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ABSTRACT

Recessions and the Labor Market Returns to Cognitive and Social Skills*

Although recessions negatively affect labor market outcomes, we find that individuals with greater cognitive skills have been less affected by recessions since 2000 compared to those in the 1980s and 1990s. This result occurs despite a decrease in the returns to cognitive skills over the last few decades, on average. We argue that changes in the provision of employer-paid training can help explain the relative return to cognitive skills during recent recessions due to lower training costs and enhanced labor productivity. Consistent with this, we find that firms provide more training to workers with higher cognitive skills during post-2000 recessions.

JEL Classification: J01, J23, J24, J31, J60, J64

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* This research was conducted with restricted access to Bureau of Labor Statistics (BLS) data. The views expressed here are those of the authors and do not necessarily reflect the views of the BLS.

1 Introduction

Significant changes in the labor market over the last few decades have influenced the returns to skills. Technological advances have led to job polarization as new technologies substituted for middle-skilled labor and complemented high-skilled labor (Autor et al. 2006; Autor and Dorn 2013). Although cognitive skills remain an important determinant of wages, the returns to cognitive skills have decreased since the 1980s (Castex and Kogan Dechter 2014). As a potential explanation for why job polarization has not increased the returns to cognitive skills, the returns to social skills have increased, and jobs requiring high levels of social interaction grew by nearly 12 percentage points as a share of the U.S. labor force between 1980 and 2012 (Deming 2017).

Recessions have the potential to change the labor market returns to skills. For example, Gervais et al. (2015) and Hershbein and Kahn (2018) find that recent recessions contributed to job polarization and a shift in the demand for skills. The decline in middle-skill employment has been significant during recessions, and the surviving occupations from these periods have become more productive and higher-skilled. However, there is still relatively little evidence on how the demand for different types of skills, including cognitive and social skills, changes during recessions and, more broadly, throughout the business cycle.

The impact of economic conditions on labor market outcomes can vary depending on an individual's skill. Skill differences among individuals might result in a differential ability to find good initial placements, which could offer significant opportunities for promotion or advancement. Additionally, during recessions, the skill requirements for jobs can increase (e.g., Hershbein and Kahn 2018). These differences can also translate into different training opportunities or skill accumulations. Advanced skills can help workers cope better with adverse economic conditions during recessions. Therefore, considering skill levels can provide better insights into understanding the negative repercussions of recessions and adapting to changing economic conditions (Jimenez et al. 2012).

In this paper, we examine how the influence of changes in the unemployment rate has varied across workers of different levels of skills over time. Using the National Longitudinal Survey of Youth 1979 (NLSY79) and 1997 (NLSY97) data, we compare cohorts aged 18 and 37 who entered the labor market in the early 1980s versus the early 2000s. For each cohort, we estimate the relationship between changes within the region (or state) over time in the unemployment rate, fully interacted with cognitive skills and social skills, and labor market outcomes.

We find that, during recessions, workers with average levels of cognitive and social skills experience a significant reduction in wages. Wages declined by roughly 7.2% for the NLSY79 cohort and 1.8% for the NSLY97 cohort for each 3 percentage point increase in the unemployment rate (the average increase seen in recessions between 1980 and 2020). Consistent with the prior literature (e.g., Beaudry et al. 2016; Deming 2017), we find that the returns to cognitive skills decreased across cohorts (from 17.0% for the NLSY79 cohort to 7.7% for the NLSY97 cohort) and that the returns to social skills increased across cohorts (from 2.1% for the NLSY79 cohort to 3.6% for the NLSY97 cohort). However, we also find that the effects of the recessions have changed across NLSY survey waves for individuals with different levels of skills. For individuals with cognitive skills that are one standard deviation above the mean and average social skills, wages increase by 3.8% for the NLSY79 cohort and by 7.7% for the NLSY97 cohort during recessions. Thus, the increasing returns to cognitive skills during recessions are enough to compensate for the negative effect of high unemployment rates and the declining return to cognitive skills for individuals observed in the NLSY97 cohort. Further, we find that the wage losses for those with low cognitive skills are due to a combination of reduced work hours and less prestigious occupations. Overall, our results show that cognitive skills significantly influence an individual's success in the labor market during difficult economic times.

The increasing returns to cognitive skills during recessions may seem surprising. A robust finding in the literature is that the demand for cognitive tasks has been declining since 2000 (Castex and Kogan Dechter 2014; Beaudry et al. 2016). To understand our empirical results, we present a simple framework clarifying why workers with higher cognitive skills recently have a relative advantage during recessions. The key idea is that firms upskill through employer-paid training in the recoveries from recessions after 2000. We focus on the importance of training in understanding the wage results, given the role of training as a determinant of wage growth (Hashimoto 1982).

In our framework, the firm chooses the optimal level of training investment in response to the business cycle by considering the benefit of the investment against its costs. Recessions can induce the firm to increase the training investment as the opportunity cost declines during recessions (which we call the "cost-saving effect"). On the other hand, firms can change training investment during recessions because of a change in production throughout the recessions (which we call the "productivity effect"). The framework posits that during recessions, entrepreneurs are more willing to invest in training for workers with high cognitive skills if their training costs are reduced and labor productivity has improved to further enhance the productivity of these workers. Consistent with the framework we outline, productivity has significantly changed over the business cycle. In recessions since 2000, productivity has increased, which is an unusual phenomenon as it typically increases during non-recession periods. Thus, in line with the framework, employer-paid training would increase, particularly for workers with high cognitive skills, during the post-2000 recessions, which would lead to higher wages for these workers.

We provide a framework for exploring increased investment in company training during recessions in the 2000s and 2010s, focusing on lower opportunity costs and increased labor productivity. The standard theory, shaped by Becker (1962), provides a systematic explanation of training investments and the associated wages of workers. However, our framework has different implications than the original view of human capital. To the best of our knowledge, our framework is the first to offer a theory of human capital accumulation in the form of training, taking into account the business cycle.

Evidence from the NLSY79 and NLSY97 cohorts supports our framework. We find that individuals with advanced cognitive skills in the NLSY97 group have a greater chance of receiving company training during economic downturns, whereas those with similar abilities in the NLSY79 cohort are less likely to receive training during such times. Although prior research has documented that firms are more likely to provide training to workers with high cognitive skills (e.g., Altonji and Spletzer 1991; Veum 1995), our results show that this relationship has increased over time during recessions. We analyze why individuals enroll in training programs. Our findings indicate that people with high cognitive skills tend to enroll in training programs to enhance their skills, which aligns with our theoretical framework.

Our findings shed light on how the job market adapts during economic recessions. Many studies have shown that there are differences in the unemployment and wage patterns of various groups within the labor force. For instance, it is well documented that changes in aggregate unemployment mask substantial variation in underlying worker flows. Men, younger workers, less educated workers, and workers from ethnic minorities tend to face steeper rises in joblessness during all recessions (e.g., Clark and Summers 1982; Gomme et al. 2004; Kydland 1984; Mincer 1991; Elsby et al. 2010). We complement this previous research by investigating how the effects of a recession vary according to workers' cognitive and social skills. We offer the first result that workers with higher cognitive skills fare relatively better during recent recessions.

This paper also contributes to the literature on the changing trends in the returns to different types of skills. Similar to Castex and Kogan Dechter (2014) and Beaudry et al. (2016), we find that the returns to cognitive skills have declined over time. Similar to Deming (2017), we find that the returns to social skills have increased over time. We add to this literature by examining the interaction between these types of skills and economic conditions over time. Our results show that the returns to social skills are not significantly influenced by recessions but that the returns to cognitive skills have increased during recent recessions.

Additionally, this paper contributes to the literature examining the role of routine-biased technological change (RBTC) as an explanation for the polarization of jobs across the skill distribution over the last few decades. Hershbein and Kahn (2018) show that the Great Recession increased the skill requirements of new openings in areas with higher rates of unemployment shows, particularly among routine occupations, and that the recession accelerated RBTC. Our paper complements this research to show that, during recessions, upskilling occurs among current workers at firms through employer-paid training for workers with high cognitive skills, in addition to the upskilling of new hires through the greater skill requirements.

2 Data

To understand the influence of economic conditions across heterogeneous skill groups on various labor market outcomes, we utilize data from the NLSY79 and NLSY97. The NLSY79 is a panel that began with a nationally representative sample of 12,686 youth ages 14 to 22 in 1979, and the NLSY97 is a panel that began with a nationally representative sample of 8,984 youth ages 12 to 16 in 1997. The NLSY79 was conducted annually from 1979 to 1993 and biannually since 1994. The NLSY97 was conducted annually from 1997 to 2011 and biannually since 2011. The NLSY panels are useful for this research because the panels span multiple recessions and contain detailed information on measures of pre-market skills, personal characteristics, and labor market outcomes. Most variables across the NLSY79 and NLSY97 are compatible. When necessary, we follow Altonji et al. (2012) to facilitate comparison.

2.1 Construction of the Variables

We use the annual unemployment rate as an indicator of macroeconomic conditions, which is consistent with the prior literature (e.g., Kahn 2010; Castex and Kogan Dechter 2014; Altonji et al. 2016). We use the national, Census regional (Northeast, Midwest, South, and West), and state unemployment rates provided by the Bureau of Labor Statistics (BLS). We use the restricted-access NLSY geocodes to determine the contemporaneous state of residence to examine the influence of state unemployment rates.[1]

The primary outcome of interest is the real log hourly wage (indexed to 2013 dollars) at the main job.[2] In addition, we examine the number of hours worked per week and

[1]Following Kahn (2010), when a state of residence is missing, we use the state ID from the most recent prior year available or the most recent following year available.

[2]Following Altonji et al. (2012) and Deming (2017), we bottom code wages so that positive values below \$3 per hour are reported as \$3 and top code wages so that values larger than \$200 per hour are reported as

the probability of being employed full-time (working at least 35 hours per week) among individuals who are employed. We further examine occupational status, measured by the occupation prestige score taken from the Duncan Socioeconomic Index (SEI). This is a widely used indicator of occupational ranking, which ranges from 0 to 100 and measures occupational status based on the educational attainment and the income level associated with each occupation.

The NLSY79 and NLSY97 contain comparable measures of cognitive, social, and noncognitive skills. We define these skill variables as consistently as possible across NLSY panels. To measure cognitive skills, we use respondents' standardized scores on the age-adjusted Armed Forces Qualifying Test (AFQT). The AFQT scores are widely used in the literature as a measure of cognitive achievement, aptitude, and intelligence (e.g., Neal and Johnson 1996; Altonji et al. 2012). Altonji et al. (2012) adjust the AFQT scores to be comparable between the NLSY79 and NLSY97 panels by considering differences in test format, age-at-test, and other idiosyncrasies. We use the raw scores from Altonji et al. (2012). Following Altonji et al. (2012) and Deming (2017), we normalize the scores to have a mean of 0 and a standard deviation of 1.

We use a measure of social skills for both cohorts following Deming (2017). Deming (2017) constructs a new measure of social skills for the NLSY79 and NLSY97 cohorts that capture behavioral extroversion and pro-social orientation since both the NLSY79 and NLSY97 do not include psychometrically valid and field-tested measures of social skills. Both behavioral extroversion and pro-social orientation are positively correlated with measures of social and emotional intelligence in meta-analyses (Lawrence et al. 2004; Declerck and Bogaert 2008). This measure of social skills in the NLSY79 is constructed using the following two variables: (i) self-reported sociability in 1981 (extremely shy, somewhat shy, somewhat outgoing, extremely outgoing) and (ii) self-reported sociability in 1981 at age 6 (retrospective). Also, we measure social skills in the NLSY97 using two questions that capture the extroversion factor from the Big Five personality inventory (e.g., Goldberg 1993; Judge et al. 1999; Barrick and Mount 1991), which is a taxonomy for personality traits. Specifically, the NLSY97 includes two variables measuring the following personality traits: (i) extroverted or enthusiastic and (ii) reserved or quiet. Possible responses ranged from 1 (disagree strongly) to 7 (agree strongly). We reverse the score of variable (ii) to ensure that both variables are increasing in social skills. Each question is normalized to have a mean of 0 and a standard deviation of 1. We take the average and then re-normalize it so that cognitive and social

$200. Since our outcome is the real log hourly wage, individuals who are not working and report zero wages are excluded from the sample. In Appendix Table A.5, we show that the results are robust to imputing a wage for these respondents.

skills have the same distribution.[3]

Lastly, we construct a measure of noncognitive skills to ensure that social skills are not a proxy for noncognitive skills. Following Heckman et al. (2006) and Deming (2017), we construct a measure of noncognitive skills using the normalized average of the Rotter Locus of Control and the Rosenberg Self-Esteem Scale in the NLSY79 sample. Following Deming (2017), the measure of noncognitive skills in the NLSY97 is derived from seven questions that capture the Big Five factor conscientiousness.[4]

2.2 Sample Restrictions

We exclude respondents under 18 and over 37 since the oldest individual in the NLSY97 turned 37 in 2017. By restricting the sample to ages 18–37, we can focus on individuals of the same ages in both panels. We further exclude individuals who enrolled in school and who are missing information on skills measures and explanatory variables. Thus, we compare potential workers in the 1980–1996 period from the NLSY79 to potential workers in the 1997–2017 period from the NLSY97. Finally, following many other studies (e.g., Heckman and Hotz 1986; Haider 2001; Kahn 2010), we restrict the sample to males; we provide results for females and for all individuals in the appendix.

2.3 Summary Statistics

In Table 1, we report the summary statistics of the analysis sample of men between 18 and 37 who are not enrolled in school. The statistics are calculated using the base year weights provided by the Bureau of Labor Statistics (BLS). Hourly wage rates (in 2013 dollars) are similar across cohorts; average hourly wages in our data are about \$19.50 in the NLSY79 and

[3]We further explore whether the main results are robust to using an alternative measure of social skills in the Appendix Table A.6. For the NLSY79 cohort in 2014, respondents were asked the Ten Item Personality Measure (TIPI). This set of questions allows us to construct an identical measure of social skills across survey waves, using the following questions: (i) extroverted, enthusiastic, and (ii) reserved, quiet. However, this is not our preferred measure of social skills for the NLSY79 cohort since it is not available until 2014, which is when the mean age of respondents is about 52. Additionally, social skills may not remain stable throughout adulthood. For our analysis, we restrict the age range for our analysis to 18–37 to maintain similar ages across the NLSY79 and NLSY97 samples. Therefore, we choose our measure of social skills, which is consistent with Deming (2017), to minimize concerns about reverse causality and endogeneity bias. Nevertheless, we find that our main results are robust to this alternative measure of social skills, although the magnitude of the coefficients is slightly larger.

[4]There is a series of questions designed to rate personality traits, taking a value from 1 to 7 in the NLSY97. The personality traits we consider to measure noncognitive skills are disorganized, conscientious, dependable, thorough, trusting, disciplined, and careless. We standardize each variable to have a mean of 0 and a standard deviation of 1. We then take the average across all seven variables and re-standardize it. For the consistency of interpretation, we transform the variables when necessary to obtain a positive scale. Higher scores indicate more socially appropriate behavior.

about \$19.06 in the NLSY97. The average hours per week decreased from 43.22 hours for the NLSY79 cohort to 38.78 hours for the NLSY97 cohort. The percent employed full-time decreased from 92% for the NLSY79 cohort to 81% for the NLSY97 cohort. The occupation prestige score is fairly constant across cohorts.

The average national unemployment rate experienced by the NLSY79 cohort was 6.62%, while the rate experienced by the NLSY97 cohort was 6.14%. The regional and state unemployment rates show similar patterns. These average unemployment rates mask substantial variation over time and across locations. For instance, the regional unemployment rates vary from 3.6% to 11.1% in the NLSY79 and 3.5% to 11% in the NLSY97 across regions and over time.

Cognitive skills increased by 0.04 standard deviations across cohorts, whereas social skills decreased by 0.10 standard deviations across cohorts. However, the differences in skills across cohorts are not statistically significant.[5] The average potential experience is somewhat lower for the NLSY97 cohort, consistent with Castex and Kogan Dechter (2014).[6] The demographic characteristics of individuals in each cohort are generally similar, but there are twice as many Hispanic individuals in the NLSY97 cohort (12% in the NLSY97 compared to 6% in the NLSY79).

3 Econometric Methods and Results

3.1 Regression Specification

To investigate how the unemployment rate has affected workers with different levels of skills in the labor market across the 1979 and 1997 cohorts of the NLSY, we regress a labor market outcome on both skills measures, the unemployment rate, and interactions between both skill measures and the unemployment rate, while controlling for a variety of other covariates. The equation is formally given by

$$\begin{aligned} Y_{ijt} = \alpha + \beta_1 U_{jt} + \beta_2 Cog_i + \beta_3 Soc_i + \beta_4 U_{jt} * Cog_i + \beta_5 U_{jt} * Soc_i \\ + \beta_6 Cog_i * Soc_i + \beta_7 U_{jt} * Cog_i * Soc_i + \beta_8 X_{ijt} + \zeta_j + \epsilon_{ijt}. \quad (1) \end{aligned}$$

[5]The reason for the changing patterns of skills across cohorts is that we normalize each skill variable after pooling all individuals in both surveys. However, the results described in the next section are robust to separately normalizing skill variables from each survey.

[6]Following Castex and Kogan Dechter (2014), we construct weights to match the potential experience distribution of the NLSY97 cohort to that of the NLSY79 cohort and find that the results are not sensitive to the distribution of workers' experience.

In equation (1), Y_{ijt} is a labor market outcome measured for individual i in the region (or state for regressions with the state unemployment rate) of residence j in year t. The dependent variables described above are log hourly wages, the number of hours worked per week, whether the individual is employed full-time, and an occupation prestige score. U_{jt} measures labor market conditions of the region (or state) j in the year t, which we define as the deviation of the unemployment rate from the sample mean to ease the interpretation of the interaction terms. Cog_i and Soc_i measure cognitive and social skills, respectively. We allow the interaction of cognitive and social skills with U_{jt}. We also allow for the interaction of cognitive skills and social skills ($Cog_i * Soc_i$) to test for skill complementarity and include the three-way interaction $Cog_i * Soc_i * U_{jt}$. X_{ijt} controls for race/ethnicity (black and Hispanic), urbanicity, a quadratic time trend, potential experience, and potential experience squared.[7,8] ζ_j is the region (or state) fixed effect. The error term ϵ_{ijt}, clustered at the individual level, captures unobserved factors that could affect a labor market outcome.

The coefficient β_1 on U_{jt} represents the impact of the unemployment rate on the labor market outcome. The coefficients β_2 and β_3 represent the direct effects of cognitive and social skills on the labor market outcome, respectively. The coefficients β_4 and β_5 on the interaction terms show whether the impact of cognitive and social skills differs based on the labor market conditions, as measured by the unemployment rate.

3.2 Results

3.2.1 Effects of Adverse Labor Market Conditions on Wages

Table 2 shows the relationship between the unemployment rate and log hourly wages. Columns (1)–(3) summarize the wage regression results using the NLSY79, and columns (4)–(6) summarize the results for the NLSY97 cohort. Columns (1) and (4) show the results from using the national unemployment rate, columns (2) and (5) show the results from using regional unemployment rates, and columns (3) and (6) show the results from using state unemployment rates.

The first three rows replicate the results from the existing literature. Looking first at the results for the national unemployment rate in columns (1) and (4), we find that the national unemployment rate is negatively associated with log hourly wages. A one percentage point

[7] In our main specification, we control for a quadratic time trend and exclude year fixed effects. This exclusion allows time-series variation to contribute to identifying the U_{jt} effects. However, our results are similar when we control for year fixed effects instead of a quadratic time trend, as shown in the appendix.

[8] We do not control for age since potential experience and age are highly correlated. Potential experience is equal to age minus the years of schooling completed minus 6. However, the main results for both cohorts do not significantly change when controlling for age groups, as shown in the appendix.

increase in national unemployment decreases wages by 2.4% per year for the NLSY79 cohort and by 0.6% per year for the NLSY97 cohort; these estimates are statistically significant at the 1% level. A vast literature explains the existence of a negatively sloped relationship between wages and unemployment, following Phillips (1958) (e.g., Blanchflower and Oswald 1995; Card 1995).

The second and third rows show the influence of cognitive and social skills on wages. The returns to cognitive skills display a significant decline across NLSY cohorts. A one standard deviation increase in cognitive skills increases real log wages by 17% for the NLSY79 cohort, compared to 7.7% for the NLSY97 cohort. The difference between the coefficients across surveys is statistically significant at the 1% confidence level.[9] This is consistent with Beaudry et al. (2016), which document the "great reversal" in demand for cognitive skills since 2000.[10]

In contrast, the returns to social skills have increased over time. A one standard deviation increase in social skills increases wages by 2.1% in the NLSY79, compared to 3.6% in the NLSY97. The difference in the coefficients on social skills across NLSY waves is statistically significant at the 10% level. These results suggest that social skills have been a more important predictor of labor market success since the 2000s, compared to the 1980s and 1990s. The increase in the returns to social skills is consistent with Deming (2017), which suggests that the growing importance of social skills can be attributed to the fact that automation cannot easily substitute social interaction.

We test if the effects of labor market conditions on labor market outcomes vary with one's cognitive and social skills level by adding interaction terms between the unemployment rate and each skill measure. Although the first three rows provide results that are consistent with the literature, the next two rows show results for the interaction terms that are new to the literature. The interaction between cognitive skills and the unemployment rate is negative in the NLSY79, suggesting that a one percentage point increase in the national unemployment rate lowers the wage returns to cognitive skills from 17% to 15% in the NLSY79. Conversely, in the NLSY97, a one percentage point increase in the national unemployment rate increases the wage returns to cognitive skills from 7.7% to 8.3%. This evidence shows a growing emphasis over time on cognitive skills during periods of increasing unemployment, in contrast to the decline, on average, of the returns to cognitive skills across survey waves.

[9] For the comparisons, we follow Clogg et al. (1995) and calculate z-values on the differences through the formula $\frac{(\beta_{NLSY79} - \beta_{NLSY97})}{\sqrt{(se^2_{NLSY79} + se^2_{NLSY97})}}$.

[10] One possible explanation for the decline in the returns to cognitive skills is a slowdown in the growth rate of technology since 2000 (e.g., Greenwood and Yorukoglu 1997; Katz 2000; Beaudry et al. 2016). For instance, the Nelson-Phelps hypothesis, which posits that skills are most valuable when workers are adapting to a changing environment, could explain why the decline in the returns to cognitive skills is associated with a slowdown in technology growth starting in the late 1990s (Nelson and Phelps 1966). The existing literature offers more evidence of the changing pace of technological progress (e.g., Castex and Kogan Dechter 2014).

We document a modest increase in the wage returns to social skills during periods of increasing unemployment across the past few decades. An increase in the national unemployment rate by one percentage point is associated with a decrease in the wage returns to social skills from 2.1% to 1.8% for the NLSY79 cohorts, although this change is not statistically significant, but an increase in the returns from 3.6% to 3.9% in the NLSY97.[11]

These results show that a recession reduces wages by 7.2% for the NLSY79 cohort and reduces wages by 1.8% for the NLSY97 cohort for an individual with the average level of cognitive and social skills if we consider that a recession is equivalent to a rise in the unemployment rate of 3 percentage points, which is approximately the average change during recessions between 1980 and 2000. During a recession, wages increase by 3.8% for the NLSY79 cohort and by 7.7% for the NLSY97 cohort for individuals with high cognitive skills, equivalent to one standard deviation above the mean, and the average level of social skills. In comparison, during a period of the average unemployment rate, the return to cognitive skills is 17% for the NLSY79 cohort and 7.7% for the NLSY97 cohort for an individual with high cognitive skills. Thus, given the growing emphasis on cognitive skills during recessions, which is sufficient to offset the negative influence of the high unemployment rate for the NLSY97 cohort, workers with high cognitive skills were not negatively affected during recent recessions. Recessions during the 1980s and 1990s significantly reduced the wage returns to high cognitive skills, while recessions during the 2000s and 2010s did not influence the wage returns to high cognitive skills.

Columns (2) and (5) show the estimates using regional unemployment rates, and columns (3) and (6) show the estimates using state unemployment rates. The estimates using regional unemployment rates include region fixed effects, while the estimates using state unemployment rates include state fixed effects. The results using subnational unemployment rates are similar, particularly for the NLSY97 cohort, but the estimates on the interaction terms are smaller when using the state unemployment rate for the NLSY79 cohort. For the results using state unemployment rates, the interaction between cognitive skills and the unemployment rate shows that a one percentage point increase in the state unemployment rate lowers the wage returns to cognitive skills from 17.0% to 15.9% for the NSLY79 cohort but increases the wage returns to cognitive skills from 7.3% to 8.0% for the NLSY97 cohort. The estimates are statistically significant at the 1% level.

[11] We add an interaction between cognitive and social skills to test the complementarity of skills, although we do not show the coefficients to conserve space. We find little evidence of complementarity between cognitive and social skills, consistent with Deming (2017). Deming (2017) documents that skill complementarity is about 30% smaller when he restricts the sample to young workers. In addition, we include the three-way interaction Cog_i x Soc_i x U_{jt} to see how the differential effect varies with the unemployment rate. It is not statistically significant across survey waves, and including the triple interaction term has little impact on the main coefficients.

In Appendix Table A.1, we show that the estimates from Table 2 are robust to different control variables, including year fixed effects instead of quadratic time trends and adding controls for education, age fixed effects, noncognitive skills, and an indicator variable denoting a recession. In Appendix Table A.2 and A.3, we show that the results are robust to pooling together the NSLY79 and NLSY97 samples. We begin by replicating the sample and results from Deming (2017) in Appendix Table A.2. Then, we demonstrate the robustness of those results by performing slight modifications in control variables and the sample to match our sample and variable definitions. In Appendix Table A.3, we use our sample and variable definitions and build upon the pooled cohort approach of Deming (2017) to include interaction terms between skills and the unemployment rate and their interaction with the NLSY97 sample indicator. Consistent with the cohort-specific regression estimates from Table 2, the pooled results from Appendix Table A.3 show that, during periods of increasing unemployment, the returns to cognitive skills decrease for the NLSY79 cohort but increase for the NSLY97 cohort. Thus, the results consistently show a growing premium to cognitive skills during periods of increasing unemployment across the NLSY waves. Further, the robustness of the results to including these additional control variables suggests that the results reflect the changing demand for skills rather than a change in individual labor market characteristics.

3.2.2 Effects of Adverse Labor Market Conditions on Labor Supply

Table 3 displays the estimates for multiple measures of labor supply: the number of working hours per week and whether the individual is employed full-time.[12] Columns (1) and (2) show the estimates for the number of working hours per week for the NLSY79 cohort and for the NLSY97 cohort, respectively. An increase in the unemployment rate decreases the hours worked for both cohorts. The returns to both skills, in terms of working hours per week, have not changed very much across survey waves; column (1) shows that a one standard deviation increase in cognitive skills is associated with an increase in work hours by about 45 minutes in the NLSY79, compared to more than half an hour in the NLSY97. However, we find no significant differences across NLSY waves. Similarly, the influence of social skills on working hours is about 35 minutes more work for both cohorts.

We include interactions between the unemployment rate and both skill measures to estimate the differential impact of economic conditions across workers of different levels of skills. The results show that the interaction between cognitive skills and the unemployment

[12]The unemployment rate in Table 3 is the regional unemployment rate. Appendix Table A.4 presents analogous results with national and state unemployment rates, which are qualitatively similar to the results presented in Table 3.

rate is positive and statistically significant for the NLSY97 cohort, while this interaction term is negative and not statistically significant for the NLSY79 cohort. A one percentage point increase in the unemployment rate increases the influence of cognitive skills on hours worked from 0.6 hours to 0.73 hours in the NLSY97 cohort, which is a change of about 8 minutes. Moreover, the interactions between social skills and the unemployment rate are small and insignificant in all specifications across the 1979 and 1997 waves of the NLSY. Overall, workers with higher cognitive skills have an advantage in a depressed labor market in the 2000s and 2010s, but the magnitude of this advantage is not large.

Columns (3) and (4) show the effects of adverse labor market conditions on full-time employment. Both the NLSY79 and NLSY97 samples show that the unemployment rate has a statistically significant negative impact on the probability of full-time work. We further document a decline in the returns to cognitive skills across the NLSY waves; column (3) shows that a one standard deviation increase in cognitive skills increases the probability of full-time employment by 2.3 percentage points in the NLSY79 sample, compared to 1.1 percentage points in the NLSY97 sample. In contrast, the returns to social skills increased over time; the impact of social skills on the probability of full-time work has increased from 0 to 1.3 percentage points.

The interaction between cognitive skills and the unemployment rate increases over time. The coefficient on this interaction is not statistically significant in the NLSY79 sample, suggesting that the unemployment rate does not have a significant impact on the returns to cognitive skills in terms of full-time work. In contrast, in the NLSY97 sample, a one percentage point increase in the regional unemployment rate is associated with an increase in the returns to cognitive skills in terms of the probability of full-time employment from 1.1 to 1.5 percentage points. This indicates that cognitive skills play a more important role during recessions in recent years compared to the 1980s and 1990s. Lastly, the interaction between social skills and the regional unemployment rate is not statistically significant across the survey waves. The effects of the unemployment rate on the returns to social skills are small and have mostly stayed constant over time.

The estimates of the influence of the unemployment rate, cognitive skills, and the interaction between the unemployment rate and cognitive skills on working hours and full-time employment suggest that the estimates of the influence on wages could be underestimated. We find that the negative effects of an increase in the unemployment rate are larger for individuals with low cognitive skills, which suggests that individuals with the lowest potential wages are less likely to work during periods of increasing unemployment. Such a response would bias our results from Table 2 towards zero. We also exclude individuals who have zero wages when examining log wages in Table 2. This exclusion could bias the estimates towards zero since we do not consider the losses due to non-employment. In Appendix Table A.5, we examine the robustness of the results from Table 2 to possible selective labor force participation using similar approaches as Oreopoulos et al. (2012) and Schwandt and Von Wachter (2019). First, we impute a small wage for individuals with zero wages. Our results are robust to this change. Second, we compare the estimates for individuals who report positive wages in nearly every year of potential experience to the estimates for all individuals with similar years of experience. To do so, we restrict the sample to workers with 1 to 10 years of potential experience and analyze whether there are differences in the estimates for all workers in this sample compared to the sample of workers who earn positive wages for at least 8 years out of their total 10 years of potential experience. The results are similar for both samples of individuals. The results from each of these robustness checks suggest that selective labor force participation does not significantly bias the results.

3.2.3 Effects of Adverse Labor Market Conditions on Occupational Prestige

Columns (5)-(6) from Table 3 present results on the occupation prestige score. An increase in the unemployment rate reduces occupational prestige for the NLSY79 cohort, but the estimate for the NSLY97 cohort is positive, small, and not statistically significant.

Workers with high cognitive skills have an advantage in occupational prestige. However, there is a significant decline in this advantage across NLSY waves; in response to a one standard deviation increase in cognitive skills, the occupation prestige score increases by 4.74 points (or 13.3% of the mean) for the NLSY79 cohorts but only 3.0 points (or 8.4% of the mean) for the NLSY97 cohorts. Conversely, we find an increase in the returns to social skills; the effect of one standard deviation increase in social skills on the occupation prestige scores increases from 0.37 points (or 1.01% of the mean) in the NLSY79 to 0.64 points (or 1.76% of the mean) in the NLSY97.

The interaction between cognitive skills and the unemployment rate has grown across NLSY waves. We find a negative coefficient on the interaction between cognitive skills and the unemployment rate in the NLSY79 of -0.35 points (or 0.97% of the mean). Adverse labor market shocks lead workers with higher cognitive skills to take poorer-quality jobs. However, the interaction in the NLSY97 is positive (0.22 points or 0.6% of the mean), suggesting that workers with high cognitive skills experience an improvement in occupational prestige during recessions. The coefficient on the interaction between social skills and the unemployment rate is negative but not statistically significant for both cohorts. Overall, we find similar results for hours worked, working full-time, and occupation prestige as the wage estimates reported in Table 2, which show a growing demand for cognitive skills during recessions over the past several decades.

To summarize, we find that recessions result in substantial wage losses for most workers. However, workers with higher cognitive skills are not negatively affected during recessions in the more recent 1997–2017 period. The differential impact of the unemployment rate on a combination of hours reduction and decreases in occupation prestige can explain in part why the wage effects are muted for workers with higher cognitive skills; those with higher cognitive skills increase their already strong advantage during recent recessions and thus experience more mild effects along the various dimensions we measure.

4 Training as a Mechanism Explaining the Increasing Importance of Cognitive Skills during Recessions

In this section, we develop a model to understand the empirical results that the returns to cognitive skills decreased during recessions in the 1980s and 1990s but increased during recessions in the 2000s and 2010s. In particular, we focus on the role of upskilling through company-provided training as a mechanism through which the returns to cognitive skills have increased during recent recessions.

We focus on training since it is an important determinant of wages. Many studies have shown that training is one of the key human capital resources used to enhance productivity growth and firm performance (e.g., Barron et al. 1989; Lynch 1992; Holzer et al. 1993; Bartel 1994; Black and Lynch 1996; Barrett and O'Connell 2001). In the literature on human capital, the primary driver of wage growth is the accumulation of human capital, particularly through on-the-job training (Hashimoto 1982). According to Barron et al. (1989), a 10% increase in training is associated with a 3% increase in productivity growth, which highlights the importance of training in determining wage and productivity growth. Additionally, the literature on work-related training reveals that skilled workers are more inclined to participate in employer training, implying that general education and employer training are complementary (e.g., Booth 1991; Asplund 2005; Caliendo et al. 2022). Therefore, developing a deeper understanding of who received employer-provided training is helpful in explaining how the influence of changes in the unemployment rate has varied across workers of different levels of skills over time.

This section begins by presenting a stylized framework to study how a firm chooses the optimal level of training investments in response to the business cycle. The firm weighs the benefit of the investment against its cost.[13] The recession may induce firms to alter the

[13]Examples of training benefits include monetary benefits such as the value from increases in production and efficiency and production downtime savings and nonmonetary benefits such as trainee attitudes, health, and safety. Training requires money and time to maintain and continue training (Cullen et al. 1978).

amount of training investment due to a change in production throughout the recession. We call this phenomenon the *productivity effect*. Additionally, as the opportunity cost declines during a recession, firms increase their investment in training. We call this phenomenon the *cost-saving effect*. Notably, recessions influence the benefits and costs of training for highly-skilled workers more than for low-skilled workers. Firms may be incentivized to invest more in high-skilled workers if their training costs decrease and labor productivity improves during recessions. In recent years, productivity in the U.S. economy has changed significantly over the business cycle (Van Zandweghe 2010). Through the recessions of the 1980s, productivity growth would typically rise and fall alongside output growth. Since then, the relationship between these two variables has weakened, and they have even moved in opposite directions recently. For instance, productivity rose during the 2007-09 recessions. Within our framework, the changes in the pattern of labor productivity over time can generate changes in the pattern of company-provided training, particularly for high-skilled workers.

We then provide evidence from the NLSY79 and NLSY97 cohorts, which supports the framework that we outline. We find that, during recessions, there was a lower likelihood of receiving training for workers with high cognitive skills in the NLSY79 cohort. In contrast, for those in the NLSY97 cohort, workers with high cognitive skills had a higher likelihood of receiving training during recessions. These results show that the patterns of receiving training during recessions have changed over time for high-skilled workers. Given the importance of training for wage growth, these results help to explain the changing labor market returns to cognitive skills during recessions.

4.1 A Stylized Framework

4.1.1 Mechanics

Consider an economy with an entrepreneur who runs a firm. The entrepreneur hires individuals to produce only one good. For simplicity, there is one input factor, labor, and no capital in the model, and therefore, consumption equals production at any point in time. This enables us to focus on the entrepreneur's decision about the level of training investment that does not stem from different capital-labor ratios (e.g., Beaudry and Green 2003). Following Acemoglu and Pischke (1998), we assume that the entrepreneur bears the costs of investment irrespective of whether skills are completely general in the sense that they can be used as effectively in other firms.[14] Lastly, the model is essentially static.

[14] Becker (1962) firstly argues that in the competitive markets, firms are unwilling to pay for entirely transferable training (i.e., perfectly general), while workers are unwilling to pay for completely transferable training (i.e., perfectly specific). However, subsequent research has shown that this strict dichotomy is not always the case due to labor market rigidities, non-competitive market structures, and training that is both

The production process is governed by a technology f. Specifically, the production function f is a positive and concave function of cognitive skills k and a negative function of labor market conditions indexed by u, so $f = f(k, u)$.[15] Workers' cognitive skills k are a positive and concave function of a firm's investment in cognitive skills, which we denote by I. Investments I can be realized through various types of "training". As in Klein and Su (1979), we include the unemployment rate u in the production function, and a higher u indicates adverse market conditions.

The investment cost λ is increasing and convex in investment I. Importantly, the recession can lower the marginal cost of investment I because of lower opportunity costs or frictions such as adjustment costs during recessions (e.g., Mortensen and Pissarides 1994; Caballero and Hammour 1996; Gomes et al. 2001; Hall 2005). More formally, $\lambda_{Iu} < 0$.

With the above assumptions and technology, we now show how the production process varies as a function of a labor market condition u and a level of cognitive skills k due to the entrepreneur's choice in investment I. We can represent the optimal decision faced by the entrepreneur as choosing I^* given by

$$\Phi(f(k(I), u)) - \lambda(I, u). \tag{2}$$

The utility function Φ represents preferences for their expected product returns. As the utility of the entrepreneur is a positive and concave function of production, $\Phi' > 0$ and $\Phi'' < 0$.

The entrepreneur chooses the optimal investment I^* to satisfy the following first-order condition:

$$\Phi' f_k k_I = \lambda_I. \tag{3}$$

Equation (3) produces the standard result that the entrepreneur sets the optimal decision I^* at which the utility gain arising from the increase in production, associated with a marginal increase in investment I, equals the increase in cost in terms of investment.

The main comparative static is the effect of the labor market condition u on the firm's decision to invest in training I, or $\frac{\partial I^*}{\partial u}$. Differentiating the first-order condition with respect

general and specific. See Acemoglu and Pischke (1999a) and Asplund (2005) for reviews of this literature.

[15] Firms may be more profitable with workers with higher social skills because social skills enable workers to work with others more efficiently. Although we assume that social skills do not contribute to production for simplicity, it is not a crucial assumption. In particular, our assumption is that the marginal product of cognitive skills is independent of the marginal product of social skills, which is validated in the empirical analysis. Specifically, we test for complementarity by adding the interaction of cognitive skills and social skills in Table 2 (not reported). Our analysis indicates that this interaction is not statistically significant, and its inclusion barely affects the coefficients on cognitive skills and their interaction with unemployment rates. This assumption that social skills do not contribute to production can be relaxed by allowing the production technology to include social skills s, that is, $f = f(k, s, u)$.

to u yields

$$\Phi'[k_I(f_{kk}k_I I_u + f_{ku}) + f_k k_{II} I_u] + \Phi''(f_k k_I I_u + f_u) f_k k_I = \lambda_{II} I_u + \lambda_{Iu}. \tag{4}$$

This gives an expression for I_u^*:

$$I_u^* = \frac{\Phi'' f_u f_k k_I + \Phi' f_{ku} k_I - \lambda_{Iu}}{\lambda_{II} - \Phi'' f_k^2 k_I^2 - \Phi'(f_k k_{II} + f_{kk} k_I^2)}. \tag{5}$$

By the assumptions regarding the functional forms described above, the denominator is always positive. In other words, the sign of I_u^* is equal to the sign of the numerator. Note that the first term $\Phi'' f_u f_k k_I$ is positive since $\Phi'' < 0$, $f_u < 0$, $f_k > 0$, and $k_I > 0$.

We refer to the second term in the numerator as the "productivity effect". The entrepreneur's investment in skills creates higher skills for workers by k_I, which increases output. Thus, since $\Phi' > 0$, the sign of the second term depends on the sign of f_{ku}. If a recession reduces the per-unit effect of a worker's cognitive skills on production ($f_{ku} < 0$), then the entrepreneur is less inclined to train workers when recessions decrease the scope for gains from training. This suggests that firms may decrease investment to equalize the marginal change in utility and investment costs in equation (3). On the other hand, if labor productivity increases during recessions ($f_{ku} > 0$), the increase in labor productivity encourages firms to invest more in employee training.

The third term in the numerator captures the "cost-saving effect". Investment costs can decrease during recessions as recessions lower opportunity costs and produce large enough shocks to overcome various types of friction (Mortensen and Pissarides 1994; Caballero and Hammour 1996; Gomes et al. 2001; Hall 2005; Koenders et al. 2005). As $\lambda_{Iu} < 0$, the "cost-saving effect" increases investment during recessions. Firms must increase investment I to satisfy the first-order condition as the right-hand side of the equation (3) falls with an increase in u.

The framework clearly shows when the sign can be positive or negative, while it cannot specify the sign of the effect. The idea of competing incentives for investment is expressed formally below:

Proposition 1. *The effect of a recession on the entrepreneur's investment decision for skill development, $\frac{\partial I^*}{\partial \mathrm{u}}$, can either be positive or negative. It is a positive function of (-λ_{Iu}), which represents the extent to which worse macroeconomic conditions can lower the per-unit cost of investment (the "cost-saving effect"). It also depends on the sign of f_{ku}, which represents the extent to which bad economic conditions lower or increase the per-unit production of workers' skills (the "productivity effect"). When $f_{ku} > 0$, $\frac{\partial I^*}{\partial \mathrm{u}} > 0$. However, when $f_{ku} < 0$, the sign* *of $\frac{\partial I^*}{\partial \mathrm{u}}$ depends on the magnitudes of the "productivity effect" and the "cost savings effect."*

The theoretical framework suggests that a firm's decision to invest in employee training can be affected by the business cycle. The sign of effect will be positive if the entrepreneur increases their investments to upskill, exploiting a situation where the opportunity cost is sufficiently lower or productivity rises during a recession. On the other hand, the sign of the effect will be negative if labor productivity sufficiently falls during contractions. Firms are willing to pay for training only if labor productivity is high enough to justify the costs during economic downturns.

4.1.2 Heterogeneity by Skill Levels in the Effects of Training

We further develop this framework to show that the two forces present in Proposition 1 can have opposing effects with a differential impact across the distribution of cognitive skills, k. We focus on cases where workers have either high cognitive skills (k^H) or low cognitive skills (k^L). Consider a rise in a firm's investment decision I and its return on training for workers with different levels of cognitive skills (i.e., $\frac{\partial k^i}{\partial I}$ for $i = H, L$). Following Altonji and Spletzer (1991), we assume that investment in training has a higher return for those with high cognitive skills compared to those with low cognitive skills (i.e., $\frac{\partial k^H}{\partial I} > \frac{\partial k^L}{\partial I}$). Training leads to a higher increase in their marginal product by f_k when workers have higher cognitive skills.

We investigate how economic conditions affect entrepreneurs' training decisions for high- and low-skilled employees. Intuitively, it seems that employers would invest more in training for high-skilled workers during recessions due to their higher marginal returns to training compared to low-skilled workers. However, if it is possible to increase the productivity of employees during recessions, why don't employers also invest more in high-skilled workers during normal times?

There is a conceptual reason that investing in high-skilled workers becomes more valuable as the economy transitions from normal times to a recession. Higher cognitive skills result in a greater return on investment in training, which in turn increases a firm's production level by f_k. This ultimately leads to an increase in the entrepreneur's marginal utility of consumption Φ'. Therefore, based on the first-order condition in equation (3), the entrepreneur may decrease investment to balance the marginal utility of consumption and the marginal cost of training.

However, unfavorable economic shocks can alter this circumstance, as can be seen from the numerator of the expression for I_u^* in equation (5). During economic downturns, firms experience a decrease in production, adversely impacting an entrepreneur's consumption utility. This motivates the entrepreneur to invest more in workers with high cognitive skills to compensate for the production loss. This claim is based on the signs assigned to the first term of the numerator in equation (5), $\Phi'' f_u f_k k_I$.

In addition, the productivity effect in the second term of the numerator can also explain why employers invest in high-skilled workers during economic downturns. This effect has a greater impact on workers with higher cognitive skills, as their marginal productivity is higher than those with lower cognitive skills. As a result, if a firm's labor productivity is not significantly affected by economic shocks or increases during recessions, the entrepreneur is more likely to invest in training for workers with high cognitive skills.

In the following proposition, we describe this idea of heterogeneity by skill levels in the effects of training throughout the business cycle.

Proposition 2. *If the firm's labor productivity either increases or remains steady during recessions (i.e., $f_{ku} \geq 0$), then employers invest more in the training of high-skilled workers rather than low-skilled workers during recessions (i.e., $I_u(k_I^H) > I_u(k_I^L)$).*

Proof. Given $f_{ku} \geq 0$, let C_i be the value such that

$$C_i = \Phi' f_u f_k k_I^i + \Phi' f_{ku} - \lambda_{Iu}.$$

for each $i = H, L$. Based on the functional forms described earlier, it is evident that $C_H > C_L$. Therefore,

$$I_u(k_I^H) - I_u(k_I^L) = (C_H - C_L)(\lambda_I I - \Phi' f_k k_{II}) + (C_H (k_H^I)^2 - C_L (k_L^I)^2)(-\Phi'' f_k^2 - \Phi' f_{kk}) > 0.$$

■

Assessing the sign of the influence of economic recessions on employer-provided training for workers with different skill levels is an empirical question. However, the sign of the changes in labor productivity during recessions has an important influence on the sign of results for training. Thus, before estimating the results for training, we next discuss the evidence on changes in labor productivity over time.

4.1.3 The Productivity Effect

The results in propositions 1 and 2 are largely influenced by the sign of f_{ku}, which measures how an increase in unemployment changes the productivity of a worker with a given level of cognitive skills. Historically, labor productivity has been procyclical (Klein and Su 1979). Firms may have lower labor productivity during recessions because of low utilization levels, particularly for financially vulnerable firms that rely on external credit to finance production (Okun 1963; Bems et al. 2013). For example, Mulligan (2009) and Elsby et al. (2010) find that productivity during recessions declined in the 1970s and 1980s. Similarly, labor productivity, measured as output per hour for all employed persons in the nonfarm business sector by the Bureau of Labor Statistics, decreased during the 1980, 1981-1982, and 1990-1991 recessions, as shown in Appendix Figure A.1. Thus, for the recessions experienced by the NSLY79 cohort, it is reasonable to infer that $f_{ku} < 0$. As described in Proposition 1, when $f_{ku} < 0$, the sign of the change in training due to an increase in unemployment depends on the magnitudes of the productivity effect and the cost savings effect.

On the other hand, labor productivity has increased during recent recessions. Productivity may not decline during recessions because a worker responds with increased effort (Lazear et al. 2016) or because firms restructure during recessions by laying off unproductive workers (Berger et al. 2012). In contrast to the recessions prior to 2000, Lazear et al. (2016) find that aggregate labor productivity increased during the Great Recession. As shown in Appendix Figure A.1, based on data from the Bureau of Labor Statistics, labor productivity increased during both the 2001 recession and the Great Recession of 2007-2009. Thus, the cyclical dynamics of productivity have changed across decades.

Routine-biased technological change (RBTC) can help explain why labor productivity changed following the recessions of the 1990s. Acemoglu and Autor (2011) proposed a revised version of the skill-biased technological change (SBTC) hypothesis, known as RBTC, to better account for changes in the employment structure, especially the phenomenon of job polarization that became more evident in the 1990s and accelerated thereafter. According to Autor and Dorn (2013), workers performing 'abstract' tasks, such as problem-solving, intuition, persuasion, and creativity, are difficult to replace with technology. Furthermore, the complementarity between technology and high-skill labor may enhance their productivity, resulting in an increasing demand for such workers. Consistent with this idea, Hershbein and Kahn (2018) find that the Great Recession accelerated the restructuring of production towards routine-biased technologies and the more skilled labor that complements them. Thus, changes in the labor market due to RBTC have increased the demand for skilled labor, which contributed to the rise in labor productivity during recessions in recent decades.

In contrast to the experiences of the NLSY79 cohort, for the recessions experienced by the NLSY97 cohort, the evidence suggests that $f_{ku} > 0$. Based on Proposition 1, for the NLSY97 cohort, training would increase as unemployment increases. Additionally, based on proposition 2, for the NLSY97 cohort, training would increase for high-skilled workers more than for low-skilled workers during recessions.

Overall, based on the empirical evidence that $f_{ku} < 0$ during the recessions experienced by the NLSY79 cohort and $f_{ku} > 0$ during the recessions experienced by the NLSY97 cohort, our theoretical model yields the following predictions:

1) Training will decrease for workers with high cognitive skills during recessions for the NLSY79 cohort if the magnitude of the productivity effect is sufficiently larger than the magnitude of the cost savings effect.

2) Training will increase for workers with high cognitive skills during recessions for the NLSY79 cohort if the magnitude of the cost savings effect is sufficiently larger than the magnitude of the productivity effect.

3) Training will increase for workers with high cognitive skills during recessions for the NLSY97 cohort.

This framework and the previous literature on the cyclicality of employer-provided training suggest that, during recent decades, firms invest in training high-skilled workers during recessions to further enhance their productivity, which increases their wages.

4.2 Labor Market Conditions and Training

The framework in Section 4.1 offers a framework in which an entrepreneur heterogeneously provides training across the distribution of cognitive skills and states of the economy. Guided by this conceptual framework, we empirically investigate whether training is distributed differently among workers of varying skill types and whether this pattern changes throughout the business cycle.

We examine the relationships between the incidence of training, skills, and the unemployment rates conditional on employee and firm characteristics in Table 4. We estimate regressions similar to equation (1) above but with the dependent variables as measures of whether the individual has received training within the past year. In particular, we focus on training for which employers provide financial support, considering our framework of a firm's decision about investing in training. The NLSY79 and NLSY97 both include information about the types of training a worker receives and whether employers provide financial support for the training.[16] We focus on measures of the incidence of training rather than the duration of training.[17]

[16] The training programs reported do not include short training spells (less than one month) in the early 1980s. This one-month minimum duration requirement was dropped starting in 1988. Following Parent (1999), we combine data throughout the NLSY79 sample, which includes years where the training program lasted at least one month and those with shorter spells.

[17] Veum (1995) finds little difference in the estimated effect of incidence and duration and documents two reasons for this. First, the total time spent in these training programs does not enhance productivity, as

In the baseline specification for training, we control for the same covariates in equation (1) that are used for the results in Table 2. We also add a range of training-related variables that are typically employed in training models (Lynch 1992; Lynch and Black 1998; Gerlach and Jirjahn 2001). Specifically, we include firm size, health status, marital status, and union status. The effects of these variables are found to be essential determinants of training in previous work. Firm size may be a critical determinant of company training because higher monitoring costs induce large firms to try to economize on monitoring through on-the-job training (Oi 1983). In particular, we employ two firm-size dummy variables; the first variable is equal to 1 if the firm has employees at more than one location and 0 otherwise, and the second variable is equal to 1 if the individual works in an establishment with over 1,000 employees and 0 otherwise. Unionized firms are expected to provide more training because labor unions may directly negotiate better training opportunities and reduce labor turnover by altering the wage structure (Acemoglu and Pischke 1999b; Beckmann 2002; Zwick 2006). We included a dummy variable to indicate whether respondents' work is limited by their health in NLSY79 and if their general health is poor in NLSY97. Lastly, we add a dummy variable that indicates the respondent is married. Note that we impute missing observations for training-related variables, although the results are similar when we drop these observations.

The results are shown in Table 4. Columns (1)–(2) show results for the 1979 cohort. Column (1) indicates that the effect of economic conditions on company training is negative and statistically significant in the NLSY79 sample. This result is consistent with Veum (1995), which finds lower company training rates for those living in areas with a high unemployment rate in 1990. Differences in cognitive skills significantly affect the possibility of receiving company training. However, there is no correlation between company training and social skills. These estimates suggest that each skill influences the likelihood of receiving company training for the NLSY79 cohorts differently. From this, we see that employers tend to train their "best" workers regarding cognitive skills. This finding is similar to estimates by Altonji and Spletzer (1991), who find that company training is strongly correlated with aptitude in the National Longitudinal Survey of the High School Class of 1972.

The interaction term of Cog_i and U_{jt} in column (1) is negative and statistically significant, suggesting that during economic recessions, companies are less likely to invest in training for employees who possess high cognitive skills. In particular, a one percentage point increase in the regional unemployment rate is linked to a 0.9 percentage point reduction in the likelihood

shorter programs may have more content related to productivity than longer programs. Second, the training duration variable may contain considerable measurement error. Individuals can provide fairly accurate information on whether they participated in training programs but have more difficulty recalling time spent in programs.

of workers with higher cognitive skills receiving training. The interaction term of Soc_i and U_{jt} is negative, small in magnitude, and not statistically significant. During periods of high unemployment, workers with high social skills are not differentially more likely to receive training.

Column (2) adds controls for other training-related variables. The results are robust to their inclusion. The negative and statistically significant coefficient on the interaction between the unemployment rate and cognitive skills is similar. This suggests that individuals in the NLSY79 cohort with high cognitive skills are less likely to receive company training during a downturn. Additionally, employees working in larger companies are more likely to receive training, which is consistent with Veum (1995).

Columns (3)–(4) examine the impact of economic conditions on the training decision of an employer for the NLSY97 cohorts. We observe similar effects on the unemployment rates and cognitive skills across the 1979 and 1997 waves of the NLSY, but the magnitudes are weaker for the NLSY97 cohorts. A difference across waves is that, in the NLSY97 sample, social skills play a larger role in training participation, although their impact is substantially smaller in magnitude than that of cognitive skills.

More importantly, workers with higher cognitive skills exhibit differences in training acquisition during recessions across the NLSY waves. In the NLSY79, the negative and statistically significant interaction term of the unemployment rate and cognitive skills suggests that the effect of cognitive skills on training is relatively weaker during economic downturns. However, in the NLSY97 sample, the interaction is positive and statistically significant. This implies that, since the 2000s, more firms tend to provide training for workers with higher cognitive skills as the economy moves into recession. In contrast, social skills do not show any differential effect during recessions.[18,19]

Lastly, the size of the company and the marital status of the employees are still important factors in deciding who participates in the training programs for both NLSY79 and NLSY97 cohorts. In the NLSY97, participants in training are more likely to have better health status and union membership compared to those who do not participate.

Overall, these results show that the pattern of training for high-skilled workers during recessions has changed over time. For workers with cognitive skills one standard deviation above the average, a recession reduced the likelihood of receiving training by 0.6 percentage

[18] Based on these results, the theoretical framework described previously only considers cognitive skills and disregards skill heterogeneity for simplicity. However, the theoretical results are similar if we broaden the framework to include social skills for a more comprehensive production technology.

[19] Caliendo et al. (2022) provide empirical evidence that noncognitive skills, measured by locus of control, influence participation in training. We test the robustness of our results to the inclusion of noncognitive skills and find that our conclusions remain unchanged (not reported).

points (or 6% of the mean) for the NLSY79 cohort but increased the likelihood of receiving training by 2.0 percentage points (or 24.2% of the mean) for the NLSY97 cohort, where we again consider a recession as equivalent to an increase in the unemployment rate of 3 percentage points.

To gain a deeper insight into the findings presented in columns (1)–(4) of Table 4, which suggest that workers with high cognitive skills are more inclined to participate in training during economic downturns since 2000, we next provide additional details on the main reason for enrolling in training in the NLSY97 in columns (5)–(6) of Table 4.[20] This question is specifically asked of respondents whose employer funds their training. Hence, these results reflect the reasons why the employer chooses to invest resources in training.

Columns (5)–(6) investigate whether workers with high cognitive skills receive training for upskilling during recessions. We estimate the regression model in equation (1), with the dependent variable being an indicator for receiving training for upskilling. Among several reasons for providing training, our focus is on upskilling. This is in line with our theoretical framework, where a firm invests in training to enhance the skills of employees. We construct the indicator variable for training for upskilling that is equal to 1 if the respondent describes that the reason for training is part of a regular program to maintain and upgrade employee skills.[21] The set of controls is the same as those in our full specification in columns (2) and (4) of Table 4.

As is evident from columns (5)–(6), employers take into account the cognitive skills of their employees when providing training to enhance their skills. This same conclusion holds during recent recessions. As the unemployment rate increases, cognitive skills exhibit larger differential effects for upskilling.

Overall, the results in Table 4 demonstrate that the probability of receiving company training is associated with cognitive skills. The results also show that during economic recessions, firms are more inclined to provide training opportunities to workers with higher cognitive skills in the 2000s and 2010s, as opposed to the 1980s and 1990s. In times of economic downturns, companies usually offer training programs to their "most talented" employees in terms of cognitive skills. These findings are consistent with our conceptual framework and the evidence on the changes in labor productivity during recessions across decades. Given the literature on the influence of training on wages, these results imply that changes in training can help explain how changes in the unemployment rate affect wages for workers with different skill levels. Further, these findings are qualitatively consistent with

[20]In the NLSY79, the question on reason for taking training is missing for several years, and its response options are not consistent across years. Therefore, we solely focus on analyzing the NLSY97 cohort.

[21]The results are similar when we examine upskilling necessary to obtain a license or certificate as the reason for training (not reported).

the impact of U_{jt} on the labor market returns to skills, which are presented in tables 2 and 3. This implies that training is an important margin for understanding labor market outcomes over the business cycle.

5 Conclusion

This paper shows that the labor market increasingly rewards cognitive skills during the 2000s and 2010s recessions. This result contrasts with the general trends in the returns to skills found in the previous literature. A growing body of work in economics recently documents that the labor market increasingly rewards noncognitive skills, including social skills and leadership skills. Meanwhile, the returns to cognitive skills have remained constant since 2000.

To understand our findings on the growing importance of cognitive skills during recent recessions, we present a framework for how recessions influence a firm's investment decision in training. Recessions may lower the opportunity cost of training. This "cost-saving effect" indicates that the greater this effect, the more significant the incentives for firms to foster training provision, raising the returns to cognitive skills. A model with adjustment cost where reallocation is concentrated in downturns can also support this result. For instance, Hall (2005) documents that firms may make productivity-enhancing improvements in a recession due to the lower opportunity cost of adjusting production. On the other hand, firms may change their investment in training due to productivity changes in recession periods. This "productivity effect" suggests that firms are more likely to invest in training workers with high cognitive skills as labor productivity increases.

The framework generates intuitive predictions about the impacts of economic conditions on company training, which we investigate employing two-panel surveys, the NLSY79 and NLSY97. We show evidence that, when the economy suffers from a recession, workers with higher cognitive skills received more company training in the 2000s and 2010s compared to the 1980s and 1990s. By studying the main reason for enrolling in company training in the NLSY97, we find that workers with higher cognitive skills are more likely to receive company training to maintain/upgrade their skills during the recession. This is in line with our framework, which helps to explain the greater returns to cognitive skills during the recessions that occurred post-2000.

Our work highlights that increased emphasis on training and upskilling would have the capacity to capture the main patterns in our data. Related to this result, Hershbein and Kahn (2018) show that the Great Recession increased the skill requirements of new openings in areas with larger employment shocks. Our results show that upskilling occurred among existing workers, in addition to the upskilling of job requirements for new workers. However, other relevant, complementary mechanisms could explain part of these results. For instance, routine-biased technological change (RBTC) is complementary to high-skill cognitive jobs (e.g., Autor et al. 2003; Autor et al. 2006; Goos et al. 2014; Michaels et al. 2014). Since exposure to this technological change has increased the demand for cognitive skills, technological progress during recent recessions strengthens cognitive skills' role in complementing new technology. Alternatively, we can focus on occupational skills requirements. Jobs that require high cognitive skills tend to be less sensitive to economic downturns, which implies that individuals with higher cognitive skills are less affected (Weinstein and Patrick 2020).

Finally, it is worth considering what implications our findings may have for the recovery of the U.S. labor market following recessions. Beaudry et al. (2016) and others document the "great reversal" in demand for cognitive skills. They show that cognitive occupations have not experienced gains in employment or wages since 2000. Although it may be the case that the U.S. economy in the post-2000 period experienced a decline in the demand for cognitive skills on average, we find evidence that such skills are still important, especially during recent recessions. In the recessions that occurred since 2000, companies have increased training among workers with high cognitive skills, indicating a need for new and advanced skills to aid in the process of recovery. As a result, productive workers become even more productive through upskilling. It is possible that workers with high cognitive skills have a substantial advantage as cognitive skills may become increasingly necessary in the recovery phase of the business cycle. Our findings can inform policymakers about the complementarity between training and human capital. Future policy work should be directed at understanding how to improve workers' initial human capital through various training provisions following a recession.

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Table 1: Summary Statistics

	NLSY79		NLSY97	
	Mean	SD	Mean	SD
Hourly wages (2013 $)	19.50	14.97	19.06	17.68
Working hours	43.22	10.73	38.78	13.20
Full-time	0.92	0.27	0.81	0.39
Occupation prestige score	36.42	14.87	36.35	14.70
Unemployment rate (national)	6.62	1.34	6.14	1.89
Unemployment rate (regional)	6.61	1.51	6.14	1.94
Unemployment rate (state)	6.68	2.1	6.07	2.17
Cognitive skills	0.12	0.99	0.16	1.01
Social skills	0.04	0.94	-0.06	0.98
Potential Experience	8.82	4.99	7.10	4.94
Age	27.61	4.98	26.92	5.02
Black	0.13	0.34	0.16	0.36
Hispanic	0.06	0.24	0.12	0.33
Urbanacity	0.77	0.42	0.75	0.43
Year	1988.89	5.18	2008.85	5.14

Notes: We use data from two surveys, the National Longitudinal Survey of Youth 1979 (NLSY79) and 1997 (NLSY97). The sample consists of men who are not enrolled in school and have non-missing wages. We restrict the age range to 18 and 37 to compare individuals of the same age across the NLSY survey waves. Wages are bottom- and top-coded to be between $3 and $200. Wages are adjusted for inflation to the year 2013. National, regional, and state unemployment rates are taken from the U.S. Bureau of Labor Statistics (BLS). Cognitive skills are measured by the Armed Forces Qualifying Test (AFQT). We use the AFQT score crosswalk developed by Altonji et al. (2012). Following Deming (2017), social skills are a standardized composite of two questions that measure extroversion in both the NLSY79 (sociability in childhood and sociability in adulthood) and the NLSY97 (two items from the Big Five personality inventory that measure extroversion). Both skills are normalized to have a mean of 0 and a standard deviation of 1. Potential experience is defined as age minus years of schooling minus 6. Observations are weighted using the BLS base year sampling weights.

Table 2: Effects of U on Wages in the NLSY79 vs NLSY97

	Log hourly wage					
		NLSY79			NLSY97	
	(1)	(2)	(3)	(4)	(5)	(6)
U	-0.024***	-0.017***	-0.015***	-0.006***	-0.006***	-0.009***
	[0.002]	[0.002]	[0.003]	[0.002]	[0.002]	[0.002]
Cognitive	0.170***	0.169***	0.170***	0.077***	0.077***	0.073***
	[0.008]	[0.008]	[0.008]	[0.009]	[0.009]	[0.007]
Social	0.021***	0.020***	0.019***	0.036***	0.036***	0.034***
	[0.007]	[0.007]	[0.007]	[0.008]	[0.008]	[0.007]
U * Cognitive	-0.020***	-0.017***	-0.011***	0.006***	0.006***	0.007***
	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]
U * Social	-0.003	-0.001	0.001	0.003*	0.003	0.002
	[0.003]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]
Unemployment rate	National	Regional	State	National	Regional	State
Demographics and time trend	o	o	o	o	o	o
Complementarity	o	o	o	o	o	o
Observations	53,580	53,580	53,580	27,808	27,808	27,808
R-squared	0.218	0.217	0.23	0.201	0.201	0.223

Notes: The results are from an estimate of our main specification in equation (1), with the dependent variable being real log wages adjusted for inflation to 2013 dollars. We use data from two surveys, the National Longitudinal Survey of Youth 1979 (NLSY79) and 1997 (NLSY97). The sample consists of men who are not enrolled in school and have non-missing wages. We restrict the age range to 18 and 37 to compare individuals of the same age across the NLSY survey waves. National, regional, and state unemployment rates, taken from the U.S. Bureau of Labor Statistics (BLS), are defined as the deviation from the sample means. Cognitive skills are measured by the Armed Forces Qualifying Test (AFQT). We use the AFQT score crosswalk developed by Altonji et al. (2012). Social skills are a standardized composite of two questions that measure extroversion in both the NLSY79 (sociability in childhood and adulthood) and the NLSY97 (two items from the Big Five personality inventory that measure extroversion). Both skills are normalized to have a mean of 0 and a standard deviation of 1. The demographic control variables include race/ethnicity (black and Hispanic), urbanicity, potential experience, potential experience squared, and region-fixed effects. Observations are weighted using the BLS base year sampling weights. Standard errors are in brackets and clustered at the individual level. *** p<0.01, **p<0.05, *p<0.10

Table 3: Effects of Regional U on Labor Market Outcomes in the NLSY79 vs NLSY97

	Working hours		Full-time		Prestige	
	NLSY79	NLSY97	NLSY79	NLSY97	NLSY79	NLSY97
	(1)	(2)	(3)	(4)	(5)	(6)
U	-0.382***	-0.142**	-0.011***	-0.011***	-0.257***	0.019
	[0.052]	[0.055]	[0.001]	[0.002]	[0.062]	[0.057]
Cognitive	0.732***	0.608***	0.023***	0.011*	4.748***	3.035***
	[0.147]	[0.185]	[0.003]	[0.006]	[0.185]	[0.230]
Social	0.579***	0.603***	0	0.013***	0.367**	0.635***
	[0.134]	[0.157]	[0.002]	[0.005]	[0.170]	[0.200]
U * Cognitive	-0.03	0.117**	0.002	0.004***	-0.355***	0.215***
	[0.049]	[0.048]	[0.001]	[0.001]	[0.058]	[0.046]
U * Social	-0.033	0.047	0	0	-0.065	-0.019
	[0.052]	[0.050]	[0.001]	[0.001]	[0.062]	[0.049]
Demographics and time trend	o	o	o	o	o	o
Complementarity	o	o	o	o	o	o
Observations	51,439	28,547	51,439	28,547	51,024	25,884
R-squared	0.043	0.036	0.034	0.03	0.205	0.226

Notes: The results are from an estimate of our main specification in equation (1). The dependent variables are the number of hours worked per week, the probability of being employed full-time (working at least 35 hours per week), and the occupation prestige score. The data sources are the National Longitudinal Survey of Youth 1979 (NLSY79) and 1997 (NLSY97). The sample includes men who are not enrolled in school with non-missing values for the dependent variable. We restrict the age range to 18–37 to compare individuals of the same ages across the NLSY survey waves. The regional unemployment rate U, taken from the U.S. Bureau of Labor Statistics (BLS), is defined as the deviation from the sample means. Cognitive skills are measured by the Armed Forces Qualifying Test (AFQT). We use the AFQT score crosswalk developed by Altonji et al. (2012). Social skills are a standardized composite of two questions that measure extroversion in both the NLSY79 (sociability in childhood and adulthood) and the NLSY97 (two items from the Big Five personality inventory that measure extroversion). Both skills are normalized to have a mean of 0 and a standard deviation of 1. The demographic control variables include race/ethnicity (black and Hispanic), urbanicity, potential experience, potential experience squared, and region-fixed effects. Observations are weighted using the BLS base year sampling weights. Standard errors are in brackets and clustered at the individual level. *** p<0.01, **p<0.05, *p<0.10

Table 4: Effects of Regional U on Training in the NLSY79 vs NLSY97

	Training				Training for upskilling	
	NLSY79		NLSY97		NLSY97	
	(1)	(2)	(3)	(4)	(5)	(6)
U	-0.007***	-0.004***	-0.003***	-0.003***	-0.001	-0.001
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
Cognitive	0.042***	0.032***	0.023***	0.021***	0.008***	0.007***
	[0.003]	[0.003]	[0.003]	[0.003]	[0.001]	[0.001]
Social	0.004	0.003	0.007***	0.005**	0.002	0.001
	[0.003]	[0.003]	[0.002]	[0.002]	[0.001]	[0.001]
U * Cognitive	-0.009***	-0.007***	0.002**	0.002**	0.001***	0.001***
	[0.001]	[0.001]	[0.001]	[0.001]	[0.000]	[0.000]
U * Social	-0.001	-0.001	0	0	0	0
	[0.001]	[0.001]	[0.001]	[0.001]	[0.000]	[0.000]
Firm > 1 location		0.094***		0.041***		0.016***
		[0.006]		[0.005]		[0.003]
Firm > 1000 Employees		0.061***		0.050***		0.021**
		[0.013]		[0.013]		[0.008]
Health status		-0.001		0.035***		0.018***
		[0.011]		[0.013]		[0.002]
Marital status		0.031***		0.038***		0.013***
		[0.005]		[0.006]		[0.003]
Union members		0.004		0.040***		0.011*
		[0.010]		[0.010]		[0.006]
Demographics and time trend	o	o	o	o	o	o
Complementarity	o	o	o	o	o	o
Observations	44,210	44,210	39,986	39,986	39,986	39,986
R-squared	0.067	0.096	0.018	0.03	0.015	0.015

Notes: The results are from an estimate of our main specification in equation (1). The dependent variables are an indicator for receiving employer-paid training (columns (1)–(4)) and for receiving training for upskilling (columns (5)–(6)), respectively. In particular, we examine upskilling as part of a regular program to maintain and upgrade employee skills. We use data from two surveys, the National Longitudinal Survey of Youth 1979 (NLSY79) and 1997 (NLSY97). The sample consists of men who are not enrolled in school and have non-missing wages. We restrict the age range to 18 and 37 to compare individuals of the same age across the NLSY survey waves. The regional unemployment rate U, taken from the U.S. Bureau of Labor Statistics (BLS), is defined as the deviation from the sample means. Cognitive skills are measured by the Armed Forces Qualifying Test (AFQT). We use the AFQT score crosswalk developed by Altonji et al. (2012). Social skills are a standardized composite of two questions that measure extroversion in both the NLSY79 (sociability in childhood and adulthood) and the NLSY97 (two items from the Big Five personality inventory that measure extroversion). Both skills are normalized to have a mean of 0 and a standard deviation of 1. The demographic control variables include race/ethnicity (black and Hispanic), urbanicity, potential experience, potential experience squared, and region-fixed effects. We additionally control the firm size, health status, marital status, and union membership for some specifications and impute missing observations for these variables. Observations are weighted using the BLS base year sampling weights. Standard errors are in brackets and clustered at the individual level.

Appendix

In this appendix, we examine the robustness of the results. Appendix Table A.1 shows the robustness of the results from Table 2 of the estimates of the interaction terms of U_{jt} and cognitive and social skills for the NLSY79 and NLSY97 cohorts separately. We focus on the regional unemployment rate in the table, but the results based on the national unemployment rate and state unemployment rates are similarly robust. Column (1) in panel (a) shows the results from Table 2 column (2) for the NLSY79, and column (1) in panel (b) shows the results from Table 2 column (5) for the NLSY97. In column (2), we include year fixed effects instead of a quadratic time trend. In column (3), we add a set of indicator variables for the highest grade completed in school. Controlling for educational attainment can account for possible bias from unmeasured ability differences and controls for the potential that individuals may experience systematically different spells of unemployment based on their educational attainment. Column (4) includes age fixed effects to account for the potential impact of age on labor market outcomes (Kahn 2010).

We also consider that our measure of social skills might proxy for noncognitive skills. To account for possible bias from this unmeasured variation in skills, we additionally control for noncognitive skills in column (5). Following the definitions of noncognitive skills in Heckman et al. (2006) and Deming (2017), we measure noncognitive skills as the normalized average of the Rotter Locus of Control and the Rosenberg Self-Esteem Scale in the NSLY79 and the normalized average of seven items from the Big Five personality factor conscientiousness in the NLSY97.

Moreover, the impact of rising unemployment on wages can vary depending on whether it occurs during a recession or non-recession period. In column (6), we include a GDP-based recession indicator derived from the Federal Reserve Economic Data (FRED). In column (7), we control for years of completed schooling indicators, age indicators, noncognitive skills, and recessions.

Overall, the results in Appendix Table A.1 show the robustness of the estimates of the interaction of the unemployment rate and cognitive skills and the interaction of the unemployment rate and social skills to the inclusion of these controls in every specification for both the NLSY79 and NLSY97. The robustness of the results suggests that the main results in Table 2 showing the growing cognitive skill premium during periods of increasing unemployment reflect the changing demand for skills rather than a change in individual or labor market characteristics.

In Appendix Tables A.2 and A.3, we examine the robustness of the results to pooling both the NLSY79 and NLSY97 cohorts. This approach follows that of Deming (2017). First, in Appendix Table A.2, we replicate the results from Deming (2017) and then examine the robustness of the results to changes in the sample and variable definitions to match those used in this paper. Then, in Appendix Table A.3, we examine trends in the interaction of the unemployment rate and skills over cohorts using the pooled sample. In both tables, we show the results for all individuals and for men and women separately.

In Appendix Table A.2, we begin by exactly replicating the results from column (4) in Table IV of Deming (2017). To evaluate the changes in skill effects on wages across the NLSY surveys, we estimate:

$$ln(wage_{ijt}) = \alpha + \beta_1 Cog_i + \beta_2 Cog_i * NLSY97_i + \beta_3 Soc_i + \beta_4 Soc_i * NLSY97_i + \beta_5 X_{ijt} + \zeta_j + \epsilon_{ijt}. \tag{6}$$

$NLSY97$ is an indicator variable for whether the individual is in the NLSY97 cohort; thus, $Cognitive * NLSY97$ and $Social * NLSY97$ show the change in the returns to skills across cohorts. In columns (2) and (3), we show the results separately for men and women. The returns to cognitive skills decreased by 6.8% across cohorts for men and decreased by 3.3% for women. The returns to social skills increased by 2.0% across cohorts for men and 0.8% for women, although neither of these estimates are statistically significant. In column (4), we use the samples constructed to estimate the results from Table 2 instead of Table IV of Deming (2017) to estimate equation (6). The data in column (5) is based on a pooled sample of two surveys that cover a more extended period, up to 2016. In column (6), we extend the age range to include individuals between 18 and 37. In column (7), we employ a quadratic time trend instead of year fixed effect. In column (8), we include potential experience and potential experience squared instead of year and age fixed effects. Finally, we present the results separately for men and women in columns (9) and (10), respectively. The results in columns (4)-(10) demonstrate the consistent wage returns to skills across survey waves, regardless of the minor changes in the specification or sample.

In Appendix Table A.3, using the samples constructed to estimate the results from columns (8)–(10) from Appendix Table A.2, we pool the sample of two cohorts of youth, the NLSY79 and the NLSY97. Specifically, we estimate:

$$\begin{aligned} Y_{ijt} = \alpha + \beta_1 U_{jt} + \beta_2 Cog_i + \beta_3 Cog_i * NLSY97_i + \beta_4 Soc_i + \beta_5 Soc_i * NLSY97_i + \beta_6 U_{jt} * Cog_i \\ + \beta_7 U_{jt} * Cog_i * NLSY97_i + \beta_8 U_{jt} * Soc_i + \beta_9 U_{jt} * Soc_i * NLSY97_i + \beta_{10} X_{ijt} + \zeta_j + \epsilon_{ijt}. \end{aligned} \tag{7}$$

These variables are defined similarly as in equation (1) with the addition of $NLSY97_i$, which is an indicator variable for whether the individual is in the NLSY97 cohort. β_3 represents the change in the return to cognitive skills across cohorts, and β_5 represents the change in the return to social skills across cohorts. β_7 and β_9, which are the coefficients of interest, represent the change in the interaction between the unemployment rate and each type of skill across cohorts. Following Deming (2017), we do not weight the observations using the BLS base year sampling weights for the estimates with the pooled sample, but the weighted results are similar.

Columns (1)–(3) of Appendix Table A.3 display the wage results for all individuals, men and women, using the national unemployment rate. Columns (4)–(6) display the wage results using regional unemployment rates, and columns (7)–(9) display the wage results using state unemployment rates. For men, women, and all individuals, the estimate of the coefficient for the three-way interaction $U_{jt} * Cog_i * NLSY97_i$ is positive and statistically significant in all specifications. These estimates are also similar to the estimates from Table 2 for each cohort separately. For example, in Table 2, the interaction term of the regional unemployment rate and cognitive skills is -0.017 for the NLSY79 cohort and 0.006 for the NLSY97 cohort; similarly, the results for men based on the regional unemployment rate in Appendix Table A.3 show a pooled estimate of 0.023. Thus, the pooled estimates are consistent with the growing returns to cognitive skills during periods of increasing unemployment across the NLSY cohorts. Further, we find similar, but slightly more muted, relationships between cognitive skills and the unemployment rate for both NLSY cohorts for women.

In Appendix Table A.4, we examine the robustness of the results from Table 3 by analyzing national and state unemployment rates in Panels A and B, respectively. We present the results for the number of hours worked per week in columns (1)–(2), the probability of being employed full-time (working at least 35 hours per week) in columns (3)–(4), and the occupation prestige score in columns (5)–(6). This analysis confirms that the results remain consistent regardless of the type of unemployment rates. Cognitive skills have become increasingly valuable during recessions for all labor market outcomes measured across the NLSY waves.

In Appendix Table A.5, we examine the robustness of our results to sample selection bias. In columns (1)–(2), we report the coefficients from our main specifications in columns (2) and (5) of Table 2 again to facilitate comparison. Following the approach of Schwandt and Von Wachter (2019), in columns (3)–(4), we include workers with zero wages to take into account the actual loss due to non-employment. Wages are bottom-coded, meaning that wages below $3 are reported as $3. Our analysis shows that there is no significant difference in all coefficients in columns (1)–(4), indicating that selective labor participation does not affect the main findings.

Following the approach of Oreopoulos et al. (2012), we compare the estimates for workers who nearly always report positive earnings in each year to all workers with similar years of potential experience. In columns (5)–(8), we include workers who have the potential experience of 1–10 years to test for selective labor force participation. Furthermore, in columns (7)–(8), we include workers who receive positive wages for at least 8 years out of their total 10 years of potential experience.[22] Our results in (7)–(8) show that the effect is similar, with only minor and statistically unimportant variations, when we incorporate employees who work for at least 8 out of 10 years. This implies that our results are not due to selective employment.

In Appendix Table A.6, we examine the comparability of the two measures of social skills across NLSY waves. We do this by employing alternative measures of social skills for the NLSY79 cohort in columns (2), (4), (6), and (8). To construct an identical measure of social skills across survey waves, we use two questions: (i) extroverted, enthusiastic, and (ii) reserved, quiet. The results from the new measure of social skills demonstrate that our findings remain consistent across all measures of social skills.

Appendix References

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[22] Similar to Oreopoulos et al. (2012), the sample for this analysis includes workers with potential experience ranging from 1 to 10 years. However, we consider workers with positive wages for at least 8 out of their 10 years of experience. This is different from Oreopoulos et al. (2012), who include workers who always have positive wages. We choose this criterion because only 15% of our sample report positive wages for 10 years. In contrast, Oreopoulos et al. (2012) focus on male college graduates who are less likely to be unemployed or out of the labor force. However, our results are not sensitive to a few years of experience being added or removed from either end of the cutoff.

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Table A.1: Effects of Regional U on Wages with Additional Controls in the NLSY79 vs NLSY97

(a) NLSY79

	Log hourly wage						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
U	-0.017***	0.005	-0.017***	-0.016***	-0.017***	-0.016***	-0.014***
	[0.002]	[0.005]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]
Cognitive	0.169***	0.168***	0.110***	0.096***	0.145***	0.168***	0.085***
	[0.008]	[0.008]	[0.009]	[0.009]	[0.009]	[0.008]	[0.009]
Social	0.020***	0.021***	0.019***	0.020***	0.015**	0.021***	0.018***
	[0.007]	[0.007]	[0.007]	[0.007]	[0.007]	[0.007]	[0.007]
U * Cognitive	-0.017***	-0.018***	-0.014***	-0.015***	-0.017***	-0.017***	-0.013***
	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]
U * Social	-0.001	-0.001	-0.002	-0.001	-0.001	-0.001	-0.001
	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]
Demographics	o	o	o	o	o	o	o
Time trend	o		o	o	o	o	o
Year FE		o					
Years of completed education			o				o
Age FE				o			o
Noncognitive skills					o		o
Recession indicator						o	o
Observations	53,580	53,580	53,580	53,580	53,543	53,580	53,543
R-squared	0.217	0.221	0.248	0.256	0.227	0.218	0.266

(b) NLSY97

	Log hourly wage						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
U	-0.006***	-0.006	-0.007***	-0.005*	-0.006***	-0.006***	-0.005*
	[0.002]	[0.012]	[0.002]	[0.003]	[0.002]	[0.002]	[0.003]
Cognitive	0.077***	0.077***	0.052***	0.041***	0.078***	0.077***	0.044***
	[0.009]	[0.009]	[0.009]	[0.009]	[0.009]	[0.009]	[0.009]
Social	0.036***	0.036***	0.036***	0.036***	0.029***	0.036***	0.031***
	[0.008]	[0.008]	[0.008]	[0.008]	[0.008]	[0.008]	[0.008]
U * Cognitive	0.006***	0.006***	0.006***	0.006***	0.006***	0.006***	0.005***
	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]
U * Social	0.003	0.003	0.002	0.002	0.003	0.003	0.002
	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]
Demographics	o	o	o	o	o	o	o
Time trend	o		o	o	o	o	o
Year FE		o					
Years of completed education			o				o
Age FE				o			o
Noncognitive skills					o		o
Recession indicator						o	o
Observations	27,808	27,808	27,677	27,808	27,808	27,808	27,677
R-squared	0.201	0.202	0.221	0.233	0.211	0.201	0.245

Notes: The results are from an estimate of our main specification in equation (1), with the dependent variable being real log wages adjusted for inflation to 2013 dollars. We use data from two surveys, the National Longitudinal Survey of Youth 1979 (NLSY79) for panel (a) and 1997 (NLSY97) for panel (b). The sample consists of men who are not enrolled in school and have non-missing wages. We restrict the age range to 18 and 37 to compare individuals of the same age across the NLSY survey waves. Regional unemployment rates, taken from the U.S. Bureau of Labor Statistics (BLS), are defined as the deviation from the sample means. Cognitive skills are measured by the Armed Forces Qualifying Test (AFQT). We use the AFQT score crosswalk developed by Altonji et al. (2012). Social skills are a standardized composite of two questions that measure extroversion in both the NLSY79 (sociability in childhood and adulthood) and the NLSY97 (two items from the Big Five personality inventory that measure extroversion). The noncognitive skill measures are a normalized average of the Rotter and Rosenberg scores in the NLSY79 and seven items from the Big Five personality factor conscientiousness in the NLSY97. All skills are normalized to have a mean of 0 and a standard deviation of 1. The recession indicator is inferred by the GDP-based recession indicator from the Federal Reserve Economic Data (FRED). The demographic control variables include race/ethnicity (black and Hispanic), urbanicity, potential experience, potential experience squared, and region-fixed effects. Additional control variables are included as indicated for each column. Observations are weighted using the BLS base year sampling weights. Standard errors are in brackets and clustered at the individual level. *** $p<0.01$, ** $p<0.05$, * $p<0.10$

Table A.2: Update of Table IV of Deming (2017)

	Log hourly wage									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Cognitive	0.203***	0.174***	0.243***	0.199***	0.198***	0.176***	0.176***	0.161***	0.155***	0.174***
	[0.005]	[0.006]	[0.008]	[0.005]	[0.005]	[0.004]	[0.004]	[0.004]	[0.006]	[0.006]
Cognitive * NLSY97	-0.052***	-0.068***	-0.033***	-0.043***	-0.031***	-0.039***	-0.040***	-0.036***	-0.051***	-0.020**
	[0.008]	[0.011]	[0.012]	[0.007]	[0.007]	[0.006]	[0.006]	[0.006]	[0.008]	[0.009]
Social	0.020***	0.022***	0.020***	0.020***	0.019***	0.019***	0.019***	0.018***	0.016***	0.019***
	[0.004]	[0.006]	[0.006]	[0.004]	[0.004]	[0.004]	[0.004]	[0.004]	[0.006]	[0.005]
Social * NLSY97	0.017**	0.02	0.008	0.013*	0.014*	0.009	0.01	0.010*	0.021**	-0.007
	[0.008]	[0.012]	[0.012]	[0.008]	[0.007]	[0.006]	[0.006]	[0.006]	[0.009]	[0.008]
Deming's sample	o	o	o							
Gender	All	Men	Women	All	All	All	All	All	Men	Women
Year FE	o	o	o	o	o	o				
Age FE	o	o	o	o	o	o	o			
Longer time period					o	o	o	o	o	o
Age	25-33	25-33	25-33	25-33	25-33	18-37	18-37	18-37	18-37	18-37
Time trend							o	o	o	o
Potential experience								o	o	o
Observations	77,845	40,346	37,499	77,827	83,944	159,529	159,529	157,439	81,388	76,051
R-squared	0.309	0.271	0.327	0.198	0.197	0.243	0.24	0.235	0.205	0.235

Notes: The results are from an estimate of equation (6), with real log hourly adjusted to 2013 dollars as the dependent variable in the indicated age group. Columns (1)–(3) replicates Table IV of Deming (2017), utilizing Deming (2017)'s sample. We use data from two surveys, the National Longitudinal Survey of Youth 1979 (NLSY79) and 1997 (NLSY97). Cognitive skills are measured by the Armed Forces Qualifying Test (AFQT). We use the AFQT score crosswalk developed by Altonji et al. (2012). Social skills are a standardized composite of two questions that measure extroversion in both the NLSY79 (sociability in childhood and adulthood) and the NLSY97 (two items from the Big Five personality inventory that measure extroversion). Both skills are normalized to have a mean of 0 and a standard deviation of 1. The demographic control variables include race/ethnicity (black and Hispanic), urbanicity, potential experience, potential experience squared, and region-fixed effects. Observations are weighted using the BLS base year sampling weights. Standard errors are in brackets and clustered at the individual level. *** $p<0.01$, **$p<0.05$, *$p<0.10$

Table A.3: Effects of U on Wages in the pooled sample of NLSY79 and NLSY97

	Log hourly wage								
	National unemployment rate			Regional unemployment rate			State unemployment rate		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
U	-0.011***	-0.014***	-0.008***	-0.009***	-0.012***	-0.007***	-0.006**	-0.010***	-0.003
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.003]	[0.003]	[0.003]
Cognitive	0.178***	0.161***	0.169***	0.178***	0.160***	0.168***	0.164***	0.158***	0.176***
	[0.004]	[0.006]	[0.006]	[0.004]	[0.006]	[0.006]	[0.005]	[0.006]	[0.007]
Cognitive * NLSY97	-0.038***	-0.054***	-0.021**	-0.037***	-0.054***	-0.020**	-0.038***	-0.054***	-0.022**
	[0.006]	[0.008]	[0.009]	[0.006]	[0.008]	[0.009]	[0.007]	[0.009]	[0.009]
Social	0.018***	0.016***	0.019***	0.018***	0.016***	0.019***	0.017***	0.015***	0.020***
	[0.004]	[0.006]	[0.005]	[0.004]	[0.006]	[0.005]	[0.004]	[0.005]	[0.005]
Social * NLSY97	0.004	0.021**	-0.006	0.004	0.022**	-0.006	0.011**	0.022***	-0.007
	[0.007]	[0.009]	[0.009]	[0.006]	[0.009]	[0.009]	[0.005]	[0.007]	[0.006]
U * Cognitive	-0.018***	-0.018***	-0.015***	-0.015***	-0.016***	-0.011***	-0.005***	-0.007***	-0.004**
	[0.001]	[0.002]	[0.002]	[0.001]	[0.002]	[0.002]	[0.001]	[0.002]	[0.002]
U * Cognitive * NLSY97	0.025***	0.026***	0.023***	0.022***	0.023***	0.019***	0.012***	0.015***	0.010***
	[0.002]	[0.002]	[0.003]	[0.002]	[0.002]	[0.003]	[0.002]	[0.003]	[0.003]
U * Social	0	-0.002	0	0	0	0	0	0.001	-0.001
	[0.001]	[0.002]	[0.002]	[0.001]	[0.002]	[0.002]	[0.001]	[0.002]	[0.002]
U * Social * NLSY97	0.001	0.004	-0.002	0	0.002	-0.002	0	0.002	-0.001
	[0.002]	[0.003]	[0.002]	[0.002]	[0.003]	[0.002]	[0.001]	[0.002]	[0.002]
Gender	All	Men	Women	All	Men	Women	All	Men	Women
Demographics and time trend	o	o	o	o	o	o	o	o	o
Complementarity	o	o	o	o	o	o	o	o	o
Observations	157,439	81,388	76,051	157,439	81,388	76,051	157,439	81,388	76,051
R-squared	0.206	0.207	0.235	0.206	0.207	0.235	0.236	0.207	0.236

Notes: The results are from an estimate of equation (7), with real log wages adjusted to 2013 dollars as the dependent variable. We use data from two surveys, the National Longitudinal Survey of Youth 1979 (NLSY79) and 1997 (NLSY97). The sample consists of men who are not enrolled in school and have non-missing wages. We restrict the age range to 18 and 37 to compare individuals of the same age across the NLSY survey waves. National, regional, and state unemployment rates, taken from the U.S. Bureau of Labor Statistics (BLS), are defined as the deviation from the sample means. Cognitive skills are measured by the Armed Forces Qualifying Test (AFQT). We use the AFQT score crosswalk developed by Altonji et al. (2012). Social skills are a standardized composite of two questions that measure extroversion in both the NLSY79 (sociability in childhood and adulthood) and the NLSY97 (two items from the Big Five personality inventory that measure extroversion). Both skills are normalized to have a mean of 0 and a standard deviation of 1. The demographic control variables include race/ethnicity (black and Hispanic), urbanicity, potential experience, potential experience squared, and region-fixed effects. Standard errors are in brackets and clustered at the individual level. *** $p<0.01$, ** $p<0.05$, * $p<0.10$

Table A.4: Effects of U on Labor Market Outcomes in the NLSY79 vs NLSY97

	Working hours		Full-time		Prestige	
	NLSY79	NLSY97	NLSY79	NLSY97	NLSY79	NLSY97
	(1)	(2)	(3)	(4)	(7)	(8)
A. National U						
U	-0.397***	-0.148***	-0.011***	-0.011***	-0.389***	0.021
	[0.056]	[0.055]	[0.002]	[0.002]	[0.064]	[0.058]
Cognitive	0.744***	0.612***	0.024***	0.011*	4.770***	3.034***
	[0.149]	[0.185]	[0.003]	[0.006]	[0.186]	[0.231]
Social	0.565***	0.604***	-0.001	0.013***	0.384**	0.630***
	[0.137]	[0.157]	[0.002]	[0.005]	[0.171]	[0.201]
U * Cognitive	-0.055	0.129***	0.001	0.004***	-0.420***	0.203***
	[0.052]	[0.048]	[0.001]	[0.001]	[0.062]	[0.045]
U * Social	-0.003	0.068	0.001	0.001	-0.107	-0.02
	[0.057]	[0.050]	[0.001]	[0.001]	[0.067]	[0.048]
Observations	51,439	28,547	51,439	28,547	51,024	25,884
R-squared	0.042	0.036	0.033	0.03	0.205	0.226
B. State U						
U	-0.300***	-0.191***	-0.008***	-0.012***	-0.220***	-0.009
	[0.050]	[0.041]	[0.001]	[0.002]	[0.048]	[0.053]
Cognitive	0.695***	0.634***	0.023***	0.012**	4.756***	3.026***
	[0.157]	[0.174]	[0.003]	[0.005]	[0.170]	[0.186]
Social	0.545***	0.605***	0	0.013**	0.265	0.684***
	[0.147]	[0.126]	[0.003]	[0.005]	[0.188]	[0.188]
U * Cognitive	0.014	0.089	0.001	0.003	-0.193***	0.205***
	[0.032]	[0.057]	[0.001]	[0.002]	[0.054]	[0.049]
U * Social	0.037	-0.006	0	-0.001	0.023	-0.064
	[0.039]	[0.046]	[0.001]	[0.002]	[0.044]	[0.062]
Observations	51,439	28,547	51,439	28,547	50,977	25,813
R-squared	0.051	0.045	0.038	0.038	0.224	0.248
Demographics	o	o	o	o	o	o
Time trend	o	o	o	o	o	o
Complementarity	o	o	o	o	o	o

Notes: The results are from an estimate of equation (1). The dependent variables are the number of hours worked per week, the probability of being employed full-time (working at least 35 hours per week), and the occupation prestige score. We use data from two surveys, the National Longitudinal Survey of Youth 1979 (NLSY79) and 1997 (NLSY97). We restrict the age range to 18 and 37 to compare individuals of the same age across the NLSY survey waves. National and state unemployment rates, taken from the U.S. Bureau of Labor Statistics (BLS), are defined as the deviation from the sample means. Cognitive skills are measured by the Armed Forces Qualifying Test (AFQT). We use the AFQT score crosswalk developed by Altonji et al. (2012). Social skills are a standardized composite of two questions that measure extroversion in both the NLSY79 (sociability in childhood and adulthood) and the NLSY97 (two items from the Big Five personality inventory that measure extroversion). Both skills are normalized to have a mean of 0 and a standard deviation of 1. The demographic control variables include race/ethnicity (black and Hispanic), urbanicity, potential experience, potential experience squared, and region-fixed effects. Observations are weighted using the BLS base year sampling weights. Standard errors are in brackets and clustered at the individual level. *** $p<0.01$, ** $p<0.05$, * $p<0.10$

Table A.5: Effects of U on Wages across Different Specifications

	Log hourly wage							
	NLSY79	NLSY97	NLSY79	NLSY97	NLSY79	NLSY97	NLSY79	NLSY97
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
U	-0.017***	-0.006***	-0.017***	-0.006***	-0.021***	-0.008***	-0.016***	-0.010***
	[0.002]	[0.002]	[0.002]	[0.002]	[0.003]	[0.003]	[0.003]	[0.003]
Cognitive	0.169***	0.077***	0.169***	0.074***	0.168***	0.075***	0.160***	0.073***
	[0.008]	[0.009]	[0.008]	[0.009]	[0.009]	[0.009]	[0.010]	[0.013]
Social	0.020***	0.036***	0.020***	0.034***	0.023***	0.034***	0.027***	0.039***
	[0.007]	[0.008]	[0.007]	[0.008]	[0.007]	[0.008]	[0.009]	[0.012]
U * Cognitive	-0.017***	0.006***	-0.017***	0.006***	-0.015***	0.011***	-0.016***	0.011***
	[0.002]	[0.002]	[0.002]	[0.002]	[0.003]	[0.003]	[0.004]	[0.004]
U * Social	-0.001	0.003	-0.001	0.003	-0.002	0.003	-0.001	0.004
	[0.002]	[0.002]	[0.002]	[0.002]	[0.003]	[0.002]	[0.004]	[0.003]
Adjusted wage (bottom-coded)			o	o				
Potential experience					1-10	1-10	1-10	1-10
Working experience							At least 8 years	
Demographics and time trend	o	o	o	o	o	o	o	o
Complementarity	o	o	o	o	o	o	o	o
Observations	53,580	27,808	53,585	28,116	32,835	19,083	21,021	10,489
R-squared	0.217	0.201	0.217	0.181	0.221	0.193	0.219	0.144

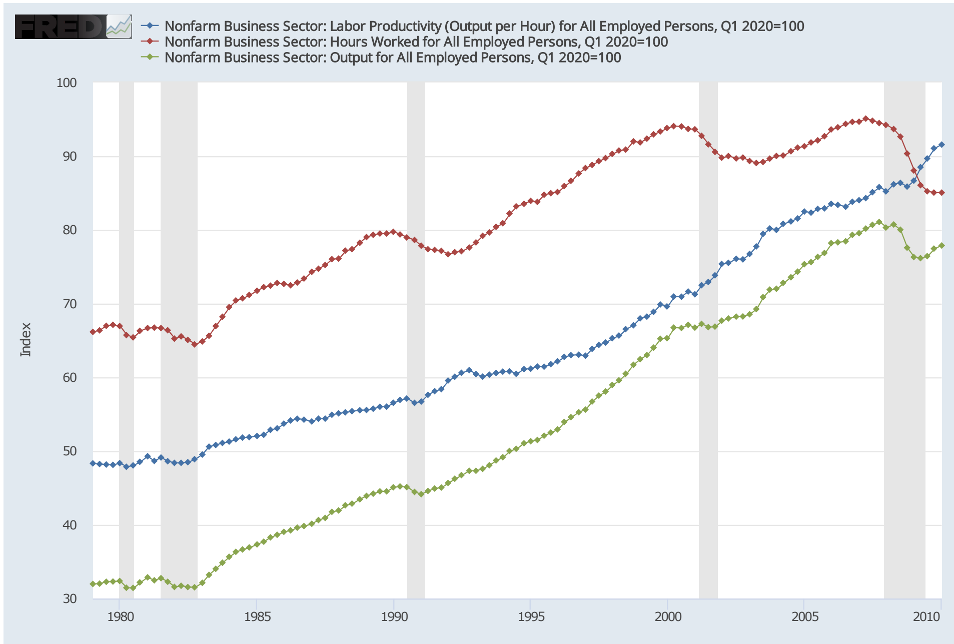
Notes: Each column reports results from an estimate of equation (1), with real log wages adjusted to 2013 dollars as the dependent variable. In columns (3)–(4), wages are bottom-coded, which means that wages below \$3 are reported as \$3. Columns (5)–(8) include only those with potential experience between 1 to 10. In columns (7)–(8), we consider only the workers who have positive wages for at least 8 of their 10 years of experience. The data sources are the National Longitudinal Survey of Youth 1979 (NLSY79) and 1997 (NLSY97). The sample includes men who are not enrolled in school with non-missing wages. We restrict the age range to 18 and 37 to compare individuals of the same ages across NLSY survey waves. Regional unemployment rates, taken from the U.S. Bureau of Labor Statistics (BLS), are defined as the deviation from the sample means. Cognitive skills are measured by the Armed Forces Qualifying Test (AFQT). We use the AFQT score crosswalk developed by Altonji et al. (2012). Social skills are a standardized composite of two questions that measure extroversion in both the NLSY79 (sociability in childhood and adulthood) and the NLSY97 (two items from the Big Five personality inventory that measure extroversion). Both skills are normalized to have a mean of 0 and a standard deviation of 1. The demographic control variables include race/ethnicity (black and Hispanic), urbanicity, potential experience, potential experience squared, and region-fixed effects. Observations are weighted using the BLS base year sampling weights. Standard errors are in brackets and clustered at the individual level. *** p<0.01, **p<0.05, *p<0.10

Table A.6: Social Skills Measure Robust to Alternative Definitions in the NLSY79

	Log hourly wage		Working hours		Full-time		Prestige	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
U	-0.017***	-0.016***	-0.382***	-0.425***	-0.011***	-0.011***	-0.257***	-0.228***
	[0.002]	[0.003]	[0.052]	[0.060]	[0.001]	[0.002]	[0.062]	[0.071]
Cognitive	0.169***	0.176***	0.732***	0.697***	0.023***	0.021***	4.748***	4.928***
	[0.008]	[0.009]	[0.147]	[0.165]	[0.003]	[0.003]	[0.185]	[0.218]
Social	0.020***	0.026***	0.579***	0.469***	0	0.004	0.367**	0.096
	[0.007]	[0.008]	[0.134]	[0.138]	[0.002]	[0.003]	[0.170]	[0.197]
U * Cognitive	-0.017***	-0.017***	-0.03	-0.044	0.002	0.002	-0.355***	-0.336***
	[0.002]	[0.003]	[0.049]	[0.055]	[0.001]	[0.002]	[0.058]	[0.069]
U * Social	-0.001	-0.003	-0.033	0.005	0	0.003*	-0.065	0.041
	[0.002]	[0.003]	[0.052]	[0.055]	[0.001]	[0.002]	[0.062]	[0.071]
New social skill measure		o		o		o		o
Demographics and time trend	o	o	o	o	o	o	o	o
Complementarity	o	o	o	o	o	o	o	o
Observations	53,580	39,481	51,439	37,464	51,439	37,464	51,024	37,377
R-squared	0.217	0.231	0.043	0.042	0.034	0.037	0.205	0.213

Notes: The results are from an estimate of equation (1). The dependent variables are the log hourly wages, the number of hours worked per week, the probability of being employed full-time (working at least 35 hours per week), and the occupation prestige score. We use data from the National Longitudinal Survey of Youth 1979 (NLSY79). We restrict the age range to 18 and 37, parallel to Table 2 and 3. Regional unemployment rates U, taken from the U.S. Bureau of Labor Statistics (BLS), are defined as the deviation from the sample means. Cognitive skills are measured by the Armed Forces Qualifying Test (AFQT). We use the AFQT score crosswalk developed by Altonji et al. (2012). Social skills in odd-number columns is a standardized composite of two variables: (i) sociability in childhood and (ii) sociability in adulthood. Social skills in even-number columns is a standardized composite of two items from the Big Five personality inventory that measures extroversion: (i) extroverted or enthusiastic and (ii) reserved or quiet. Both measures of social skills are normalized to have a mean of 0 and a standard deviation of 1. The demographic control variables include race/ethnicity (black and Hispanic), urbanicity, potential experience, potential experience squared, and region-fixed effects. Observations are weighted using the BLS base year sampling weights. Standard errors are in brackets and clustered at the individual level. *** p<0.01, **p<0.05, *p<0.10

Figure A.1: Labor Productivity (Output per Hour)



Notes: The figure plots the amount of U.S. real output (green), the overall number of hours worked (red), and labor productivity (blue). These indexes are produced by the U.S. Bureau of Labor Statistics (BLS) and retrieved from the Federal Reserve Economic Data (FRED). The index plot is based on the year 2020, which is set as 100. Shaded areas indicate periods of recession in the U.S.