitudinal Project, 2017). These data thus provide a two-period panel on individuals' skills in Germany—a unique opportunity to use longitudinal data in this setting.

B. *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 to 59 in 2011 to 2015 faced during their labor-market-entry years, time series that go back in time to the late 1960s and early 1970s are needed. I gathered these time series from various sources, listed in table 2.

Table 2 also lists, for each country, the beginning and end of each series. The criteria for how many years to include in the unemployment series are to go forward up until the year in which the respective PIAAC survey began (listed in table 2) and 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 nineteen countries with different labor market characteristics and institutions. In such a setting, the same unemployment rate can represent very different labor market conditions across countries: 8% unemployment can represent good economic times in Spain and bad times in Japan.

I normalize the unemployment time series in a way that makes 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.[17] 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.[18]

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 by combining 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.[19]

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 and 25. The figure summarizes the variation used in the analysis: for different countries, different cohorts faced good or bad economic conditions between ages 18 and 25, and the time (cohort) trends differ across countries.

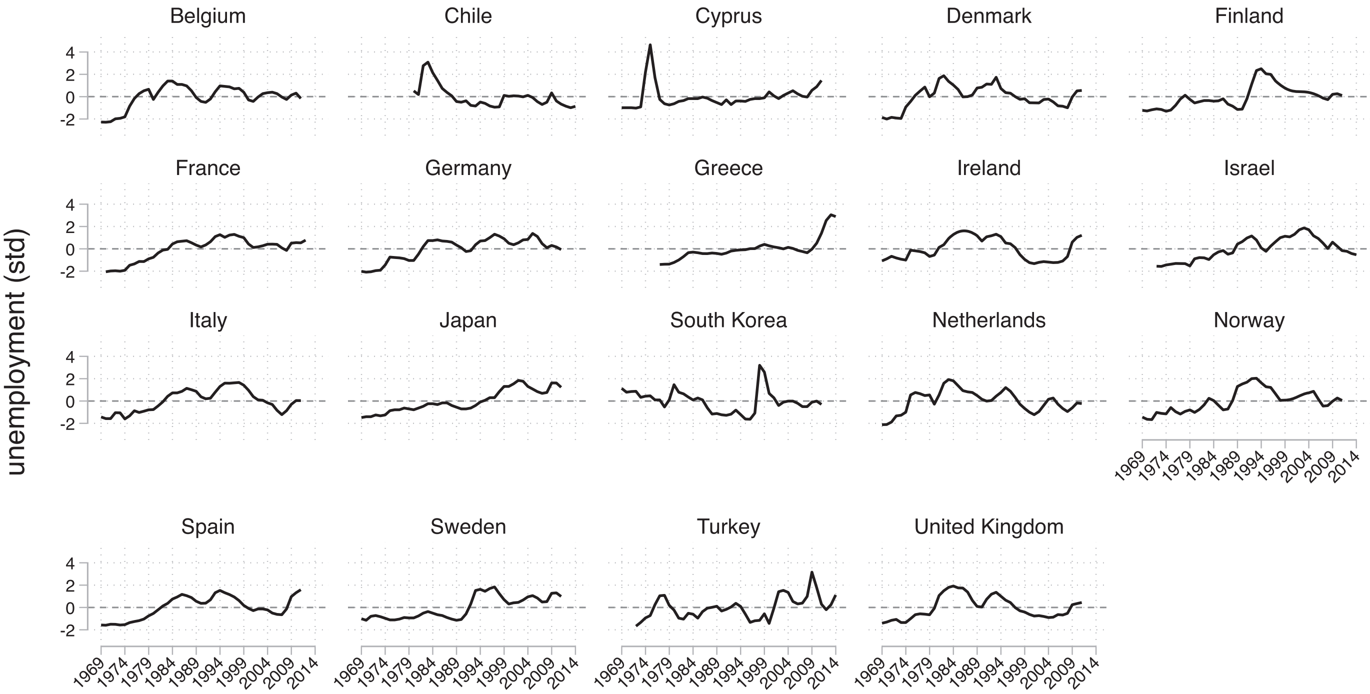
Choice of age range 18 to 25. Following the conceptual framework, the goal is to capture the age range during which the majority of survey respondents finish their formal

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

[18]I later show that results are robust to using alternative measures. Appendix figure A3 shows the time series in levels.

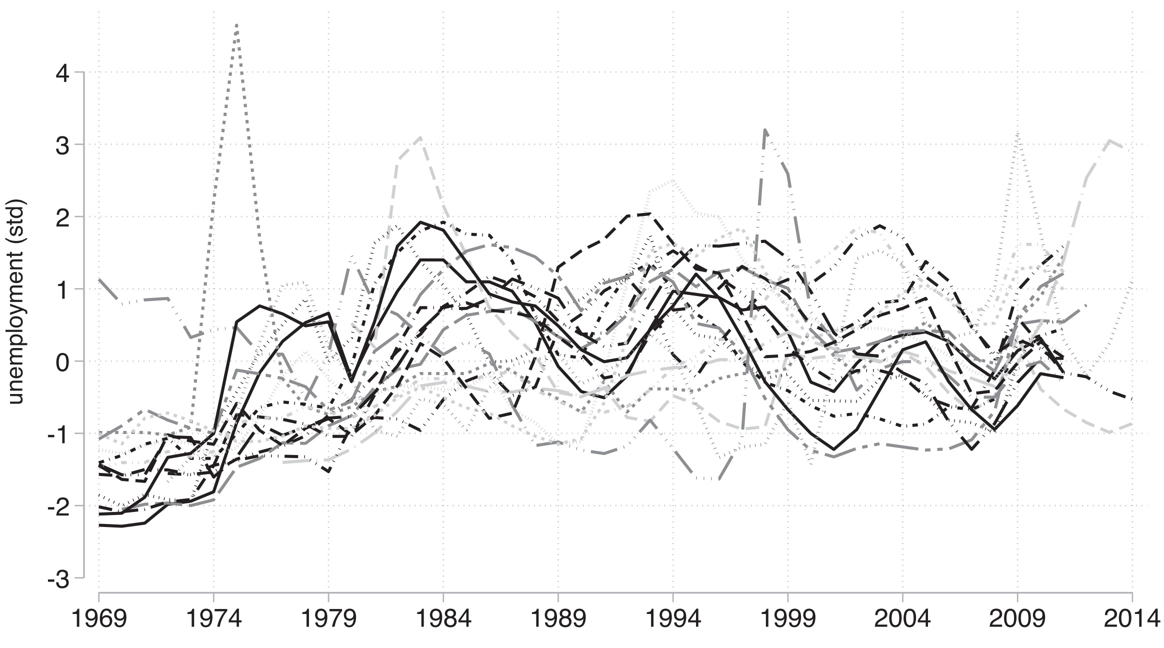
[19]Appendix figure A4 shows, year by year, the 75th, 50th, and 25th percentiles of the unemployment distribution across countries.

FIGURE 2.—NATIONAL STANDARDIZED UNEMPLOYMENT TIME SERIES BY COUNTRY



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

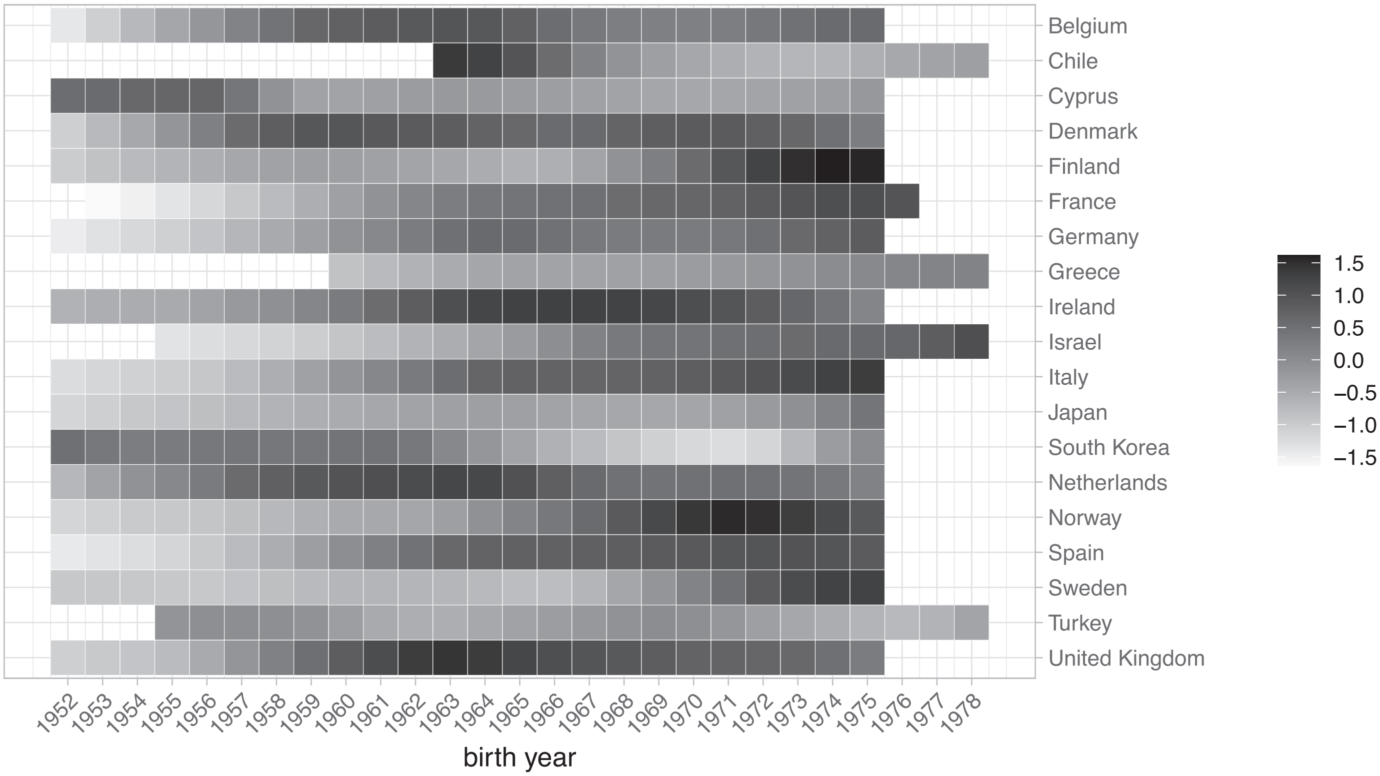


Time series of standardized unemployment rates for each of the nineteen countries in the sample.

education and take their first steps in the labor market. To this aim, I focus on ages 18 to 25. Using ages younger than 25 as the upper limit would risk missing the education-to-work transition of many college-educated respondents. While in the United States the norm is to finish undergraduate studies at age 22, in many of the countries in my sample, the typical graduation age of first-stage university-level education was between 23 and 25 (see OECD, 1997, table X1.2d). Moreover, many of the cohorts in my sample were subject to some type of compulsory military service, further delaying labor market entry.[20]

[20]Previous work on the impact of recessions while young has also focused on the age range 18 to 25 (Giuliano & Spilimbergo, 2013). As an additional

FIGURE 4.—UNEMPLOYMENT BETWEEN AGES 18 AND 25: ACROSS COUNTRIES AND COHORTS



Average standardized unemployment rate faced between ages 18 and 25 by each country cohort; sample summarized in table 1.

IV. Empirical Approach

Using the sample of 36 to 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:

$$y_{ic} = \beta u^{18-25}_{a(i)c} + \delta_c + \delta_{a(i)} + \delta_c a(i) + \delta_c a(i)^2 + X_i'\gamma + \varepsilon_{ic}, \quad (3)$$

where i indexes people, c countries, and a ages. The outcome y_{ic} is person i's skill level (numeracy or literacy), and $u^{18-25}_{a(i)c}$ is the average unemployment rate that i faced in her country of residence between ages 18 and 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 changes in education institutions. Finally, 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 and 25. Since u^{18-25} is measured in terms of country-specific standard deviations, β measures the effect on skill levels of a 1 standard deviation increase in the average unemployment rate people faced in their country of residence between ages 18 and 25.

The parameter β has a causal interpretation under the assumption that there are no unobserved cohort-level determinants of skill accumulation that are correlated with the unemployment rates a cohort encounters at ages 18 to 25. This seems a plausible assumption given the exogeneity of macroeconomic conditions together with the fact that cohorts are defined by a person's country and year of birth, which are fixed and predetermined characteristics.

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

$$y_{ic} = \beta_1 u^{18-25}_{a(i)c} + \beta_2 u^{26-30}_{a(i)c} + \beta_3 u^{31-35}_{a(i)c} + \delta_c + \delta_{a(i)} + \delta_c a(i) + \delta_c a(i)^2 + X_i'\gamma + \varepsilon_{ic}. \quad (4)$$

In this specification, β_1 captures the effect of higher unemployment between ages 18 and 25, keeping constant

test, I estimate models allowing the effect of unemployment conditions at ages 18 to 21 to differ from those at ages 22 to 25, and I find no evidence of these effects being meaningfully different.

Table 3.—Countercyclical Education Responses

	=1 If Postsecondary 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	34,066	35,317	36,460	36,460	34,066	35,317	36,460	36,460

OLS estimates of regressions at the worker level, using survey weights. Sample consists of employed, experienced (ages 36–59) workers residing in the nineteen countries listed in table 1, who are natives or immigrated before age 18. Dependent variable in left panel is a dummy that equals 1 if the worker has completed any postsecondary education. Dependent variable in right panel is a dummy that equals 1 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, and ***0.01.

unemployment experienced between ages 26 and 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 their late teens and early twenties are more relevant than those in their late twenties and early thirties, we would expect β_1 to be larger in magnitude than β_2 and β_3.

I estimate equations (3) and (4) through OLS using survey weights and clustering standard errors at the country-age level (Abadie et al., 2017). Standard errors are adjusted to take into account that skills are measured through multiple plausible values, following the procedure from OECD (2013b).[21]

Measurement error might bias estimates toward zero since I infer the country in which someone lived at ages 18 to 25 (and 26 to 30) from country of birth, and country of residence at the time of the survey (ages 36 to 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.

V. Results

A. *Education Responses*

I test the first prediction of the conceptual framework: 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 (3) using as outcome dummy variables for the completion of two incremental levels of education: postsecondary education and college education.[22] 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 to 25 average.[23]

A 1 standard deviation increase in unemployment rates faced at ages 16 and 17 has a positive impact on the probability of postsecondary education completion, with estimates equal to 0.027 and 0.025 (6%–7% of the sample mean). A 1 standard deviation increase in unemployment rates at age 18 has a positive impact on both postsecondary 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 and 25, point estimates are still positive (0.008 and 0.013) but imprecisely estimated.

Heterogeneity by parental education. In table 4, I reestimate the above parameters, allowing them to vary across three categories of parental education.[24] 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 conceptual framework argues, this heterogeneity could come from varying 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.[25]

[21] I find that this adjustment increases standard errors for most coefficient estimates by between 2% and 9%, but sometimes the adjustment reaches 17%.

[22] Table 1 shows that 39% of sample respondents have completed postsecondary education and 24% have completed a college education (the latter are a subset of the former).

[23] 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.

[24] PIAAC reports respondents' parental education in three categories using ISCED97. 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 respondents the maximum level of education between their two parents. In the sample, 49% had parents in the low education category, 33% in the medium category, and 18% in the high category (see table 1).

[25] Appendix table A1 augments table 4 by additionally showing results for age 17.

TABLE 4.—COUNTERCYCLICAL EDUCATION RESPONSES: HETEROGENEITY BY PARENTS' EDUCATION

	=1 If Postsecondary 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(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	.388	.388	.238	.235	.235
SE Clusters	406	443	443	406	443	443
N	34,066	36,460	36,460	34,066	36,460	36,460

OLS estimates of regressions at the worker level, using survey weights. Sample consists of employed, experienced (ages 36 to 59) workers residing in the nineteen countries listed in table 1, who are natives or immigrated before age 18. Dependent variable in left panel is a dummy that equals 1 if the worker has completed any postsecondary education; in right panel is a dummy that equals 1 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 over mother and father), and a native-born dummy. Parents' education categories are: 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, and ***0.01.

TABLE 5.—EARLY-CAREER LABOR MARKET CONDITIONS AND SKILLS

	Numeracy 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	37,160	36,465	37,160	36,465	37,160	36,465	37,160	36,465

OLS estimates of regressions at the worker level, using survey weights. Sample consists of employed, experienced (ages 36 to 59) workers residing in the nineteen countries listed in table 1, who are natives or immigrated 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, and ***0.01.

B. Numeracy Skills at Ages 36 to 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 (3), 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% to 10% of its standard deviation.

The third and fourth columns of table 5 show estimates of equation (4). The estimates of β_1 (capturing the effect of unemployment at ages 18 to 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% to 2.7% of the sample mean, 11.8% to 14% of the standard deviation), without and with controls, respectively.

Interestingly, the estimates of β_2 (unemployment through ages 26 to 30) and β_3 (unemployment through ages 31 to 35) are quite smaller in magnitude, and none of them are statistically different from 0. Estimates of β_2 are equal to -0.87 and -1.29. Estimates of β_3 are equal to -2.14 and -1.89.

TABLE 6.—EARLY-CAREER LABOR MARKET CONDITIONS AND SKILLS: HETEROGENEITY BY PARENTS' EDUCATION

	Numeracy 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	36,465	36,465	36,465	36,465

OLS estimates of regressions at the worker level, using survey weights. Sample consists of employed, experienced (ages 36 to 59) workers residing in the nineteen countries listed in table 1 who are natives or immigrated 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, and ***0.01.

Overall, the left panel of table 5 indicates that workers who face higher unemployment rates when aged 18 to 25, even if they are more likely to get postsecondary education, have lower skill levels when aged 36 to 59. These negative effects are moderately sized: 2% of the sample mean and 10% to 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.

Table 5 also documents more muted impacts of unemployment faced between ages 26 and 35, with estimated effects that are between four and eight times smaller in magnitude than the effect of unemployment at ages 18 to 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.

C. *Literacy Skills at Ages 36 to 59*

The right panel of table 5 shows estimation results for equations (3) and (4) using literacy skills as an outcome variable. The pattern that arises is similar to the one in numeracy skills, but point estimates are smaller in magnitude and estimates of β or β_1 are statistically significant only at the 10% level (with controls). We still see negative effects of unemployment at ages 18 to 25 (point estimates between −3.42 and −5.41; 1.3% to 2% of the sample mean, or 7.3% to 11.5% of the standard deviation), and much more muted effects for ages 26 to 30 and 31 to 35 (point estimates equal to −0.88 and −1.06, and equal to −1.23 and −1.11, respectively).[26]

D. *Skills Inequality: Heterogeneity by Parental Education*

I reestimate equations (3) and (4) 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 suggests that those with higher education costs bear disproportionately negative effects. In this framework, education costs—more than just the tuition price tag—are broadly thought of as barriers that prevent an optimal education response (e.g., liquidity constraints, access to finance, or information frictions). Such costs are likely to be more prevalent for young people from more disadvantaged backgrounds.[27]

Table 6 shows results for the parameters of interest interacted with the three categories of 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% to 36% higher in absolute value than those from the

[26] Interestingly, more muted effects in literacy test scores with respect to numeracy test scores is a common result for children's test scores across a wide variety of treatments (Chetty, Friedman, & Rockoff, 2014).

[27] An alternative possibility, not considered by my conceptual framework, is that even conditional on a nominal level of education, young people from wealthier families have access to more productive education. While this is a possible additional channel, results from section VA support the channel modeled in my framework: the college education responses to higher unemployment rates are driven by those whose parents were more educated.

pooled sample (for both numeracy 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 affected suggests that cohorts exposed to an unemployment shock during the education-to-work transition end up not only with lower average skills but also with higher skills inequality.

Liquidity constraints—preventing optimal education responses, like results from table 4 suggest—are a potential reason that young people from more disadvantaged backgrounds have higher skills losses. Furthermore, liquidity constraints might influence their first job choice (Coffman et al., 2019), making disadvantaged youth more willing to accept any job regardless of potentially poor skill-development prospects.

E. Other Measures of Unemployment and Robustness Tests

I explore alternative measures of early unemployment conditions and perform a variety of robustness tests.

Maximum unemployment rate between ages 18 and 25. I explore the importance of the average and maximum unemployment rates experienced between ages 18 and 25. This sheds light on whether a bad year, prolonged bad conditions, or both drive negative effects on skills. Appendix table A6 presents the results. The first column for each skill shows the baseline result from table 5. The second column uses the maximum instead. The effect of the maximum is still negative but smaller in magnitude than the average (−3.22 versus −7.29 for numeracy).[28] The third column includes both the average and the maximum, and both have negative effects. For numeracy, the coefficient on the maximum is −2.87, and the coefficient on the average is −4.89 (although the latter is not statistically significant at the 10% level). This suggests that, conditional on a given peak unemployment between 18 and 25, sustained bad conditions also have negative effects.

Interaction with unemployment trend. I now check whether, conditional on a given average unemployment between ages 18 to 25, the unemployment trend has an impact on skill development. I estimate the baseline model, interacting the average unemployment rate while ages 18 to 25 with a dummy variable equal to 1 if the unemployment rate at 25 was greater than that at 18. The fourth column for each skill in appendix table A6 presents results. For both skills, the interaction effect and the main effect of the dummy variable are both close to 0 and not statistically significant.

Alternative age range choice: Breaking up ages 18 to 25 into 18 to 21 and 22 to 25. I reestimate results from table 5 allowing for unemployment conditions at ages 18 to 21 and 22 to 25 to have different effects. Appendix table A7 shows results from this exercise. The main takeaway is that the estimate on 18 to 21 is rather similar to that on 22 to 25, especially when controlling for unemployment conditions at ages 26 to 35.

Deviations from a country-specific linear trend. I use an alternative measure of unemployment rates to address the potential concern that in the same way that unemployment levels across countries might not be comparable, the same might happen within a country across distant periods of time. I 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 A2 and A3 show estimates analogous to those of tables 5 and 6 using this alternative measure. The results are very similar to baseline, reflecting the fact that the empirical model already controls for country-specific trends successfully.

No standardization of unemployment. Appendix tables A4 and A5 show results equivalent to those of tables 5 and 6 obtained using raw unemployment rates (shown in appendix figure A3). Although without standardization, the magnitudes have a less clear interpretation, the qualitative patterns remain the same: negative effects of unemployment at ages 18 to 25, more muted impacts from unemployment at ages 26 to 30, and 31 to 35, and heterogeneous effects by parental education.

Alternative sample: All active persons. The baseline sample focuses on employed workers. Appendix tables A8 and A9 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 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 have an impact on labor force participation at ages 36 to 59. I test for this possibility by estimating models equivalent to those in equations (3) and (4), where the outcome variable is a dummy for labor force participation. Appendix table A10 shows results for this test. The estimated effects are very close to 0 for both men and women, and we cannot reject that they are 0 at conventional significance levels.

Test for endogenous sample selection due to migration. In principle, differential international 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 estimate specifications (3) and (4) at the cohort level, where the outcome variable is survey-weighted cohort size. Appendix table A11 shows results for this test. For two different

[28]This is to be expected since an average of 1 standard deviation over eight years requires a maximum that is weakly greater than that.

cohort size definitions and for both specifications, 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 0 and the p-values range between 0.42 and 0.79. The data fail to reject a zero relationship between cohort size and unemployment conditions when young.

F. *Skill Effects in Terms of Earnings*

I quantify the negative effects of early unemployment conditions on skills using as a metric the earnings returns to PIAAC skills estimated by Hanushek et al. (2015). They find that 1 standard deviation higher numeracy skills is associated with 18.2% higher earnings for workers aged 35 to 54 (see their table 3). My results in table 5 show that a 1 standard deviation higher average unemployment rate between ages 18 and 25 leads to between 9–14% standard deviations lower numeracy skills. Using Hanushek et al.'s (2015) estimates, the skill losses I document would translate to earnings losses between 1.6% and 2.6%. Earnings losses associated with unemployment rates of 1.5 standard deviations (the upper end in figure 4), would be about 2.5% to 3.8%.

VI. A Mechanism: Skill Growth and Firm Size

In this section, I provide evidence consistent with some of the mechanisms discussed in the conceptual framework, where on-the-job human capital accumulation is heterogeneous across bad and good states of the economy. This differential could be partly due to matching with employers that provide worse skill-development opportunities.

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 & Kuhn, 2014; Arellano-Bover, 2020). The cyclicality of large- versus 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.[29]

A. *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 to 59) compared to younger ones (18 to 35). To the extent that this pattern is (at least in part) driven by age effects, it suggests two things: (a) as time in the labor market increases, more skilled workers sort into larger firms (Haltiwanger et al., 2018), and/or (b) 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.

B. *Estimating Skill Growth Differentials by Firm Size*

The German panel PIAAC data allow me to observe two different skill assessments for each person—one in 2012 and another 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 to 10 employees are the omitted category):

$$\begin{aligned} y_{it} = {} & \delta^{11-50}_{J(i,t-1)} + \delta^{51-250}_{J(i,t-1)} + \delta^{251-1000}_{J(i,t-1)} + \delta^{>1000}_{J(i,t-1)} \\ & + \theta y_{i,t-1} + X'_{i,t-1}\gamma + \varepsilon_{it}, \end{aligned} \tag{5}$$

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 $\delta^k_{J(i,t-1)} \equiv \delta^k \times \mathbf{1}\{size_{J(i,t-1)} \in k\}$ for $k \in \{$11–50, 51–250, 251–1,000, $>1{,}000\}$. $y_{i,t-1}$ 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 (5), the δ parameters have the following interpretation (omitting covariates $X_{i,t-1}$):

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

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 equation (5) to let the firm-size differentials in skill growth vary across workers' age (normalized with respect to age 18):

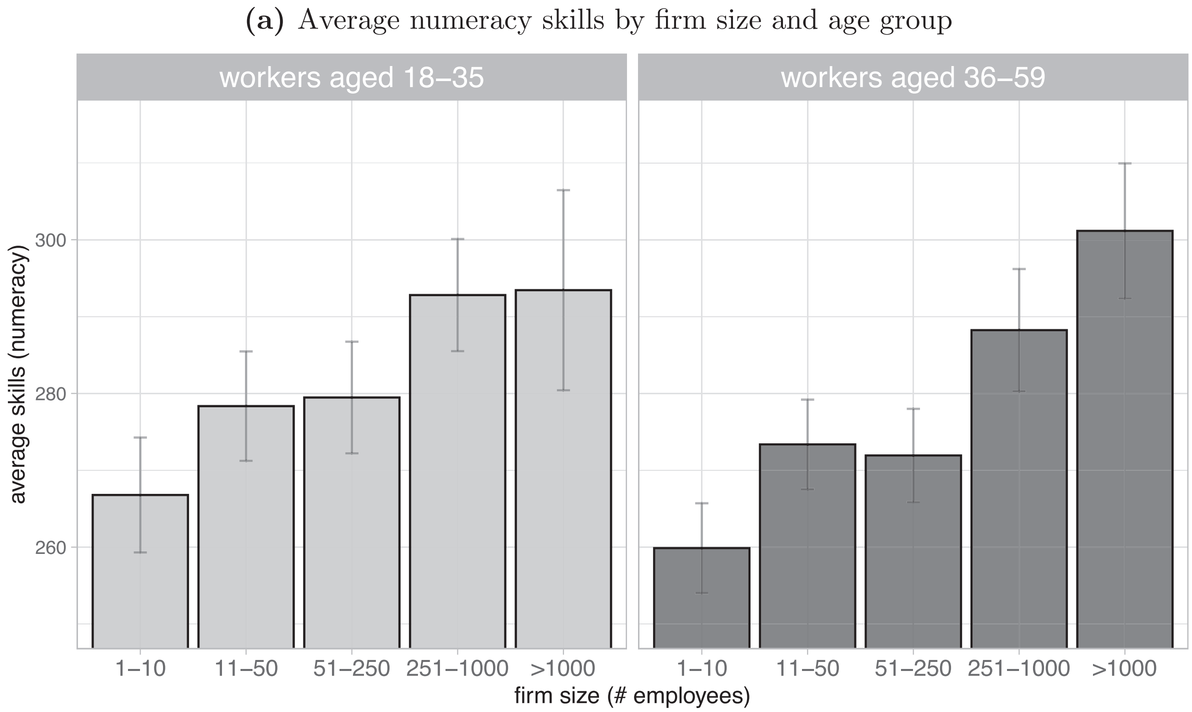
$$\begin{aligned} y_{it} = {} & \sum_k \left[\delta^k_{J(i,t-1)} + \phi^k_{J(i,t-1)} \times (age_{i,t-1} - 18)\right] \\ & + \theta y_{i,t-1} + X'_{i,t-1}\gamma + \varepsilon_{it}. \end{aligned} \tag{6}$$

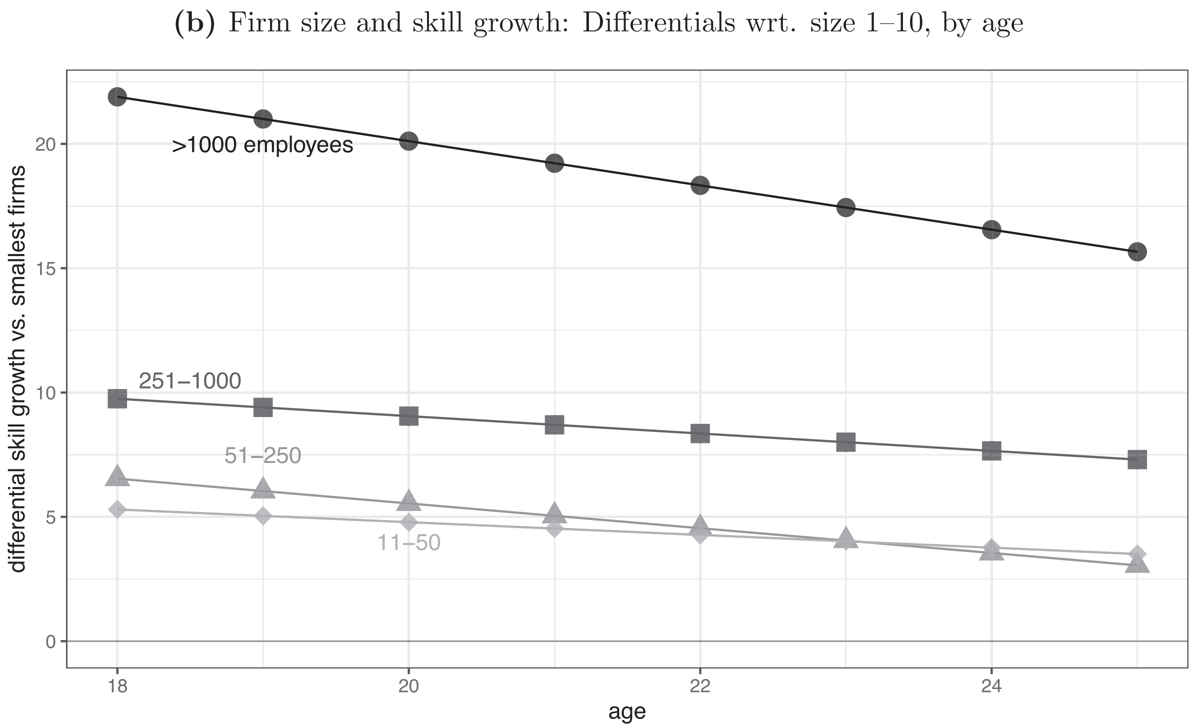
I now have the following age-varying differentials, with δ^k capturing the differential for those who are age 18, and ϕ^k capturing the (linear) age gradient of these differentials:

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

[29] Arellano-Bover (2020) shows evidence consistent with young workers experiencing better on-the-job skill development at large firms (using data on wages, not skills).

Figure 5.—Firm Size and Skills in Germany





(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. (b) Estimated differentials in skill growth by firm size group and age. Uses estimates from equation (6) found in table 7.

C. *Skill Growth Differentials by Firm Size: Results*

Table 7 shows estimation results of equations (5) and (6) for numeracy skills. Estimates of equation (5), which imposes a common firm-size differential for workers of all ages, are small and not statistically different from 0. The results are quite different, however, for equation (6), 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

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) × firm size =				
11–50			−0.26	−0.25
			(0.33)	(0.34)
51–250			−0.50	−0.50
			(0.35)	(0.36)
251–1,000			−0.35	−0.35
			(0.36)	(0.36)
>1,000			−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	1,321	1,316	1,321	1,316

OLS estimates of different specifications of equations (5) and (6) 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 were private sector workers in 2012 between the ages of 18 and 59. Firm size categories refer to the size of the firm where a worker was employed in 2012. Omitted category is firm size 1 to 10. Outcome is the level of numeracy skills in 2015. All regressions control for numeracy skills in 2012, a quadratic in age and gender. Specifications labeled "Industry FE" further control for seven categories of industry fixed effects. Robust standard errors in parentheses take into account PIAAC survey and assessment design, including that skills are measured through multiple plausible values. *0.10, **0.05, and ***0.01.

(over 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 affected by the type of firm in which they find themselves. The similarity of the estimates in columns 3 and 4 implies that controlling for seven broad industry categories does not affect the main conclusion.

Differential growth across firm size is not as pronounced for literacy skills. Appendix table A12 shows estimation results of equations (5) and (6) for literacy skills. Point estimates for young workers at the largest firm categories (251 to 1,000 and over 1,000) are positive but smaller in magnitude and not statistically significant (9.25 and 6.12 without industry fixed effects). This is in line with the more muted impacts on literacy skills in section V, and it could be due to the numeracy skills assessment being heavier on work-related tasks than the literacy one.

Panel b of figure 5 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 to 25). The differential skill growth of between fifteen and twenty units, relative to that occurring in the smallest firms (1 to 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).[30]

[30] Appendix figure A6 plots the over 1,000 differential together with confidence intervals.

Overall, these results suggest that young German workers enjoy better skill-development opportunities at large firms.

D. *Skill Growth Differentials: Robustness*

Restricting the sample to "stayers." The previous estimates are obtained assigning workers the size of their employer in 2012, irrespective of whether they change jobs between 2012 and 2015. Appendix table A13 shows estimates restricting the sample to those who do not change jobs. Results are very similar to those from baseline in table 7 but slightly larger in magnitude. This is consistent with greater learning at large firms, since stayers have spent more time at a large firm between survey waves.

Skill changes as outcome variable. An alternative to equation (5) is

$$\Delta y_{it} = \delta^{11-50}_{J(i,t-1)} + \delta^{51-250}_{J(i,t-1)} + \delta^{251-1000}_{J(i,t-1)} + \delta^{>1000}_{J(i,t-1)} + X'_{i,t-1}\gamma + \varepsilon_{it}, \tag{7}$$

while an alternative to equation (6) is

$$\Delta y_{it} = \sum_k \left[\delta^k_{J(i,t-1)} + \phi^k_{J(i,t-1)} \times (age_{i,t-1} - 18)\right] + X'_{i,t-1}\gamma + \varepsilon_{it}, \tag{8}$$

where Δy_{it} is a change in levels ($\Delta y_{it} = y_{it} - y_{i,t-1}$) or in percentage terms ($\Delta y_{it} = 100 \times (y_{it} - y_{i,t-1})/y_{i,t-1}$). Appendix tables A14 and A15 show numeracy skills estimation results for equations (7) and (8) using changes in level and percentage terms, respectively. The interpretation of the results is very similar in this case. When Δy_{it} is measured in levels, results in appendix table A14 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.

VII. Conclusion

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. This effect arises even though these groups of workers were more likely to obtain postsecondary education in response to bad economic conditions. Further, the impacts of unemployment conditions at the beginning of their working life (ages 18 to 25), are much more important than impacts of unemployment conditions at later ages (26 to 35). Finally, these long-term negative effects are most felt by workers whose parents were less educated. This finding 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 on-the-job skill investments being quantitatively important and sufficiently heterogeneous across good and bad economic times, and 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 long-term skill effects.

Overall, by documenting direct evidence of an underlying human capital channel, this paper shows that attempts to explain the long-term wage losses arising from entry in bad labor market conditions should incorporate damaged skill acquisition for young workers. This is relevant since, in principle, search frictions, mobility costs, or imperfect information could generate persistent wage losses, even while keeping constant young workers' human capital.

The fact that many young people exposed to negative shocks in their entry years lose earnings *and* skills in the long term could inform policies intended to support them and help them catch up in the long run with luckier cohorts. For youth from disadvantaged backgrounds experiencing the education-to-work transition, these policies could take the form of subsidies for further education. For youth already in the labor market during bad times, possibly in jobs with poor skill-development prospects, these policies could take the form of wage subsidies at firms with a proven record of effectively investing in their young workers' skills.

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