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The Transforming Importance of Social Skills in the Labor Market in the 2010s

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"No man is an island,

entire of itself;

every man is a piece of the continent,

a part of the main." – John Donne, "Meditation 17" (1623)

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Abstract

The growing importance of social skills has led to an increase in returns to wages and employment for workers specializing in social skill-intensive occupations. Between 2012 and 2019, social skill-intensive occupations grew by 3 percentage points as a share of the U.S. labor force. Math-intensive occupations also grew by a similar amount during this time. To analyze these patterns, I utilize a model of team production where workers trade tasks to exploit their comparative advantage. Social skills reduce coordination costs between workers and allow them to specialize and cooperate with other workers more effectively by trading tasks. This model predicts that workers adept in social skills sort into occupations that utilize and reward their abilities more, which is evaluated by looking at the changes between the NLSY79 and NLSY97 survey waves. Using various skill measures and covariates across these waves, I find that the positive labor market returns to social skills slightly diminished in the 2010s when compared to the greater returns of the 2000s.

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I. Introduction

There is an increasing amount of attention given to the role of artificial intelligence, machine learning, and computerization in the automation of jobs and how they have contributed to the change in task content throughout the twenty-first century. This concern has only been further exacerbated by the COVID-19 pandemic in recent years as workers have been forced to work remotely and change how they undergo what were once everyday tasks in a work environment. Although the consequences of this dramatic change in work tended to affect better educated and higher paid occupations more, the effects were far-reaching (Bartik et al. 2020).

As demonstrated by previous papers in the past two decades, computers began to substitute for labor in routine tasks (or middle-skill ones) and aided abstract and high-skill tasks, which contributed to a "hollowing out" of the labor market and job polarization (Autor *et al*. 2003). Most of the middle-skill workers that had roles or tasks taken over by computerization were pushed to lower-skill jobs or jobs with a higher manual task content. Most of this movement and whether certain workers decided to move vertically or horizontally to other jobs largely depended on their age and education (Hudomiet and Willis 2021). This "hollowing out" phenomenon, which started in the 1990s, has been shown to contribute to the increasing income inequality that has approached levels not seen since the Gilded Age in the late nineteenth and early twentieth centuries.

However, there has been very little demonstrated employment growth in high-paying jobs as there should be given the trends discussed in the previous paragraph. Furthermore, there has been mostly slow growth in high cognitive-intensive occupations in the U.S. labor market in the early twenty-first century (Beaudry et al. 2016). While this may have recently changed to higher growth than before (Hershbein and Macaluso 2018), it still lags the growth rate of technology. If the change in technology is skill-biased, why has this growth not changed at a similar pace with it? Also, why has growth affected each wage percentile much differently from one another in skill requirements and task content? One explanation is that the boom of technological process in the 1980s and 1990s in computerization has largely slowed down (Gordon 2012). This explanation points to the fact that in the preceding century and a half, we have seen innovation never seen elsewhere in human history and may not see again. On the flip side, it is possible that computers, AI and machine learning are enabling workers to complete a wider variety of tasks, so that higher-skilled workers are the only people able to perform such tasks. Machine learning and AI could also be substituting for abstract tasks and even higher-skilled routine tasks, blurring the lines of what is and is not routine and abstract tasks (Autor 2014; Konidaris 2019).

Figure I looks at this explanation by showing the relative change in employment between 2012 and 2019 for the same set of high-cognitive occupations that Beaudry et al. (2016) focuses on. As a share of the U.S. labor market, STEM jobs grew by 1.33 percentage points from 1980 to 2000, while they shrank by 0.12 percentage points between 2000 and 2012. After adding in data to 2019, STEM jobs began to grow again, led by a massive increase in the number of computer science, programming, and tech support jobs. Roles that had seen a decrease in the relative employment like engineering and science technicians from 2000 to 2012 saw increases and other occupations that were already positive had even higher growth. All other managerial and professional occupations also saw positive increases in their relative change in employment as a share of the U.S. labor force during this period. That said, the roles with the highest increase in relative employment change do not fit into a specific task content category. While those roles relying on interpersonal interaction, like managers, nurses, primary school teachers, therapists, social workers, counselors, and clergy saw a lot of relative job growth, so did jobs that relied on mathematical skills like programming, engineering, and statisticians.

This paper aims to extend Deming's (2017) paper to include the years leading up to the COVID-19 pandemic to examine how the importance of cognitive, social, and non-cognitive skills has changed since 2012. Social skills have proven difficult to automate thus far, but not impossible (Autor 2015). Reinforcement learning and neural networks, among other breakthroughs in AI, have allowed them to have a semblance of social skills, but the inability as of yet to perform task-specific abstract representations keeps them from fully being able to automate social skills because they are unable to perform empathetic functions based on their surroundings and unable to perform basic human interaction (Konidaris 2019). Using Deming's models to analyze the trends, I will present his Ricardian trade model demonstrating how workers with higher social skills are able to specialize and trade tasks with other workers with lesser social skills in a comparative advantage scenario. This model predicts that there are positive and significant social skill returns in the labor market. These predictions will be analyzed using the National Longitudinal Survey of Youth 1979 and 1997 surveys.

This model also links routine tasks and social skills from variance of productivity over workplace tasks. While the variance of tasks performed in the workplace cannot be directly measured, the returns to social skills by each job varying in routineness can be measured through the Occupational Information Network (O*NET) and its database of occupational characteristics and work requirements. Secondly and as mentioned, there is a vast amount of literature in labor economics showing the decline in routine tasks over time (Bloom & Van Reenen 2011; Autor *et al*. 2013). Furthermore, using the more recent waves of the NLSY79 and NLSY97, I show that higher social skills are increasingly an even better predictor of employment and wages in the newer survey waves than the older ones. I also find that the positive returns to social skills have slightly decreased in the last decade.

In the rest of this paper, I first discuss the previous literature and data used in section II. In section III, I then explain the models and their predictions, followed further by the results of each model, before concluding with a discussion of the results, how the government should look to education to address disparities, and how these results can be further exacerbated by the COVID-19 pandemic.

II. The Setting, Data, and Descriptive Statistics

Background

A seminal work by Autor, Levy, and Murnane (2003) (ALM, hereafter) analyzed the change in the occupational task content of the U.S. labor force from the 1970s to the end of the 1990s. They separated each job into a composition of two task categories: routine and non-routine (manual and abstract) tasks. Routine tasks are those that are completed by machines following explicit programmed rules, whereas nonroutine tasks are those that are not able to be understood in computer code and completed by machines following programmed rules. For example, jobs with repetitive assembly, calculation, or record-keeping would fall under routine tasks, where jobs with medical diagnosis, truck driving, janitorial tasks, and so on would fall under nonroutine tasks, even if there can be a wide disparity between the abstraction of the tasks being done. What matters is if the task can be automated by computer programming rules. ALM found three main trends: one, that the labor market for routine cognitive and manual tasks declined dramatically from the 1980s on; two, that the labor market for nonroutine cognitive analytic and interpersonal tasks grew dramatically from 1980s on; and three, that the decline of nonroutine manual tasks decelerated after 1990.

Perhaps the most important part of this discussion had to do with the connection to lower, middle, and upper classes of income in the United States and which tasks pertained more to each respective class. For instance, abstract nonroutine tasks tended to make up a majority of upper-class jobs; manual nonroutine tasks tended to make up a majority of lower-class jobs; and routine tasks tended to make up a majority of middle-class jobs. The decline of routine tasks due to computerization led to a decline in the working class and inevitably an increase in income inequality that has only been exasperated in the last twenty years as these workers were often pushed to lower paying occupations.

Autor and Price (2013) updated the original ALM paper to include updated findings on the time since. They also measured the changes in non-routine analytical, non-routine interpersonal, routine cognitive, routine manual, and non-routine manual tasks. They found that the first two trends from the original ALM paper held for the updated findings but found that the labor market of nonroutine cognitive tasks declined dramatically after the start of the 2000s. Similarly, nonroutine analytical and nonroutine interpersonal tasks also declined, but only between 2000 and 2006, before rebounding afterwards.

ALM's original paper included the discovery of the rise of interpersonal tasks as a part of the overall labor market's task content, but Autor and Price (2013) found mixed results on if that trend was continuing or not. So, Deming (2017) looks at the change in task content building off Autor and Price's (2013) paper and methodology and includes social skills as an important occupational task to look at relative to analytical, cognitive, and manual tasks. One of Deming's main contributions came in the form of introducing a model of team production in the workplace wherein workers "trade tasks" through their competitive advantage of social skills. These skills reduce coordination costs, which allow these workers to work more efficiently because they can specialize better than their peers. Deming used this model to study the changes in employment and wage returns of higher social skills, and he found increases in both from the 1980 through 2012 period.

This paper aims to update and extend Deming's task content analysis through the year 2019, similarly to Autor and Price's (2013) update to the original ALM paper. I carefully recreated the original work done by Deming (2017) and modified the procedures to accommodate later revisions to the data sources which Deming (2017) drew on. I then extended the time series to describe the change in the labor market of job tasks through 2019. This next section of the paper describes the data used, before expounding on the model, and finishing with the results and interpretations of the updated findings. My Data Appendix thoroughly documents the procedures I used to construct and analyze the data.

Data

I used Census and American Community Survey data, the Occupational Information Network (O*NET), the 1979 and 1997 National Longitudinal Surveys of Youth (NLSY79 and NLSY97 respectively). In each case, I had to update various datasets and crosswalks to reflect changes in recent years and keep consistency throughout them respectively.

American Community Survey and the Census

Following Deming (2017), I used Autor and Dorn's (2013) panel of occupation codes covering the 1980-2000 Censuses and 2005 ACS data. Deming updated this panel through 2012, and I updated the panel through the 2019 ACS dataset. Furthermore, I updated these occupational crosswalks to reflect further changes made to the 2008-2012 occupation codes and completing other edits as necessary.

O*NET

The O*NET survey, which is conducted by the U.S. Department of Labor on a random sample of workers in the U.S. of every measurable occupation, was used because of its questions on tasks, skills, and abilities required for each occupation. It is the follow-up to the U.S. Department of Labor's Dictionary of Occupational Titles (DOT), which saw surveys ask similar questions. Given the newness of O*NET (having started in 1998), this paper uses the 1998 O*NET results to accurately reflect the task content of workers in the years before the survey.[1]

There are three main indicators of task content that are evaluated using O*NET in order to gauge positive or negative changes: one, how much is an occupation defined by routine tasks (which answers the questions "how much is this occupation automated?" and "how important is it to repeat the same activities over and over again without stopping for the job?"); two, how much an occupation is composed of nonroutine analytical tasks using ALM's model through averaging three O*NET variables—mathematical reasoning, applied mathematics, and mathematical knowledge; and three, how much an occupation is defined by social skills through use of four O*NET variables—social perceptiveness, negotiation, coordination, and persuasion abilities.[2]

NLSY79 and NLSY97

The NLSY79 and NLSY97 are annual panel surveys youth (ages 14-22 for the NLSY79 and ages 12-16 for the NLSY97). The NLSY79 is a nationally representative sample of nearly thirteen thousand men and women born between 1957 and 1964 and living in the U.S. at the time of the survey in 1979. These people were interviewed annually from 1979 through 1993 until it was switched to a biannual survey from 1994 through 2019. The NLSY97, similarly, is a nationally representative sample of nearly nine thousand men and women born between 1980 and 1984 and living in the U.S. at the time of the survey in 1997. These people were interviewed annually from 1997 to 2011 and then biannually afterwards.

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[1] Figure A.I reflects the similarities of trends and numbers for the mean task input between similar task measures between the DOT and O*NET data sources from 2012 to 2019.

[2] Figure A.II measures routine tasks and social skills for occupations using these O*NET measures and finds that they are very strongly negatively correlated (Deming 2017).

The main outcome variable from these samples is the real log hourly wage (indexed to 2019 dollars). Furthermore, I exclude those under 23 and those enrolled in school, and following Altonji *et al*. (2012), exclude values of the real log hourly wage below 3 and above 200. For measuring cognitive skill, the paper uses the American Forces Qualifying Test (AFQT hereafter) and maps it across each of the NLSY survey waves according to Altonji *et al*. (2012). There is not one way to measure social skills, so the paper uses Deming's (2017) use of four variables to construct a social skill pre-market measure for the NLSY79 survey wave: self-reported sociability in 1981 at the time of the survey and at the age of six, the number of clubs the survey respondent was a part of in high school, and whether the respondent was a part of any high school sports. These variables are averaged and re-standardized so that cognitive and social skills have the same distribution.

The reason these variables are chosen are due to their connection between measuring extraversion and prosocial orientation and social and emotional intelligence (Lawrence et al. 2004; Declerck & Bogaert 2008; Mayer et al. 2008). One potential concern is the overlap of social skills and cognitive or "non-cognitive" skills (similar to the connection of IQ and EQ), but there was found to be a similar level of correlation between the AFQT and social skills as the measured correlation between IQ and EQ (Mayer et al. 2008; Baker et al. 2014). In accounting for any potential unmeasured ability differences biases, various results are controlled for completed years of education along with the AFQT measure.

In comparing the two survey waves, the NLSY97 measures social skills by only using the self-reported sociability in 1981 at the time of the survey and at the age of six variables to maximize the ability to compare the two survey waves. Furthermore, the sample is restricted to those between the ages of 25 and 33 so that the returns to social skills for those of similar ages and experience are compared. Both survey waves have their occupation codes matched to the O*NET and DOT codes from Census occupation crosswalks from Autor and Dorn (2013).

III. The Model

The models used in the data analysis come from Deming (2017).[3] The first model is a human capital model modified with variables for the skills required for a job and the actual tasks that go into it:

$$y_j(i) = A_j\ \alpha_j(i) l_j(i)$$

where $y_j(i)$ is the production function for each j worker (with a cognitive skill of A_j) for each i task multiplied by a task-specific productivity parameter $\alpha_j(i)$. This is then multiplied by the quantity of l labor for each i task.

If workers are specializing in task productions where they have a comparative advantage to other workers, we can use a Ricardo (1891) trade model to analyze productivity gains from it. Instead of countries trading by specializing in the productions of goods for which they are comparatively better in, this model sees workers trading tasks for mutual benefits with other workers, which is what is seen as teamwork in the workplace. This makes social skills important because they reduce the cost of trading tasks with other workers. Each worker is going to maximize output through trading for tasks from the lowest-cost producer of the task. They trade tasks as defined by efficiency units of labor. Thus, the worker specific price of task i is:

$$p_j(i) = \frac{w_j}{A_j \alpha_j(l)}$$

where w_j is the wage paid to worker j for one unit of labor.

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[3] The models shown in this paper come directly from Deming (2017). I am only including the end models used for data analysis here, but Deming explains in detail the mathematical evolution from a base human capital model to the more complicated end models shown here.

Next, we are looking for the equilibrium demand and wages for each worker. The equilibrium wage is determined by the demand for tasks, where the price-adjusted quantity of output for the marginal task must be the same for each worker. This yields the following equilibrium condition for the demand for tasks:

$$\omega = \frac{i^*}{1-i^*}$$

Using this equation and adding in social skills as a variable, the equilibrium wages for worker 1 and worker 2 are the following:

$$w_1 = P^* A_1^{iH} (S^* A_2 \omega)^{1-iH} \exp[\int_0^{i^H} \ln\alpha_1(i)di + \int_{i^H}^1 \ln\alpha_2(i)di]$$

$$w_2 = P^* A_2^{1-iL} (S^* A_1 \omega)^{iL} \exp[\int_0^{i^L} \ln\alpha_1(i)di + \int_{i^L}^1 \ln\alpha_2(i)di]$$

Model-Specific Empirical Predictions

1. There will be a positive and statistically significant return to both cognitive and social skills in the U.S. labor market. This prediction will be evaluated using the NLSY79 and the measures of worker skills for each person in the survey.
2. Cognitive and social skills are complementary to one another. This prediction will be evaluated using the NLSY79 and analyze how cognitive and social skill measures interact with one another in a Mincerian earnings regression.
3. Workers who have higher social skills are able to sort into non-routine occupations and earn more. Positive increases in θ yield a better return for those with higher social skills as opposed to workers with lesser social skills, so they have more incentives to sort into

non-routine occupations utilizing their skills and giving them higher wages.[4] This prediction will be evaluated using the NLSY79 and allow the tracking of changes in returns to various skills when those workers switch jobs for any reason.

4. There will be a positive and statistically significant increase in returns to social skills over time. This prediction will be evaluated by comparing the NLSY79 and NLSY97 survey waves and, more specifically, how the returns to social skills have differed between the two waves over time.

[4] θ is used in Deming's (2017) models as a variance parameter that one can interpret as a measure of predictability or a general production technology parameter applying to all occupations.

IV. Results

The Continued Importance of Social Skills

I will begin by discussing the results of the analysis that extends Deming's datasets of 1980 to 2012 by incorporating data from 2013 to 2019. I will then proceed to focus on the isolated results from 2013 to 2019.

The first two model predictions are as follows: one, there will be positive returns to cognitive and social skills in the labor market; and two, that cognitive and social skills are complements of one another. The regression used to test that is based on regressing log hourly wages on measures of skill and interactions with it (while controlling for other covariates). This model is as follows:

$$\ln(wage_{ijt})=\alpha+\beta_1 COG_i + \beta_2 SS_i + \beta_3 COG_i*SS_i+\gamma X_{ijt}+\delta_j+\zeta_t+\varepsilon_{ijt}$$

where α represents the task-specific productivity parameter, COG_i represents the cognitive skill, SS_i represents the social skill, ζ_t is the year fixed effect, δ_j is the age fixed effect, γX_{ij} represents the race-by-gender indicators, and ε_{ijt} are the standard errors clustered at the individual level.

The results of this regression can be seen in Table I. Deming (2017) found a positive and statistically significant return to social skills from 1980 through 2012. These results extend to 2019 as the regression results in Table I show a positive and statistically significant return to social skills but show that these returns have decreased by a small margin. Column 1 can be interpreted as follows: a one standard deviation increase in social skills will translate to an increase in real hourly wages by 10.6%. Column 2 adds the Armed Forces Qualifying Test as a proxy for cognitive skill and finds similar statistically significant results. Here, a one standard deviation increase in cognitive skills will translate to an increase in real hourly wages by 19.6%.

Row 1 demonstrates the effect of cognitive skills to the regression, which lowers the increase in real hourly wages due to social skills to 5.7%. The third column of Table I tests for complementarity with cognitive skills and social skills on real hourly wages. This is still positive and statistically significant, but it does not dramatically change the coefficients of the other skills. The fourth column of Table I tests for non-cognitive skills along with cognitive and social skills and while it is positive and statistically significant, similarly to column three, it does not dramatically change the coefficients of the other skills. In fact, it changes them even less than column three's complementarity test with cognitive and social skills did. The fifth column adds educational year attained as a control and lowers the coefficients of the other skills by a good margin, while making the controls for social and cognitive skills less statistically significant. These results potentially indicate that cognitive and social skills measure some of the same skills and underlying abilities of workers. To test this, the sixth column adds an interactive variable between cognitive and non-cognitive skills. The interaction variable in the sixth column is not statistically significant and is zero when controlled for education. This means that wages are not determined by a single ability and that the complementary nature between cognitive and social skills holds exclusively for them.

Table II demonstrates that these returns are statistically significant and positive for all groups of race, gender, and education. It can be interpreted as follows: a one standard deviation increase in social skills leads to a 4.2% increase in wages for females and a 2.0% increase in wages for nonwhites. Note that in general, the returns are greater for males, white, and college workers than women, nonwhite, and no college workers. However, when including the 2012-2019 data, the returns to social skills have increased for every group relative to Deming (2017) except for males. These results are consistent with existing literature studying the differences in returns to skills and experience (Goldmith *et al.* 2006; Liu *et al.* 2020). The increase in cognitive skills leads to higher returns to wages for women and nonwhite workers than the returns of their counterparts. Furthermore, there is still evidence of greater returns to skills for workers with some college education as opposed to workers without any college education, which is consistent with the growing complementarity between cognitive and social skill findings of Weinberger (2014).

Next, I will test the third model prediction that workers will sort into non-routine and social skill-heavy occupations if they have higher levels of social skills. Table III is constructed using the same regression as used in Table I except Table III uses the task content of occupations as the dependent variable. Covariates from Table I are controlled for along with completed education (in years) and industry fixed effects. In Table III, a one standard deviation increase in social skills decreases the routine task intensity of the worker's job by 1.94 percentiles and is statistically significant. Note that this number is higher than Deming's 1.88 percentile decrease, which means that the same increase in social skills has led to a lower routine task intensity of the worker's job from 2012 through 2019. The second column in Table III controls for both math task intensity and other related O*NET cognitive task measures. A one standard deviation increase in cognitive skills increases the routine task intensity of the worker's job by 1.55 percentiles compared to decreasing it by 0.73 percentiles without the controls. The decrease in routine task intensity of a worker's occupation from an increase in social skills went down as well. The third and fourth columns of Table III use parallel estimating with social skill intensity as the outcome instead of routine task intensity. The results are the exact opposite signs of those seen in columns 1 and 2 and prove the idea that workers with higher social abilities sort into nonroutine and social skill heavy occupations. These workers are just sorting into jobs where their skills pay them more.

Now I will show the returns to skills by occupational task intensity for the NLSY79 survey wave before comparing it to the NLSY97 survey wave. The first column in Table IV shows significantly higher wage returns for workers who sort into routine occupations. However, the wage returns from sorting into non-routine occupations are increasing in social skills as predicted. There is also a negative coefficient on cognitive skills and the interaction between cognitive and social skills. The second column looks at social skill task intensity instead of routine task intensity. Deming (2017) found that workers who switch into a job that is 10 percentiles higher in social skill intensity earn 3.9 percent higher wages. However, when I factor in the new data extending the data to 2019, this number is almost 0 and not statistically significant. The third column looks at both routine and social skill task measures and increases the coefficients on social skill interactions while being statistically significant. These results show that social skill O*NET task measures are better predictors of the returns to social skills when including for routine and social skill task measures than when using them separately.[5]

Next, Table V looks at the increasing returns to various skills in employment and wages across NLSY waves.[6] Columns 1 through 3 show results for changes in full-time employment. The first column shows how a one standard deviation increase in cognitive skills increases the probability of a worker being full-time employed by 6.8 percentage points. Involving the NLSY97 sample indicator is statistically significant, which suggests that the returns to cognitive skill for full-time employees has changed across survey waves (albeit not very much), which is

[5] The results found between the interactions of skills and math task intensity are not statistically significant, which indicates that the higher returns to skills required for social skill-intensive occupations are not proxies to the complexity of a job or the requirements of it. This is a continued trend from Deming (2017) as shown in Figure.

[6] With an age restriction of 25- to 33-year-olds.

consistent with past literature (Murnane *et al*. 1995; Castex and Dechter 2014). For social skills, a one standard deviation increase in social skills for workers leads to an increased probability of full-time employment for workers of 0.7 percentage points in the NLSY79 dataset but went up to 2.9 percentage points in the NLSY97 dataset. This demonstrates the continued importance of social skills in predicting a worker being employed full-time. The second column in Table V controls for years of completed education and slightly reduces the coefficients of social and cognitive skills. The third column controls for non-cognitive skills and finds them to be positive and statistically significant to increasing returns on full-time employment. A one standard deviation increase in non-cognitive skills increased the probability of full-time work for workers by 0.8 percentage points in the NLSY79 dataset but went up to 2.2 percentage points in the NLSY97 dataset. It also further reduces the coefficients of social and cognitive skills, although not drastically. The fourth, fifth, and sixth columns analyze the change in the impact of various skills (cognitive, social, and non-cognitive) on hourly wages among full-time workers. Column 6 shows that a one standard deviation increase in cognitive skills increased the hourly wages for full-time workers by 11.3 percent in the NLSY79 dataset but went down to 8.0 percent in the NLSY97 dataset. These returns are the only ones that are statistically significant while accounting for social and non-cognitive skills. Still, the growth in returns to increased social skills has continued through 2019, whereas the returns to increased cognitive skills have continued to decline relatively.

Finally, I am going to study the changes in relative returns to various skills across occupations by studying whether the wage gains from sorting into social skill-intensive occupations have changed across the NLSY survey waves. Table VI analyzes the changes in the relative returns to skill across all the occupations from the 1979 and 1997 NLSY survey waves.

The first two columns in this table include interactions between task intensity measures and the NLSY97 indicator. The first column shows the wage gain for workers switching to an occupation with a higher social skill-intensity. It shows that workers who sort into more social-skill intensive occupations have significantly higher wage gains than other workers. The within-worker return to a 10 percentile increase in social skill intensity is equal to about zero in the NLSY79 survey wave, but it is 2.1 percent in the NLSY97 wave and is statistically significant. This coefficient is about the same as Deming (2017), which means the same gains have held through 2019. The second column adds math tasks as a measure with an NLSY97 indicator. The within-worker return to a 10 percentile increase in math skill intensity is equal to 1.7 percent in the NLSY79 survey wave, but it is 1.2 percent in the NLSY97. Adding a math task measure increases the growth in returns for increased social skills in the NLSY97 wave. Columns three and four add interaction terms between social skill, social skill task intensity, and NLSY waves, and shows increased complementarity between social skills and jobs of social interaction in the NLSY97 sample. Thus the evidence suggests that the wage gain from sorting into social-skill intensive occupations has continued to increase over time in similar amounts as found in Deming (2017).

In sum, the comparison between the NLSY79 and NLSY97 datasets and the returns to social skills show that the importance of social skills has decreased very slightly from 2012 to 2019, while still being responsible for large positive returns to a worker’s full-time employment probability and hourly wages. The next section will discuss the results that further demonstrate this minor change from 2012 to 2019.

The Decrease in Relative Importance of Social Skills in the Last Decade

I will begin with the trends in employment and wage growth in the U.S. labor market between 2012 and 2019, as seen in Figure II. Figure II represents the changes in the employment-weighted mean of each task relative to the importance of them in 1980, extending the work done in Autor et al. (2003) and their O*NET task measures.[7] The portion of routine tasks factoring into labor input has continued to slightly decline since 2012. Nonroutine analytical tasks and social skill tasks as labor inputs both slightly decreased from 2012 to 2016, but then rebounded from 2016 to 2019. While nonroutine analytical skills had been decreasing since their peak in 2000, in 2019, they had once again reached 2000 levels. Tasks requiring social skills continued to outgrow nonroutine analytical and routine tasks during this period, continuing the trends seen in Deming (2017).

I will next present the relative change trends in employment shares between 2012 and 2019 as seen in Figure III (with the changes being relative to 2012). From 2012 to 2016, the relative changes in employment share by each task intensity did not change very drastically, aside from the solid increase in high social and high math tasks. As for the period from 2016 to 2019, there are bigger relative changes from high social and high math occupations and low social and low math occupations, with the former continuing to increase and the latter decreasing drastically. Employment for high math and high social skill jobs increased almost two percent over these seven years, whereas employment for low math and low social skill jobs decreased more than two percent. Figure IV shows the changes in real hourly wages by occupation task intensity for the occupations from 2012 to 2019 (with the changes being relative to 2012). Wages for high math and high social skill jobs grew by almost five percent in those seven years. This is

[7] The measures are still built off the idea that each task has a mean of 50 centiles in 1980 to show continuation from Deming (2017).

also the case for wages for high math and low social jobs. Low social and low math jobs had a relatively decent increase in real hourly wages from 2012 to 2016, before landing at about a 2.2 percent increase by 2019. As for high social and low math jobs, their real hourly wages decreased relatively from 2012 through 2016, before increasing dramatically from 2016 to 2019 to settle at an increase of just over 2.0%.[8] The dramatic wage growth of high math jobs in general is likely due to increased demand in STEM jobs as seen in Figure 1, with employers behind on being able to find enough people to fill those roles. This contrasts with the dramatic employment and wage growth of high math and high social skill jobs, where the demand is high, but employers are less behind on being able to find people to fill these roles.

Finally, I will discuss the changes in employment and wages by occupation task intensity in the Census and American Community Survey. Table VIII shows the changes in employment by occupational task intensity. While most of the results are not statistically significant, the ones that are show some isolated evidence as to the decreased importance of social skills on higher returns to full-time employment from 2012 through 2019 when compared to 1980 through 2012. Furthermore, the importance of routine task intensity on higher returns to full-time employment has decreased, while the importance of service task intensity has increased from 2012 through 2019. Table VII shows the returns to changes in wages by occupational task intensity from the Census and ACS datasets. Most of the coefficients here are also not statistically significant, but the ones that are contribute to the idea that social skills have continued to grow in importance

[8] Figure A.III shows the changes in employment by occupational task intensity from 2012 through 2019. The demonstrated employment growth for social skill-intensive occupations has affected all occupations regardless of their percentile in the 1980 wage distribution, similar to Deming (2017). Figure A.IV shows the changes in median wages by occupational task intensity from 2012 through 2019. The demonstrated wage growth for social skill-intensive occupations has also affected all occupations regardless of their percentile in the 1980 wage distribution, similar to Deming (2017).

from 2012 through 2019 in increasing a worker’s wages. While the growing importance of the service task intensity from 2012-2019 increased the probability of full-time employment, it led to a decrease in hourly wages during the same period.

V. Conclusion

Many of the trends identified in Deming's original paper have continued from 2012 through 2019. The change in relative employment for high math occupations from 2012 through 2019 have continued to increase, largely due to increases in computer science, programming, and technical support roles and engineers. This is a trend that is likely to continue into the next decade and be accelerated by the COVID-19 pandemic. Social skills continue to increase relatively as a percentage of worker task loads, as do nonroutine analytical tasks, while routine tasks continue to decline. The relative changes in employment share and real hourly wages by occupation task intensity have also continued to favor jobs with higher social skill intensity from 2012 to 2019. Furthermore, the changes in employment and median wages by occupational task intensity measured by the occupation's percentile in the 1980 wage distribution still do not seem to have affected any occupation more than the other except near the top of the wage distribution, where high social skills mattered the most in determining higher returns to wages.

The returns to hourly wages and employment of higher social skill decreased from 2012 to 2019, showing a slightly decreased importance of social skills in the job market since 2012 (Deming 2017). While computers had been bad at simulating interaction, advances in computing power in super computers, AI, blockchain and machine learning have reduced the importance of key social skill intensive tasks. AI is still largely behind the game in human interaction given the inability of programming to explicitly write out rules of human interaction and empathy. That said, the increased ability of these technologies over the past decade have started to edge at more difficult levels of routine tasks, and even some abstract task-intensive jobs, where those with higher social skills tend to reside.

Of course, it will be worthwhile to conduct a similar analysis from 2020 to 2022 to evaluate the impacts of the COVID-19 pandemic on these trends. Remote work was much more common during the pandemic from workers who are better educated and in higher paid occupations (Bartik et al. 2020). The workers who tend to be in this group are those who have higher social skills (Deming 2017). This is further proven by the fact that the jobs with the most remote work potential are those in company management, information technology, finance and insurance, and professional services (Althoff et. al 2022)—three of the four being social skill-intensive occupations. The incredibly quick move to remote work has many of those in urban areas providing these services leaving and destroying the service economy in these areas that had previously catered to their needs, causing low-skill workers to endure most of the economic hardship during this time.

Given the regional and labor gentrification during this period, these trends are useful to study the disruptions in the labor market coming from changes in technology and how they will likely continue to push a wider wedge in the high levels of income inequality today. If and how the government chooses to reallocate educational funds on programs promoting social skills is important for the future of the U.S. labor market and the returns on the market and innovation within it. High-quality education for children in early childhood and elementary school has been linked to improving social skills in a cost-effective way that translate to the workplace later in life. Furthermore, companies interested in taking advantage of the positive returns to social and nonroutine analytical skills would be well-suited to see how that fits into their corporate strategy model and how they can leverage it for higher returns. Workplace-based programs teaching social skills also have promising returns to businesses (Kautz et al. 2014). If education in the U.S. could continue to teach social skills through high school and beyond instead of focusing exclusively on literacy and mathematics after elementary school, there would likely be much larger and sustained social skill returns for next generations. This speculation and analysis are important for the future of work in a post-COVID-19 pandemic world where the nature of work has changed for millions across the country in the span of a few years.

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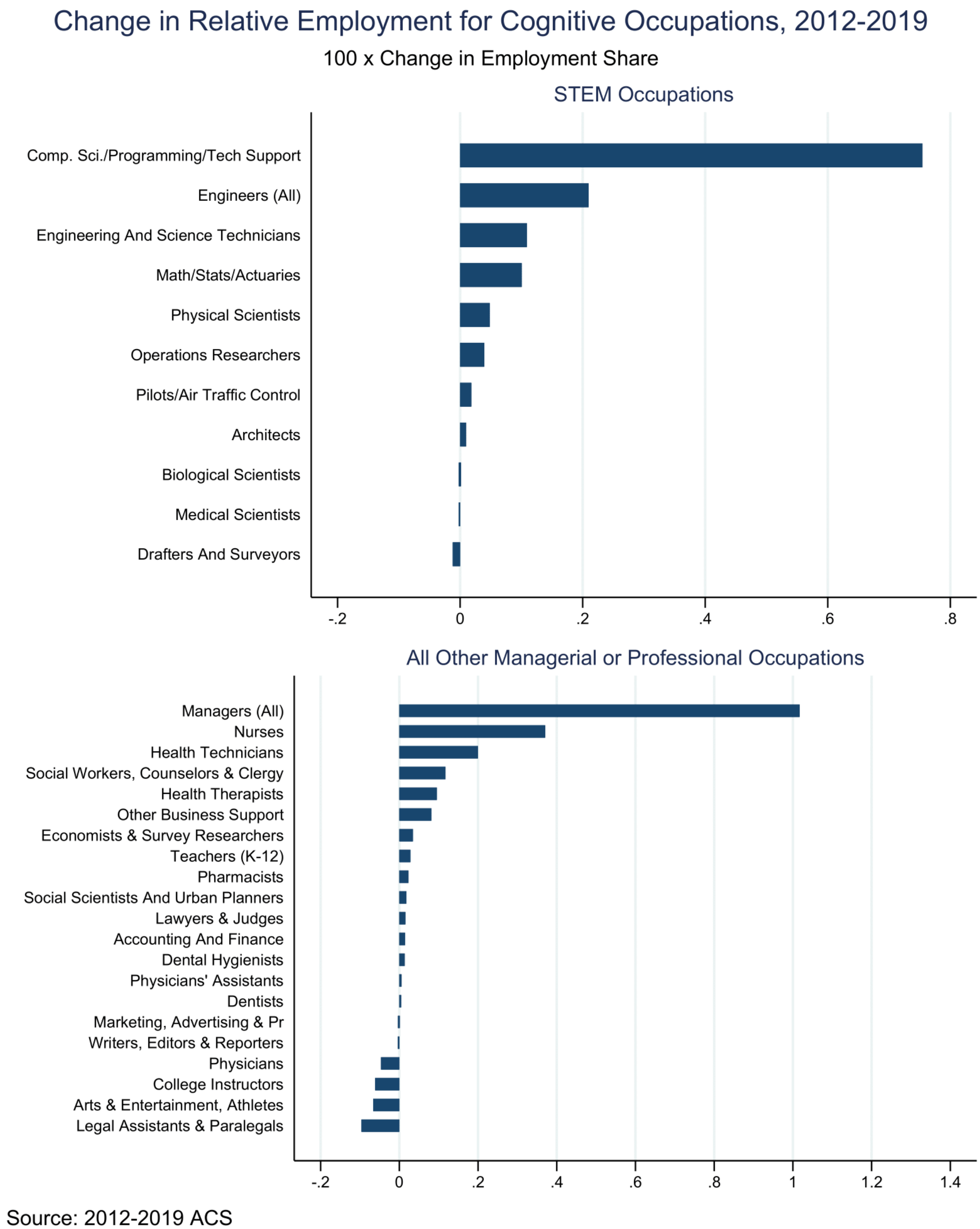
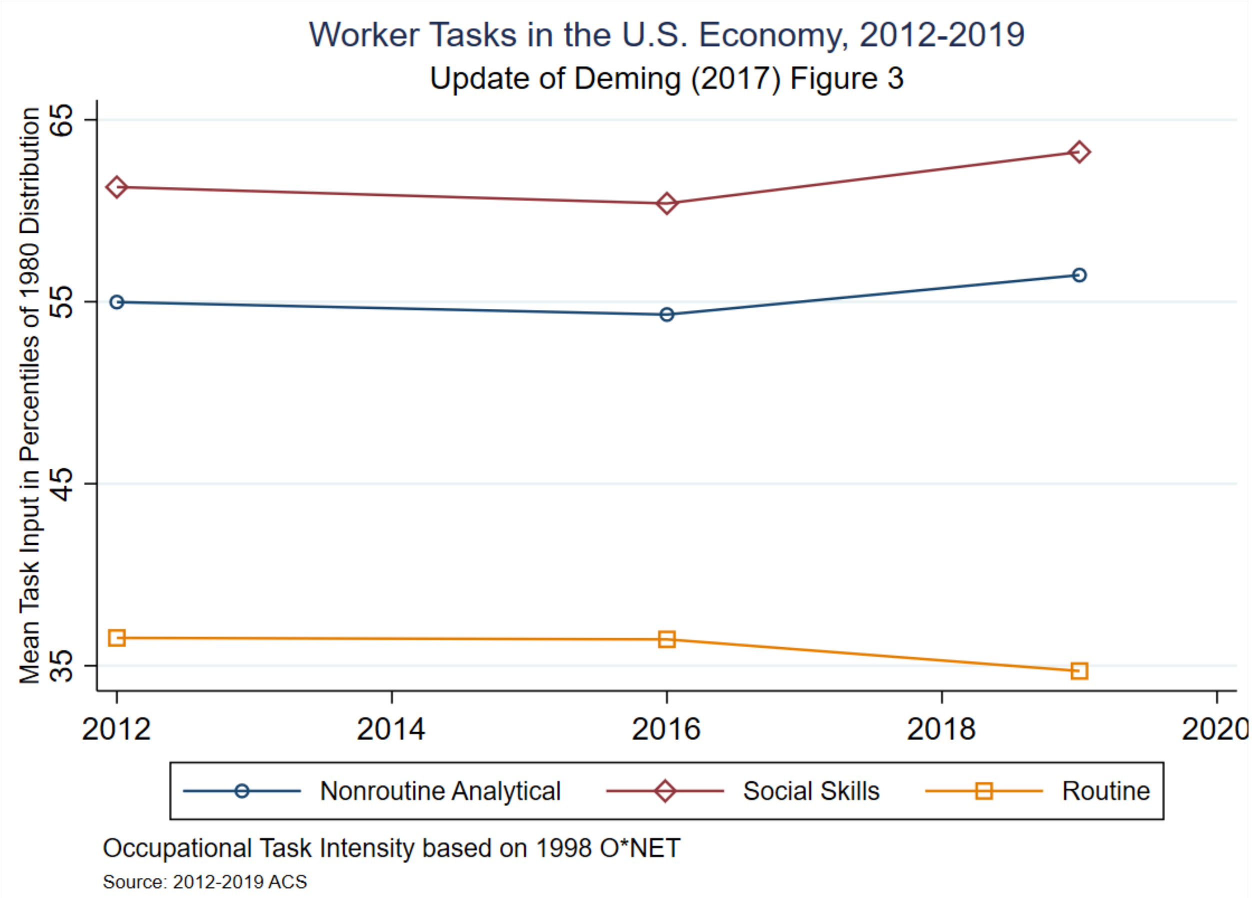
Figures

Figure I



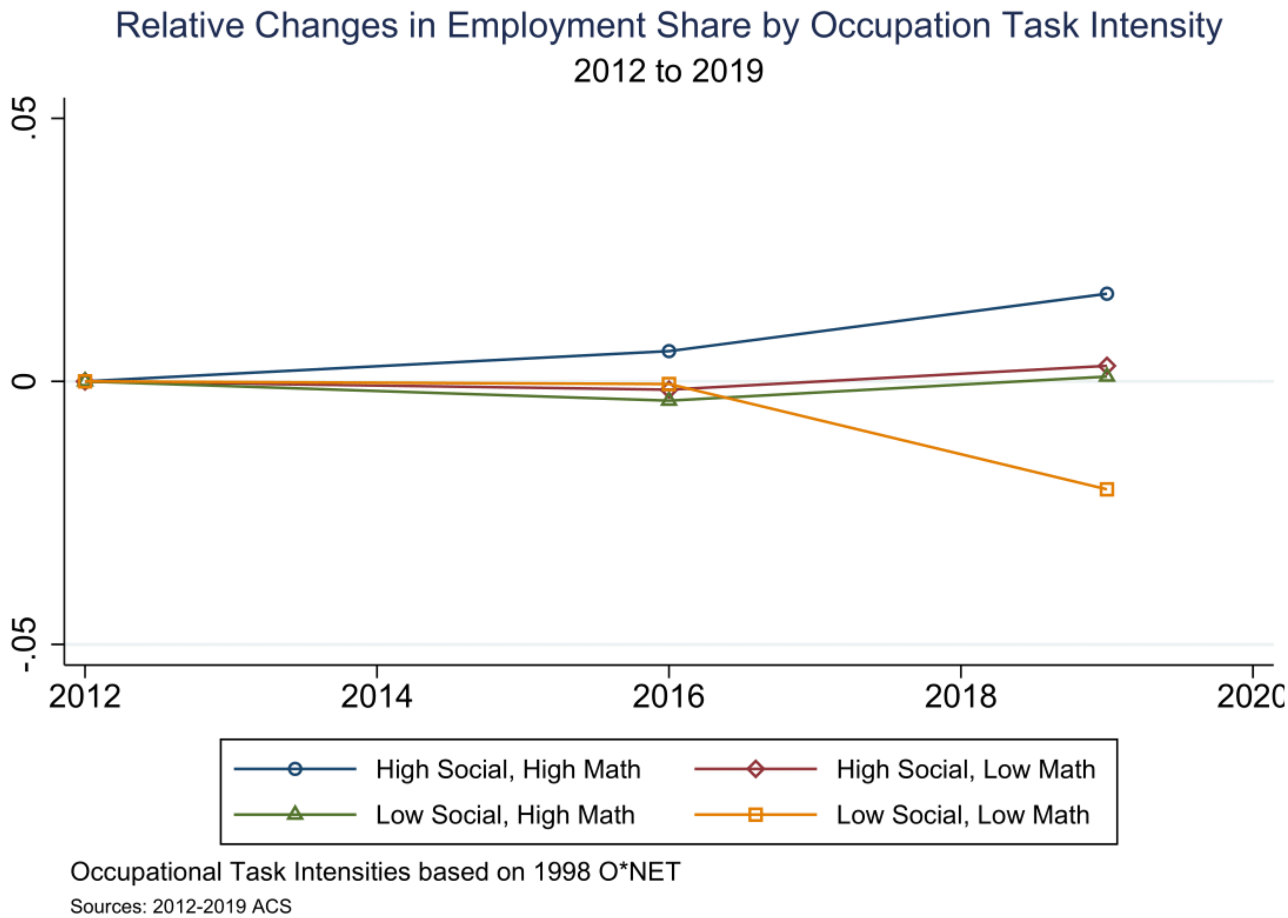
Notes: Each row presents 100 times the change in employment share between 2012 and 2019 for the indicated occupations. Consistent occupation codes for 2012-2019 are updated from Deming (2017) and consolidated.

Figure II



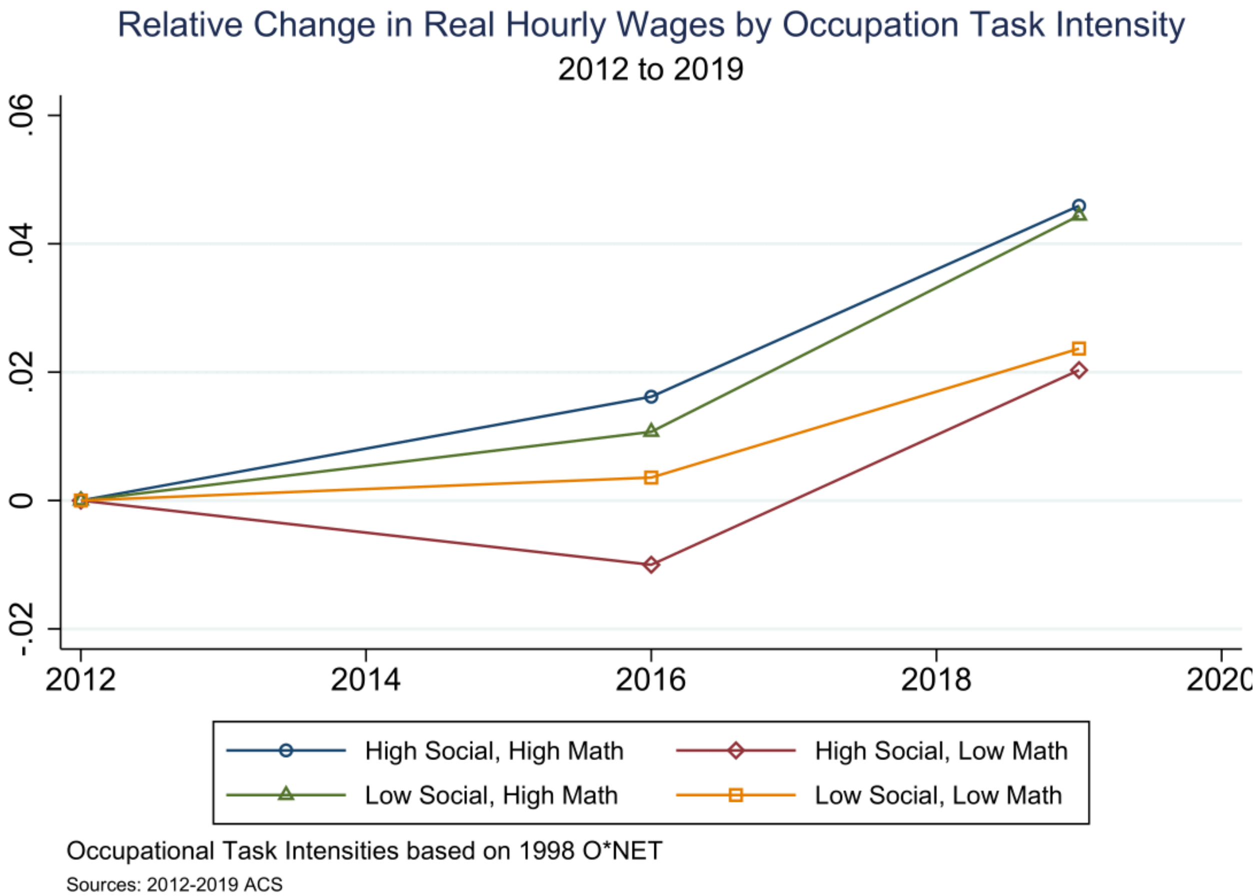
Notes: O*NET 1998 task measures by occupation are paired with data from the IPUMS 2012-2019 American Community Survey samples. Consistent occupation codes for 2009-2017 are updated by me for this paper. Data are aggregated to industry-education-sex cells by year, and each cell is assigned a value corresponding to its rank in the 1980 distribution of task input. Plotted values depict the employment-weighted mean of each assigned percentile in the indicated year.

Figure III



Notes: Each line plots 100 times the change in employment share – relative to a 1980 baseline - between 2012 and 2019 for occupations that are above and/or below the 50th percentile in nonroutine analytical and social skill task intensity as measured by the 1998 O*NET. Consistent occupation codes for 2009-2017 are updated by me for this paper.

Figure IV



Notes: Each line plots the percent change in mean hourly wages – relative to a 2012 baseline and in constant 2019 dollars - between 2012 and 2019 for occupations that are above and/or below the 50th percentile in nonroutine analytical and social skill task intensity as measured by the 1998 O*NET. Consistent occupation codes for 2009-2017 are updated by me for this paper.

Tables

Table I

TABLE I

LABOR MARKET RETURNS TO COGNITIVE SKILLS AND SOCIAL SKILLS IN THE NLSY79

Outcome is Log Hourly Wage (in 2019 dollars)	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Cognitive Skills (AFQT, standardized)		0.196***	0.196***	0.179***	0.117***	0.179***	0.117***
		[0.006]	[0.006]	[0.007]	[0.008]	[0.007]	[0.008]
Social Skills (standardized)	0.106***	0.057***	0.051***	0.045***	0.031***	0.046***	0.031***
	[0.006]	[0.005]	[0.005]	[0.005]	[0.005]	[0.005]	[0.005]
Cognitive * Social			0.019***	0.019***	0.009*	0.017***	0.009*
			[0.005]	[0.005]	[0.005]	[0.005]	[0.005]
Non-cognitive Skills (standardized)				0.048***	0.039***	0.046***	0.040***
				[0.006]	[0.006]	[0.006]	[0.006]
Cognitive * Noncognitive						-0.056	-0.057
						[0.158]	[0.157]
Demographics and Age/Year Fixed Effects		X	X	X	X	X	X
Years of Completed Education					X		X
Observations	98,922	98,922	98,922	98,873	98,873	98,873	98,873
R-squared	0.276	0.327	0.327	0.331	0.347	0.331	0.347

Notes: Each column reports results from an estimate of regressing log hourly wages on skill and interaction with real log hourly wages as the outcome and person-year as theunit of observation. The data source is the NLSY79. Cognitive skills are measured by each NLSY79 respondent's score on the Armed Forces Qualifying Test (AFQT), and are normalized to have a mean of zero and a standard deviation of one. I use the AFQT score crosswalk developed by Altonji, Bharadwaj and Lange (2012). The regression also controls for race-by-gender indicator variables, age, year, census region, and urbanicity fixed effects - plus additional controls as indicated. *** p<0.01, ** p<0.05, * p<0.10

Table II

TABLE II

HETEROGENEITY IN RETURNS TO SKILLS

Outcome is Log Hourly Wage	Males	Females	Nonwhite	White	No College	Some College
(in 2019 dollars)	(1)	(2)	(3)	(4)	(5)	(6)
Cognitive Skills (AFQT, standardized)	0.149***	0.216***	0.195***	0.175***	0.124***	0.165***
	[0.009]	[0.010]	[0.008]	[0.008]	[0.010]	[0.012]
Social Skills (standardized)	0.052***	0.042***	0.020**	0.046***	0.030***	0.039***
	[0.008]	[0.007]	[0.009]	[0.007]	[0.009]	[0.009]
Cognitive * Social	0.023***	0.013*	-0.008	0.023***	0.001	0.017**
	[0.007]	[0.007]	[0.008]	[0.007]	[0.009]	[0.009]
Non-cognitive Skills (standardized)	0.047***	0.047***	0.052***	0.047***	0.035***	0.051***
	[0.008]	[0.009]	[0.007]	[0.007]	[0.008]	[0.009]
Demographics and Age/Year Fixed Effects	X	X	X	X	X	X
Observations	51,325	47,548	43,975	54,898	53,814	45,059
R-squared	0.315	0.303	0.300	0.331	0.283	0.329

Notes: Each column reports results from an estimate of regressing log hourly wages on skill and interaction, with the natural log of real hourly wages as the outcome and person-year as the unit of observation. The data source is the National Longitudinal Survey of Youth 1979 cohort (NLSY79). Cognitive skills are measured by each NLSY79 respondent's score on the Armed Forces Qualifying Test (AFQT), and are normalized to have a mean of zero and a standard deviation of one. The regression also controls for race-by-gender indicator variables, age, year, census region, and urbanicity fixed effects - plus additional controls as indicated. Standard errors are in brackets and clustered at the individual level. *** p<0.01, ** p<0.05, * p<0.10

Table III

TABLE III

OCCUPATIONAL SORTING ON SKILLS IN THE NLSY79

	Routine		Social Skills	
*Outcomes are O*NET Task Measures*	(1)	(2)	(3)	(4)
Cognitive Skills (AFQT, standardized)	-0.073**	0.155***	0.337***	-0.049**
	[0.029]	[0.033]	[0.028]	[0.020]
Social Skills (standardized)	-0.194***	-0.155***	0.204***	0.123***
	[0.021]	[0.024]	[0.020]	[0.014]
Cognitive * Social	-0.060***	-0.052**	0.016	0.006
	[0.021]	[0.023]	[0.018]	[0.014]
Demos, Age/Years, Education Fixed Effects	X	X	X	X
Controls for O*NET Cognitive Tasks		X		X
Observations	106,004	106,004	106,004	106,004
R-Squared	0.218	0.231	0.305	0.660

Notes: Each column reports results from an estimate of estimate of regressing log hourly wages on skill and interaction, with the indicated 1998 O*NET task intensity of an occupation as the outcome and person-year as the unit of observation. The task measures are percentiles that range from 0 to 10 and are weighted by labor supply to conform tothe 1980 occupation distribution. The additional O*NET cognitive task measures are Nonroutine Analytical, Number Facility, Inductive/Deductive Reasoning, and Analyze/Use Information. See the text and Appendix for details on the construction of each O*NET task measure. The data source is the NLSY79. Cognitive skills are measured by each NLSY79 respondent's score on the Armed Forces Qualifying Test (AFQT), and are normalized to have a mean of zero and a standard deviation of one. I use the AFQT score crosswalk developed by Altonji, Bharadwaj and Lange (2012). The regression also controls for race- by-gender indicator variables, age, year, census region, and urbanicity fixed effects - plus additional controls as indicated. Standard errors are in brackets and clustered at the individual level. *** p<0.01, ** p<0.05, * p<0.10

Table IV

TABLE IV

RETURNS TO SKILLS BY OCCUPATIONAL TASK INTENSITY IN THE NLSY79

Outcome is Log Hourly Wage (in 2019 dollars)	(1)	(2)	(3)
Routine Task Intensity	0.0118***		0.0167***
	[0.0011]		[0.0014]
Cognitive * Routine Task Intensity	-0.0048***		-0.0006
	[0.0012]		[0.0014]
Social Skills * Routine Task Intensity	-0.0021*		-0.0006
	[0.0012]		[0.0015]
Cognitive * Social * Routine Task Intensity	-0.0025**		-0.0032**
	[0.0011]		[0.0014]
Social Skill Task Intensity		0.0006	0.0113***
		[0.0013]	[0.0016]
Cognitive * Social Skill Task Intensity		0.0112***	0.0107***
		[0.0014]	[0.0017]
Social Skills * Social Skill Task Intensity		0.0043***	0.0037**
		[0.0014]	[0.0018]
Cognitive * Social * Social Skill Task Intensity		0.0017	-0.0003
		[0.0014]	[0.0018]
Worker Fixed Effects	X	X	X
Observations	98,922	98,922	98,922
Number of Individuals	10,976	10,976	10,976
R-squared	0.2980	0.2977	0.3010

Notes: Each column reports results from an estimate of predicting workers switching occupations and the wage increases resulting from it, with real log hourly wages as the outcome and person-year as the unit of observation. The data source is the NLSY79. Cognitive skills are measured by each NLSY79 respondent's score on the Armed Forces Qualifying Test (AFQT), and are normalized to have a mean of zero and a standard deviation of one. I use the AFQT score crosswalk developed by Altonji, Bharadwaj and Lange (2012). All models control for worker fixed effects, age, year, census region, and urbanicity fixed effects - plus additional controls as indicated. The interactions between cognitive/social skills and 1998 O*NET task intensities measure whether the returns to skills vary with the task content of the worker's occupation. The task measures are percentiles that range from 0 to 10 and are weighted by labor supply to conform to the 1980 occupation distribution. *** p<0.01, ** p<0.05, * p<0.10

Table V

TABLE V
LABOR MARKET RETURNS TO SKILLS IN THE NLSY79 V. NLSY97

	Full-Time Employment			Log Real Hourly Wage		
	(1)	(2)	(3)	(4)	(5)	(6)
Cognitive Skills (AFQT, standardized)	0.068***	0.041***	0.039***	0.201***	0.126***	0.113***
	[0.003]	[0.003]	[0.003]	[0.005]	[0.006]	[0.006]
Cognitive Skills * NLSY97	0.009**	0.007	0.010**	-0.039***	-0.050***	-0.033***
	[0.004]	[0.004]	[0.004]	[0.008]	[0.008]	[0.008]
Social Skills (standardized)	0.007***	0.005**	0.004*	0.020***	0.015***	0.011**
	[0.002]	[0.002]	[0.002]	[0.004]	[0.004]	[0.004]
Social Skills * NLSY97	0.022***	0.020***	0.018***	0.015*	0.015**	0.011
	[0.004]	[0.004]	[0.004]	[0.008]	[0.008]	[0.008]
Cognitive * Social	-0.007***	-0.006**	-0.007**	0.006	0.003	0.002
	[0.003]	[0.003]	[0.003]	[0.004]	[0.004]	[0.004]
Cognitive * Social * NLSY97	-0.006	-0.006	-0.005	-0.004	-0.003	-0.001
	[0.004]	[0.004]	[0.004]	[0.007]	[0.007]	[0.007]
Non-Cognitive Skills (standardized)			0.008***			0.042***
			[0.003]			[0.005]
Non-Cognitive Skills * NLSY97			0.014***			0.016**
			[0.004]			[0.008]
Demographics and Age/Year Fixed Effects	X	X	X	X	X	X
Years of Completed Education		X	X		X	
Observations	108,885	108,477	108,431	80,798	80,537	80,505
R-squared	0.081	0.096	0.097	0.332	0.358	0.362

Notes: Each column reports results from an estimate of changes in returns to skills across each NLSY79 and NLSY97 cohort, with an indicator for being employed full-time as the outcome in Columns 1 through 3, real log hourly wages as the outcome in Columns 4 through 6, and person-year as the unit of observation. I restrict the age range to 25-33, which allows for a comparison of NLSY respondents at similar ages across survey waves. Cognitive skills are measured by each NLSY respondent's score on the Armed Forces Qualifying Test (AFQT), and are normalized to have a mean of zero and a standard deviation of one. I use the AFQT score crosswalk developed by Altonji, Bharadwaj and Lange (2012) which adjusts for differences across survey waves in age-at-test and test format.. The regression also controls for anindicator for whether the respondent was in the NLSY97 wave, race-by-gender indicator variables, age, year, census region, and urbanicity fixed effects - plus additional controls as indicated. Standard errors are in brackets and clustered at the individual level. *** p<0.01, ** p<0.05, * p<0.10

Table VI

TABLE VI

RETURNS TO SKILLS BY OCCUPATION TASK INTENSITY IN THE NLSY79 V. NLSY97

Outcome is Log Hourly Wage (in 2019 dollars)	(1)	(2)	(3)	(4)
Social Skill Task Intensity	0.0002	-0.0098***	-0.0097***	-0.0098***
	[0.0013]	[0.0015]	[0.0015]	[0.0015]
Social Skill Task Intensity * NLSY97	0.0210***	0.0234***	0.0210***	0.0211***
	[0.0030]	[0.0036]	[0.0035]	[0.0035]
Math Task Intensity		0.0175***	0.0176***	0.0177***
		[0.0015]	[0.0015]	[0.0015]
Math Task Intensity * NLSY97		-0.0051*	-0.0052*	-0.0054*
		[0.0030]	[0.0030]	[0.0030]
Cognitive Skill * Social Skill Task Intensity			0.0068***	0.0073***
			[0.0013]	[0.0016]
Cognitive Skill * Social Skill Task Intensity * NLSY97			0.0058*	0.0033
			[0.0031]	[0.0038]
Social Skill * Social Skill Task Intensity			0.0008	0.0011
			[0.0013]	[0.0016]
Social Skill * Social Skill Task Intensity * NLSY97			0.0036	0.0060*
			[0.0029]	[0.0035]
Observations	80,798	80,798	80,798	80,798
Number of individuals	15,124	15,124	15,124	15,124
R-squared	0.1096	0.1128	0.1138	0.1139

Notes: Each column reports results from an estimate of regressing log hourly wages on skill and interaction, with real log hourly wages as theoutcome and person-year as the unit of observation. The data are a pooled sample of two cohorts of youth - the NLSY79 and NLSY97 waves. I restrict the age range to 25-33, which allows for a comparison of NLSY respondents at similar ages across survey waves. Cognitive skills are measured by each NLSY respondent's score on the Armed Forces Qualifying Test (AFQT), and are normalized to havea mean of zero and a standard deviation of one. I use the AFQT score crosswalk developed by Altonji, Bharadwaj and Lange (2012) which adjusts for differences across survey waves in age-at-test and test format. The regression also controls for age, year, census region, and urbanicity fixed effects - plus additional controls as indicated. The interactions between cognitive/social skills and 1998 O*NET task intensities measure whether the returns to skills vary with the task content of the worker's occupation. The task measures are percentiles that range from 0 to 10 and are weighted by labor supply to conform to the 1980 occupation distribution. See the text and Appendix for details on the construction of each O*NET task measure. Standard errors are in brackets and clustered at the individual level. *** p<0.01, ** p<0.05, * p<0.10

Table VII

TABLE VII

CHANGES IN WAGES BY OCCUPATION TASK INTENSITY IN THE CENSUS/ACS

		1980-2019		1980-2012	2012-2019	
Outcome is Log Hourly Wage	(1)	(2)	(3)	(4)	(5)	(6)
Math Task Intensity	0.0442***	0.0474***	0.0081	0.0145	-0.0102	0.0041
	[0.0082]	[0.0105]	[0.0248]	[0.0245]	[0.0229]	[0.0250]
Social Skill Task Intensity	0.0484***	0.0520***	0.0555***	0.0577***	0.0428***	0.0590***
	[0.0063]	[0.0154]	[0.0164]	[0.0160]	[0.0142]	[0.0161]
Math * Social		-0.0009	-0.0038	-0.0035	-0.0011	-0.0045*
		[0.0029]	[0.0024]	[0.0023]	[0.0024]	[0.0025]
Routine Task Intensity			0.0084	0.0053	0.0072	0.0074
			[0.0055]	[0.0057]	[0.0049]	[0.0052]
Service Task Intensity			-0.0154*	-0.0143*	-0.0163**	-0.0262***
			[0.0079]	[0.0082]	[0.0066]	[0.0080]
Sex-Education-Industry Fixed Effects	X	X	X	X	X	X
Controls for Other O*NET Task Measures			X	X	X	X
Exclude Mgmt, Healthcare and Education						X
Observations	44,191	44,191	44,191	44,191	52,446	42,247
R-squared	0.483	0.483	0.503	0.568	0.504	0.473

Notes: Each column reports results from a regression of the natural log of real (indexed to 2019) median hourly wages in the indicated end year on log hourly wages in the indicated base year, the O*NET task measures and sex-education-industry fixed effects. The data come from the 1980-2000 U.S. Censuses and the 2005-2019 American Community Surveys and are collapsed to year-occupation-industry-sex-education cells, with each cell weighted by labor supply. The O*NET task measures are percentiles that range from 0 to 10. The additional O*NET task measures are the O*NET variables Number Facility, Inductive and Deductive Reasoning, and Analyzing and Using Information, Require Social Interaction, Coordinating the Work and Activities of Others, and Communicating with Supervisors, Peers, or Subordinates. See the text and Appendix for details on the construction of each O*NET task measure and for details on which occupations are classified as Managers, Health Care or Education (Column 7). Standard errors are in brackets and clustered at the occupation level. *** p<0.01, ** p<0.05, * p<0.10

Table VIII

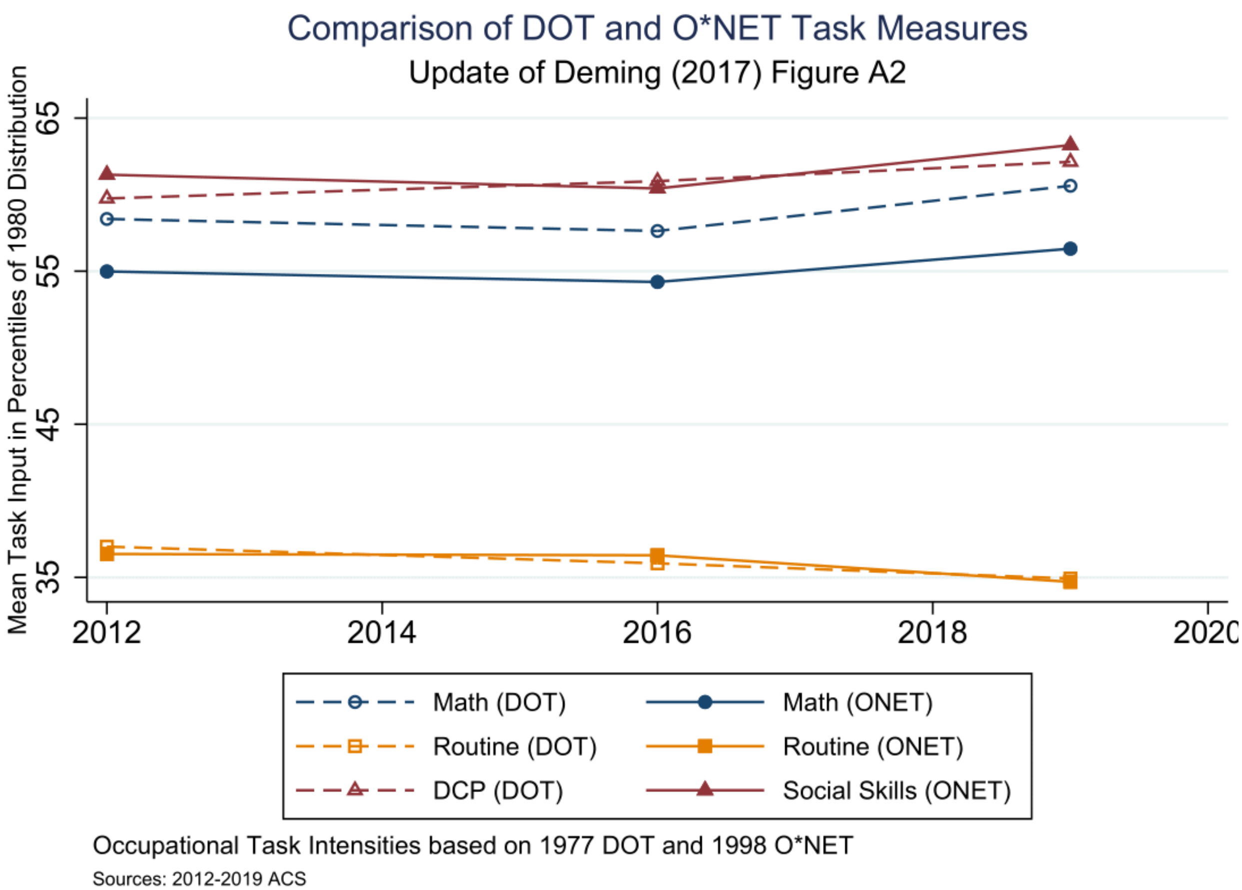
TABLE VIII

CHANGES IN EMPLOYMENT BY OCCUPATION TASK INTENSITY IN THE CENSUS/ACS

	1980-2019			1980-2012	2012-2019	
Outcome is Log Employment (LS Weighted)	(1)	(2)	(3)	(4)	(5)	(6)
Math Task Intensity	-0.027	-0.037	-0.076	-0.115	-0.018	-0.010
	[0.029]	[0.054]	[0.113]	[0.103]	[0.071]	[0.062]
Social Skill Task Intensity	0.042*	0.031	-0.075	-0.015	-0.100*	-0.049
	[0.021]	[0.045]	[0.078]	[0.073]	[0.054]	[0.046]
Math * Social		0.002	0.015	0.013	0.015*	0.003
		[0.010]	[0.011]	[0.011]	[0.009]	[0.007]
Routine Task Intensity			-0.075*	-0.040	-0.050**	-0.036**
			[0.045]	[0.042]	[0.020]	[0.016]
Service Task Intensity			0.089**	0.043	0.079***	0.059**
			[0.041]	[0.039]	[0.022]	[0.025]
Sex-Education-Industry Fixed Effects	X	X	X	X	X	X
Controls for Other O*NET Task Measures			X	X	X	X
Exclude Mgmt, Healthcare and Education						X
Observations	44,191	44,191	44,191	44,191	49,746	42,247
R-squared	0.508	0.508	0.519	0.570	0.669	0.656

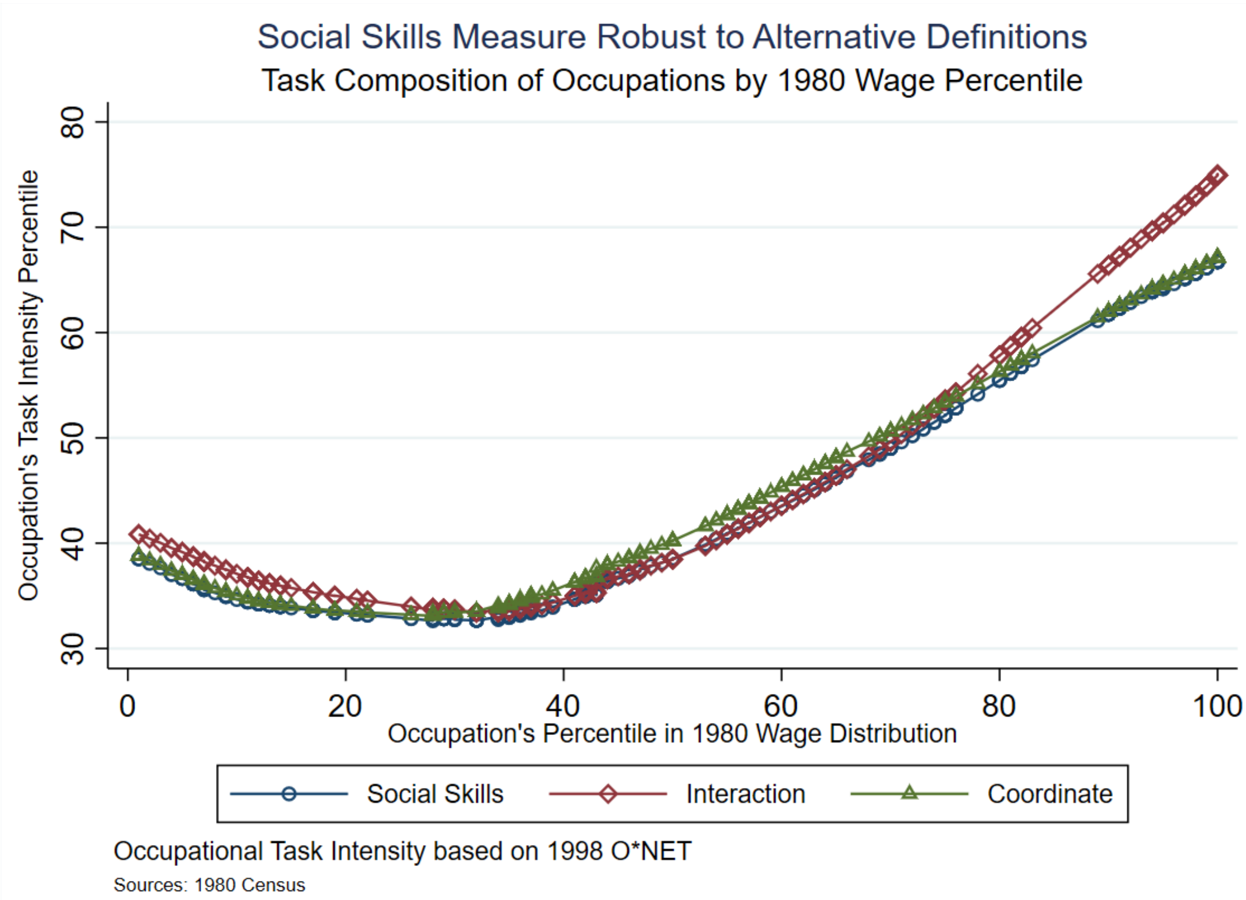
Notes: Each column reports results from a regression of the natural log of employment in the indicated end year on log employment in the indicated base year, the O*NET task measures and sex-education-industry fixed effects. The data come from the 1980-2000 U.S. Censuses and the 2005-2019 American Community Surveys and are collapsed to year-occupation-industry-sex-education cells, with each cell weighted by labor supply. The O*NET task measures are percentiles that range from 0 to 10. The additional O*NET task measures are the O*NET variables Number Facility, Inductive and Deductive Reasoning, and Analyzing and Using Information, Require Social Interaction, Coordinating the Work and Activities of Others, and Communicating with Supervisors, Peers, or Subordinates.. See the text and Appendix for details on the construction of each O*NET task measure and for details on which occupations are classified as Managers, Health Care or Education (Column 7). Standard errors are in brackets and clustered at the occupation level. *** p<0.01, ** p<0.05, * p<0.10

Data Appendix
Figure A.I



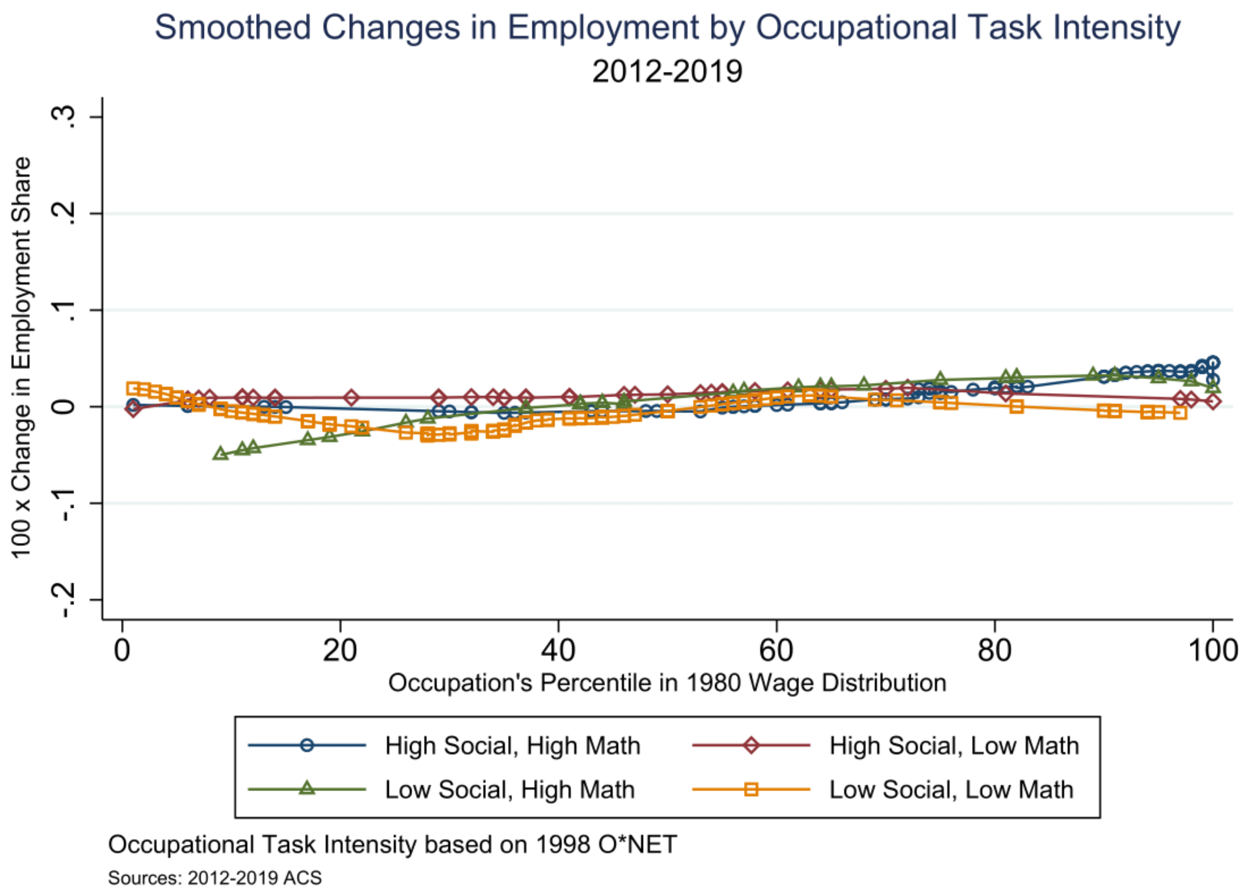
Notes: O*NET 1998 and DOT 1977 task measures by occupation are paired with data from the 2012-2019 American Community Survey samples. Consistent occupation codes for 2009-2017 are updated by me for this paper. Data are aggregated to industry-education-sex cells by year, and each cell is assigned a value corresponding to its rank in the 1980 distribution of task input. Plotted values depict the employment-weighted mean of each assigned percentile in the indicated year. See the text and Appendix for details on the construction of O*NET task measures.

Figure A.II



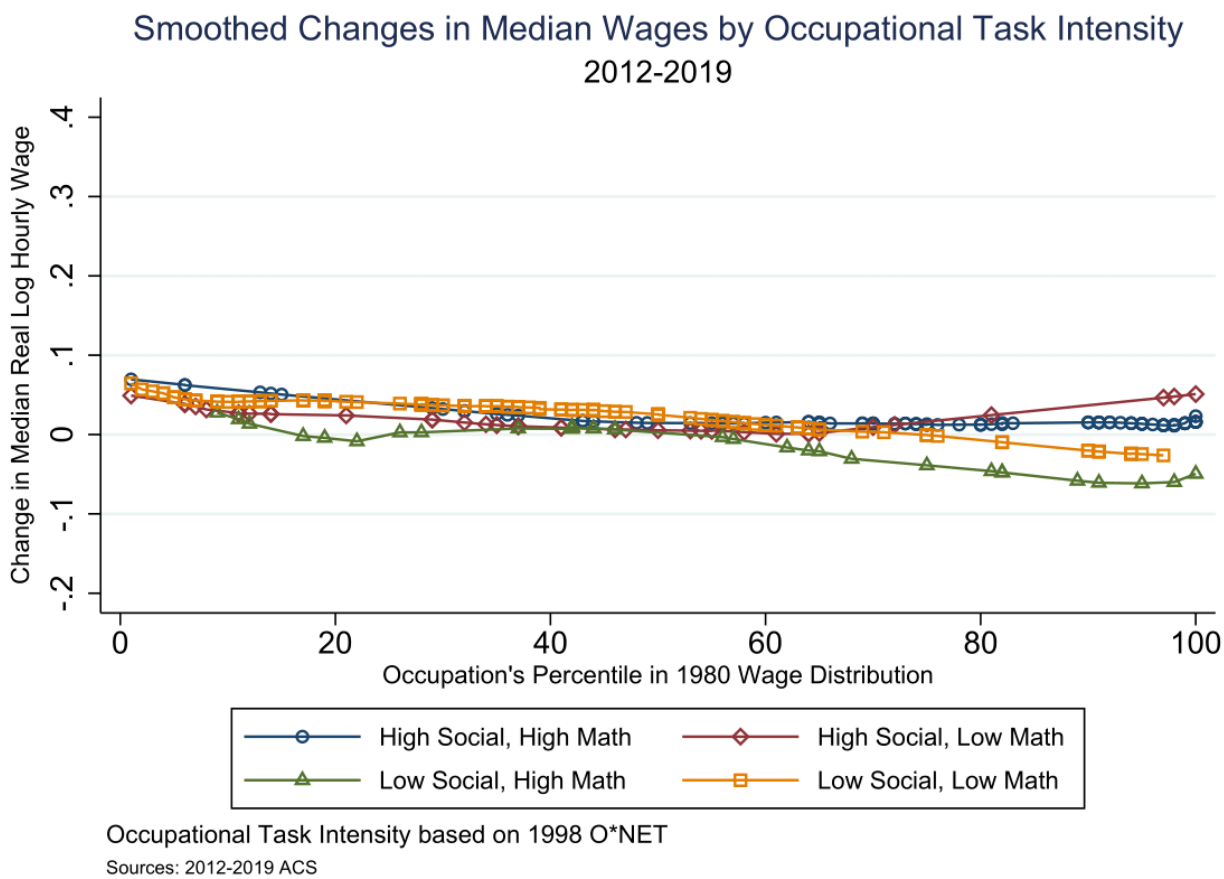
Notes: Each line plots the average task intensity of occupations by wage percentile, smoothed using a locally weighted regression with bandwidth 0.8. Task intensity is measured as an occupation's employment-weighted percentile rank in the Census IPUMS 1980 5 percent extract. All task intensities are taken from the 1998 O*NET. Mean log wages in each occupation are calculated using workers' hours of annual labor supply times the Census sampling weights. Consistent occupation codes for 2009-2017 are updated by me for this paper.

Figure A.III



Notes: Each line plots 100 times the change in employment share between 2012 and 2019 for occupations that are above and/or below the 50th percentile in nonroutine analytical and social skill task intensity as measured by the 1998 O*NET. Lines are smoothed using a locally weighted regression with bandwidth 1.0. Wage percentiles are measured as the employment-weighted percentile rank of an occupation's mean log wage in the Census IPUMS 1980 5 percent extract. Consistent occupation codes for 2009-2017 are updated by me for this paper.

Figure A.IV



Notes: Each line plots 100 times the change in median log hourly real wages between 2012 and 2019 for occupations that are above and/or below the 50th percentile in nonroutine analytical and social skill task intensity as measured by the 1998 O*NET. Lines are smoothed using a locally weighted regression with bandwidth 1.0. Wage percentiles on the horizontal axis are measured as the employment-weighted percentile rank of an occupation's mean log wage in the Census IPUMS 1980 5 percent extract. Consistent occupation codes for 2009-2017 are updated by me for this paper.

Changes to Deming's (2017) Parameters and Code

This section serves to detail the measures taken to update and alter various parameters and code bits of Deming's (2017) paper. I am breaking the Data Appendix up into two sections based on the data and methods used to analyze that data being altered for this paper: one, the ACS/Census Datasets and respective code; and two, the NLSY79 and NLSY97 datasets and respective code.

ACS/Census Changes

I changed the Census-ACS data to clean the data from 1980 through 2013 to 2013 through 2019. Imputed weeks worked for the 2014-2017 and 2018-2019 ACS datasets instead of the 2008-2010 and 2011-2013 ACS datasets. That said, I continued to impute using the 2006 Census dataset and kept the other code the same. Also continued to exclude workers with inapplicable code occupations or part of the military, but changed the occupation codes if necessary from the now-old codes. Furthermore, I inflated log hourly wages to 2019 dollars for the new data instead of using 2012 data.

One of the biggest changes to the project was changing the occupation crosswalk that was used by Autor-Dorn and Deming in his 2017 paper. This meant including new occupational codes for 2012-2018 and 2018-2019, but it also included updating occupational crosswalks for the 2000-2012 datasets because they had changed as well. Once this was done, then the occupation crosswalk was implemented for the 2014-2017 and 2018-2019 datasets. Furthermore, I dropped any datapoint that did not have any occupational data, which was something I had to add in order to get the new cleaning file to successfully complete what I needed to get done. I continued to use the AKK occupational crosswalk, but only for the new datasets and combined industries in order to make sure that each industry is represented throughout the new period in a consistent manner.

As for the analysis do file, I altered Figure 1 to look at the new data (2012-2019) as opposed to 2000-2012. I also altered some of the occupational code groupings to better represent the updated codes. The occupation share variable was also changed to look at the new data as opposed to the old dataset. In sum, I altered the following figures and tables in order to analyze the 2012-2019 dataset as opposed to Deming's (2017) analysis: Figure I, Figure II, Figure III, Figure IV, Figure VI, Figure VII, Table X, and Table XI.

NLSY79 and NLSY97

For every variable in the NLSY do files (employment, hourly wage, educational attainment, urbanicity and religion, age, etc.), I extended them to use the new dataset (2012-2019) and cleaned the data accordingly. I also made sure to use the occupational crosswalk necessary for each period and inflated wages to 2019 wages. Otherwise, there were no other changes to the analysis for tables or figures that resulted from running this code.

Deming's Paper as Addition to Appendix

I am including Deming's (2017) paper as an addition to the appendix that will follow the end of this page.

THE GROWING IMPORTANCE OF SOCIAL SKILLS IN THE LABOR MARKET*

DAVID J. DEMING

May 24, 2017

Abstract

The labor market increasingly rewards social skills. Between 1980 and 2012, jobs requiring high levels of social interaction grew by nearly 12 percentage points as a share of the U.S. labor force. Math-intensive but less social jobs - including many STEM occupations - shrank by 3.3 percentage points over the same period. Employment and wage growth was particularly strong for jobs requiring high levels of both math skill and social skill. To understand these patterns, I develop a model of team production where workers "trade tasks" to exploit their comparative advantage. In the model, social skills reduce coordination costs, allowing workers to specialize and work together more efficiently. The model generates predictions about sorting and the relative returns to skill across occupations, which I investigate using data from the NLSY79 and the NLSY97. Using a comparable set of skill measures and covariates across survey waves, I find that the labor market return to social skills was much greater in the 2000s than in the mid 1980s and 1990s. JEL Codes: I20, I24, J01, J23, J24, J31

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"We can never survey our own sentiments and motives, we can never form any judgment concerning them; unless we remove ourselves, as it were, from our own natural station, and endeavour to view them as at a certain distance from us. But we can do this in no other way than by endeavouring to view them with the eyes of other people, or as other people are likely to view them." - Adam Smith, *The Theory of Moral Sentiments* (1759)

I. Introduction

A vast literature in economics explains increasing returns to skill as a product of the complementarity between technology and high-skilled labor, or skill-biased technological change (SBTC) (e.g. Katz & Murphy 1992; Bound & Johnson 1992; Juhn *et al.* 1993; Acemoglu & Autor 2011). Beginning in the 1990s, the labor market "hollowed out" as computers substituted for labor in middle-skill routine tasks and complemented high-skilled labor, a phenomenon referred to as job polarization (Autor *et al.* 2003, 2006; Michaels *et al.* 2014; Goos *et al.* 2014).

However, while job polarization implies rising demand for skilled labor, there has been little or no employment growth in high-paying jobs since 2000, and this slow growth predates the Great Recession (Acemoglu & Autor 2011; Beaudry *et al.* 2014, 2016). Beaudry *et al.* (2016) show evidence of slow growth in cognitive skill-intensive occupations in the U.S. labor market during the 2000s, and Castex & Dechter (2014) find smaller returns to cognitive test scores in the 2000s compared to the 1980s. These findings are especially puzzling in light of the rising heterogeneity in worker-specific pay premiums found in studies that use matched employer-employee data (Card *et al.* 2013, 2016). If technological change is skill-biased, why have the returns to cognitive skill not increased over the last decade?

One possible explanation is that weak growth in high-skilled jobs is caused by a slowdown in technological progress. Beaudry *et al.* (2016) argue that the slowdown in demand for cognitive skill can be explained as a boom-and-bust cycle caused by the progress of information technology (IT) from adoption to maturation, and Gordon (2012) shows that innovation and U.S. productivity growth slowed down markedly in the early 2000s.

On the other hand, Brynjolfsson & McAfee (2014) discuss advances in computing power that are rapidly expanding the set of tasks that machines can perform. Many of the tasks that they and others highlight - from automated financial management and tax preparation to legal e-discovery to cancer diagnosis and treatment - are performed by highly skilled workers (Levy & Murnane 2012; Brynjolfsson & McAfee 2014; Remus & Levy 2015). Thus another possibility is that computer capital is substituting for labor higher up in the skill distribution, redefining what it means for work to be "routine" (Autor 2014; Lu 2015).

Figure 1 investigates this possibility by showing relative employment growth between 2000 and 2012 for the set of high-skilled, "cognitive" occupations that are the focus of Beaudry *et al.* (2016).[1] The upper panel of Figure 1 focuses on science, technology, engineering and mathematics (STEM) jobs, while the lower panel shows all other cognitive occupations.

Figure 1 shows clearly that the relative decline in high-skilled employment over the last decade is driven by STEM jobs. STEM jobs shrank by a total of 0.12 percentage points as a share of the U.S. labor force between 2000 and 2012, after growing by 1.33 percentage points over the previous two decades. By comparison, all other cognitive occupations grew by 2.87 percentage points between 2000 and 2012, which surpasses the growth rate of 1.99 percentage points in the previous decade. Most importantly, the fastest growing cognitive occupations - managers, teachers, nurses and therapists, physicians, lawyers, even economists - all require significant interpersonal interaction.

In this paper, I show that high-paying jobs increasingly require social skills. Technological change provides one possible explanation. The skills and tasks that cannot be substituted away by automation are generally complemented by it, and social interaction has - at least so far - proven difficult to automate (Autor 2015). Our ability to read and react to others is based on tacit knowledge, and computers are still very poor substitutes for tasks where programmers don't know "the rules" (Autor 2015). Human interaction requires a capacity that psychologists call theory of mind - the ability to attribute mental states to others based on their behavior, or more colloquially to "put oneself into another's shoes" (Premack & Woodruff 1978; Baron-Cohen 2000; Camerer *et al.* 2005).

I begin by presenting a simple model of team production between workers. Workers perform a variety of tasks on the job, and variation in productivity generates comparative advantage that can be exploited through specialization and "task trade". I model cognitive skills as the mean of a worker's productivity distribution and social skills as a reduction in trading costs. Workers with higher social skills can specialize and "trade tasks" with other workers more efficiently. This takes on the structure of a Ricardian trade model, with workers as countries and social skills as inverse "iceberg" trade costs as in Dornbusch *et al.* (1977) and Eaton & Kortum (2002).[2]

[1]Following Beaudry *et al.* (2016), Figure 1 displays employment growth for what the U.S. Census refers to as managerial, professional and technical occupation categories. Autor & Dorn (2013) create a consistent set of occupation codes for the 1980-2000 Censuses and the 2005-2008 ACS - I follow their scheme and update it through the 2010 Census and the 2011-2013 ACS - see the Data Appendix for details. Following Beaudry *et al.* (2016), "cognitive" occupations include all occupation codes in the Data Appendix between 1 and 235. I group occupation codes into larger categories in some cases for ease of presentation (e.g. engineers, managers).

[2]Acemoglu & Autor (2011) develop a Ricardian model of the labor market with three skill groups, a single skill index, and comparative advantage for higher-skilled workers in relatively more complex tasks. I follow

The model generates several predictions, which I investigate using data from the National Longitudinal Survey of Youth 1979 (NLSY79). I first demonstrate that there is a positive return to social skills in the labor market and that cognitive skill and social skill are complements in a Mincerian wage equation. This follows recent evidence from Weinberger (2014), who finds growing complementarity over time between cognitive skills and social skills using different data sources. Complementarity emerges naturally in the model, because the value of lower trade costs increases in aworker's average productivity (i.e. cognitive skill).[3] Importantly, I do not find complementarity between cognitive skill and widely-used measures of "non-cognitive" skills (e.g. Heckman *et al.* 2006).

The model provides a key link between social skills and *routineness* through the variance of productivity over workplace tasks. Some high-skilled occupations (such as a computer programmer, or engineer) require the repeated execution of explicit rules, while others are less structured and require a diverse range of tasks (such as manager, or consultant). I model this as an increase in the variance of productivity over the tasks that workers perform on the job. Higher variance in productivity broadens the scope for gains from "task trade" and thus increases the return to social skills.

While I cannot directly measure the variance of workplace tasks, I use two empirical analogs. First, I compare the returns to social skills across occupations that vary in their routineness, as measured by data from the Occupational Information Network (O*NET). I find that workers with higher social skills self-select into nonroutine occupations, and that this sorting leads to within-worker wage gains that are increasing in social skills.[4] These empirical patterns are consistent with the predictions of the model. Notably, I find no evidence of greater returns to social skills in math-intensive occupations.

Next, I draw on a large literature in organizational economics which shows that all occupations are becoming less routine over time. Information and communication technology (ICT) has shifted job design away from rigid categorization and toward increased job rotation and worker "multi-tasking" (Bresnahan 1999; Lindbeck & Snower 2000; Caroli & Van Reenen 2001; Bloom & Van Reenen 2011). Case studies of ICT implementation show

a long literature that treats teamwork as a tradeoff between the benefits of increased productivity through specialization and the costs of coordination (Becker & Murphy 1992; Bolton & Dewatripont 1994; Lazear 1999; Garicano 2000; Garicano & Rossi-Hansberg 2006)

[3]A related literature studies job assignment when workers have multiple skills (Heckman & Scheinkman 1987; Yamaguchi 2012; Lindenlaub 2014; Lise & Postel-Vinay 2014). Models of this type would treat social skill as another addition to the skill vector, with Roy-type selection and linear (or log-linear) wage returns rather than the specific pattern of complementarity between cognitive skill and social skill.

[4]Krueger & Schkade (2008) show that gregarious workers sort into jobs that involve more social interaction. They interpret this as a compensating differential, suggesting that workers have preferences for interactive work. However, if skill in social interaction had no value in the labor market but interactive jobs were preferred by workers, compensating differentials imply that interactive jobs should pay *less* all else equal.

that computerization leads to the reallocation of skilled workers into flexible, team-based settings that facilitate adaptive responses and group problem-solving (e.g. Autor *et al.* 2002; Bresnahan *et al.* 2002; Bartel *et al.* 2007). This literature shows a clear link between the computerization of the labor market and the decline of routine work. Yet the link between the increased variability of workplace tasks, team production and social skills has not previously been explored.

I investigate the growing importance of social skills in two ways. First, I present evidence of increasing relative demand for social skills in the U.S. labor market. Between 1980 and 2012, social skill-intensive occupations grew by 11.8 percentage points as a share of all jobs in the U.S. economy. Wages also grew more rapidly for social skill-intensive occupations over this period. I find that employment and wage growth has been particularly strong in occupations with high math *and* social skill requirements. In contrast, employment has declined in occupations with high math but low social skill requirements, including many of the STEM jobs shown in Figure 1. Contemporaneous trends in the labor market over this period such as offshoring, trade and shifts toward the service sector can partially - but not completely - explain these patterns.[5]

Second, I test directly for the growing importance of social skills by comparing the returns to skills in the NLSY79 and the National Longitudinal Survey of Youth 1997 (NLSY97) surveys. Comparing cohorts between the ages of 25 and 33 who entered the labor market in the mid 1980s versus the mid 2000s, I find that social skills are a significantly more important predictor of full-time employment and wages in the NLSY97 cohort. Cognitive skills, social skills and other covariates are similarly defined across survey waves, and the results are robust to accounting for other contemporaneous trends such as increasing educational attainment and female labor force participation. Finally, I show that the within-worker wage gain from sorting into a social skill-intensive occupation is much greater in the NLSY97 cohort.

I am aware of few other papers that study social skills. In Borghans *et al.* (2014), there are "people" jobs and "non-people" jobs and the same for skills, with workers sorting into jobs based on skills and relative wages. Kambourov *et al.* (2013) develop a model where high lev-

[5] Autor & Dorn (2013) explain the rise of low-wage service occupations as computers replacin routine production tasks rather than service tasks (which are more difficult to automate). However, this does not explain growth of social skill-intensive jobs at the top of the wage distribution. Autor *et al.* (2015) compare the impact of import competition from China to technological change and find that the impact of trade is concentrated in manufacturing and larger among less-skilled workers. Oldenski (2012) shows that production requiring complex within-firm communication is more likely to occur in a multinational's home country. Karabarbounis & Neiman (2014) show that the share of corporate value-added paid to labor has declined, even in labor-intensive countries such as China and India, suggesting that offshoring alone is unlikely to explain the decline of routine employment and the growth in social skill-intensive jobs.

els of “relationship skill” (as measured by a worker’s occupation) are associated with stable marriage and employment outcomes. McCann *et al.* (2014) develop a multi-sector matching model with teams of workers who specialize in production tasks and a manager who specializes completely in communication tasks. In contrast, there are no communication tasks in my model, nor are there formal teams.[6] This is consistent with case studies of modern teamwork, where workers are organized into temporary, fluid and self-managed groups to perform customized sets of tasks (e.g. Lindbeck & Snower 2000; Hackman 2002; Bartel *et al.* 2007; Edmondson 2012).

While the model considers teamwork in production, one can view many customer-oriented occupations - consulting, health care, teaching, legal services - as requiring joint production between worker and customer. Katz (2014) discusses growing demand for artisanal workers who can provide a creative, personal touch and customize production to the needs of clients. Social skills in production will be important for customer service occupations to the extent that the final product is uncertain and crafted specifically for the needs of the client.

Are social skills distinct from cognitive skills, or are they simply another measure of the same underlying ability? When surveyed, employers routinely list teamwork, collaboration and oral communication skills as among the most valuable yet hard-to-find qualities of workers (e.g. Casner-Lotto & Barrington 2006; Jerald 2009). In 2015, employers surveyed by the National Association of Colleges and Employers (NACE) listed “ability to work in a team” as the most desirable attribute of new college graduates, ahead of problem-solving and analytical/quantitative skills (NACE 2015). Tests of emotional and social intelligence have beendeveloped and validated by psychologists (Salovey & Mayer 1990; Mayer *et al.* 1999; Baron-Cohen *et al.* 2001; Goleman 2006). Woolley *et al.* (2010) show that a test designed to measure social intelligence predicts team productivity even after controlling for the average intelligence of team members.[7]

A growing body of work in economics documents the labor market return to “noncognitive” skills, including social skills and leadership skills (Kuhn & Weinberger 2005; Heckman *et al.* 2006; Lindqvist & Vestman 2011; Borghans *et al.* 2014). This paper builds on the seminal observation of Heckman (1995) that since measured cognitive ability (i.e. g) explains

[6] In McCann *et al.* (2014), workers who specialize in communication become managers of a team, and the communication skills of the other workers on the team are irrelevant. Models with communication or “people” tasks face the challenge of specifying exactly what is being produced. Are workers who spend an entire day in meetings communication task specialists? The model here treats communication as a friction. Workers who spend more time in meetings - conditional on total output - have lower social skill.

[7] Woolley *et al.* (2010) randomly assign individuals to groups and then ask the groups to perform a variety of tasks. Group performance is positively correlated with the “average social sensitivity” of group members as measured by a test called “Reading the Mind in the Eyes”. This test was originally developed to assist in the diagnosis of Autism and Asperger Syndrome, but has since been demonstrated as psychometrically valid and able to detect subtle differences in individual social sensitivity (e.g. Baron-Cohen *et al.* 2001).

only a small fraction of the variation in earnings, productivity is likely influenced by multiple dimensions of skill. Subsequent work, summarized in Heckman & Kautz (2012), finds that "noncognitive" or "soft" skills explain important variation in adult outcomes. This paper should be viewed as an attempt to extend and formalize the definition of one particular dimension of "soft" skills - the ability to work with others.

The remainder of the paper proceeds as follows. Section 2 presents the model and develops specific empirical predictions. Section 3 describes the data. Section 4 explores the predictions concerning the returns to social skill across occupations using the NLSY79. Section 5 studies the growing importance of social skills over time, using both Census/ACS data and a comparison of the returns to skills in the NLSY79 and NLSY97. Section 6 concludes. All appendix material - including supplementary tables and figures, a more detailed data description, and proofs for the model - can be found in the online appendix to the paper.

II. Model

In a standard human capital model, worker skill takes a simple factor-augmenting form, where the output of worker j is increasing in some measure of skill (such as cognitive ability or education) A_j times L_j, the quantity of labor supplied:

$$y_j = A_j L_j \tag{1}$$

Recent work has enriched the standard model by drawing a distinction between skills and job tasks (e.g. Autor *et al.* 2003; Acemoglu & Autor 2011; Autor & Handel 2013). In the spirit of this "task framework", consider the following modification of the human capital model:

$$y_j(i) = A_j \alpha_j(i) l_j(i) \tag{2}$$

where $y_j(i)$ specifies the production function for task i as worker j's cognitive skill A_j (still taking the factor-augmenting form) times a task-specific productivity parameter $\alpha_j(i)$ times labor supplied to task i.

Any job can be separated into an infinite number of discrete tasks that must be performed jointly to produce some final good Y. Following Acemoglu & Autor (2011), I assume that workers perform a continuum of tasks indexed over the unit interval according to a Cobb-Douglas technology:

$$Y_j = \exp[\int_0^1 \ln y_j(i) di]. \tag{3}$$

For simplicity, I assume that each worker supplies one unit of labor inelastically:

$$\int_0^1 l_j(i)di = L_j = 1. \tag{4}$$

Equation (2) allows two workers with the same cognitive skill level A_j to vary in their productivity over individual tasks. This suggests that workers can specialize in the production of tasks in which they have a comparative advantage.

To think about how the productivity gains from specialization can be realized, I develop a model in the spirit of Ricardo (1891). In Ricardo (1891), countries specialize in the production of goods and trade with each other for mutual benefit. In this model, workers can increase their total output Y_j by producing tasks in which they have comparative advantage and then trading for mutual benefit, just as countries trade goods in Ricardo's classic formulation. Thus I conceive of teamwork as "trading tasks".

Applying the Ricardian framework to task trade between workers yields two important benefits. First, it provides an explanation for *why* social skills matter that is grounded in economic theory. I argue that social skills are valuable because they reduce the cost of "trading tasks" with other workers.

Specifically, let $S_{i,n} \in (0,1)$ be a depreciation factor that is applied proportionately to any trade in tasks between workers - $S_{i,n} = S_i * S_n$ for $i \neq n$. Moreover let $S_{i,i} = 1$, $\forall i$ so workers can trade costlessly with themselves. Workers with higher social skill pay a lower coordination cost to trade with other workers. This allows them to earn higher wages by specializing in their most productive tasks and trading their output with others.[8] Workers with high cognitive skill A_j but low social skill S_j have high average productivity, but will perform "too many" tasks themselves rather than working in a team.

The second important feature of the model is that it generates intuitive predictions about when social skills will matter. The return to social skills and the benefits of task trade will be increasing in the variance of productivity over tasks (the α_j's), because higher productivity dispersion increases the scope for gains from trade. To see this, consider the limiting case where $\alpha_j(i)$ takes the same value for all tasks i. In this case, equation (2) collapses to (1)

[8]In Becker & Murphy (1992), the benefits of specialization are balanced against the costs of coordinating increasingly specialized workers. In their analysis, coordination costs are features of the economy or of particular sectors. Here I treat coordination costs as attributes of individual workers. The definition of social skills in this paper is closely related to the formulation of "iceberg" trade costs between countries as in Dornbusch *et al.* (1977) and Eaton & Kortum (2002). The main difference is that iceberg trade costs are defined at the country-pair level (i.e. S_{ni}) and do not necessarily have a common worker (country) component. This is a particular definition of social skill, and it does not rule out other ways that sociability might affect productivity and wages (i.e. taste discrimination by firms, differential rates of on-the-job learning or information acquisition). One convenient interpretation of S is that it represents the probability that a worker will correctly communicate her productivity schedule to another worker.

and becomes the standard human capital model. With zero variance in productivity over tasks, cognitive skill A_j is the sole determinant of relative productivity and there are no gains from trade.

If a worker has very low social skills, she will produce the same combination of tasks regardless of her comparative advantage relative to others. On the other hand, the task mix of a worker with high social skills will be quite sensitive to changes in the relative productivities of her co-workers. Thus another sensible interpretation of S_j is that it represents flexibility.

Here I develop the case with bilateral task trade between two workers. This two-worker model is isomorphic to the two-country Ricardian trade model of Dornbusch *et al.* (1977). Thus I keep the presentation brief and refer the reader to the Appendix for proofs and more detailed exposition.[9] With only two workers, two dimensions of skill and one final good, the model developed below is highly stylized. However, it yields a set of intuitive predictions that help guide the empirical work below.

II..A Setup

Consider a competitive market where Y is the unique final good - produced according to (3) - and labor is the only factor of production. Identical firms hire pairs of workers and pay market wages that are equal to output Y_j times an exogenous output price P^*. Thus workers maximize output Y_j, subject to the labor supply constraint in (4). Firms maximize profits, defined as total revenue $[P^*(Y_1+Y_2)]$ minus the wages paid to workers (w_1+w_2).

Since the order of tasks over the unit interval is arbitary, it is convenient to index tasks in order of decreasing comparative advantage for worker 1 (i.e. $\frac{\alpha_1(0)}{\alpha_2(0)} > \cdots > \frac{\alpha_1(i)}{\alpha_2(i)} > \cdots > \frac{\alpha_1(1)}{\alpha_2(1)}$). Define the comparative advantage schedule over tasks as:

$$\gamma(i) \equiv \frac{A_1\alpha_1(i)}{A_2\alpha_2(i)}, \tag{5}$$

with $\gamma'(i) < 0$ by assumption.

For concreteness, I assume that the comparative advantage schedule takes the form:

$$\gamma(i) = \bar{A}\exp(\theta(1-2i)), \tag{6}$$

with $\bar{A} = A_1/A_2$. This functional form for $\gamma(i)$ can be derived from an underlying process where worker productivity in task i is drawn from a log-normal distribution with a mean

[9] An earlier draft of this paper developed a Ricardian model with multiple workers which closely followed Eaton & Kortum (2002). Adding multiple workers yields identical predictions and has a very similar structure, but requires a strong distributional assumption and comes with much added complexity.

that is increasing in cognitive skill A_j, and a variance that is increasing in θ.[10]

A_j indexes worker j's mean productivity across tasks, while θ indexes the variance of task productivities and the steepness of the comparative advantage schedule. When $\theta = 0$, workers with higher cognitive skill are more productive in all tasks by the same ratio $\bar{A}$. In that case, there is no comparative advantage and thus no possibility for gains from trade. Thus this model nests the standard human capital model as a special case when $\theta = 0$. As θ increases, productivity over individual tasks is more dispersed.

II..B Equilibrium with Costless Trade

Each worker maximizes output by obtaining tasks from the lowest-cost producer, including herself. Workers trade tasks with each other at "prices" defined by efficiency units of labor, with a budget equal to each worker's labor supply constraint in (4). The worker-specific price of task i as:

$$p_j(i) = \frac{w_j}{A_j \alpha_j(i)}, \tag{7}$$

where w_j is the endogenously determined wage paid to worker j for a unit of labor. The equilibrium price for each task is the lower of the two offered prices: $p(i^*) = \min\{[p_1(i), p_2(i)]\}$. Since $\gamma'(i) < 0$ and there is a continuum of tasks, it is clear that in equilibrium there will be a marginal task i^* such that

$$\omega = \gamma(i^*) \tag{8}$$

where $\omega = w_1/w_2$. Worker 1 will perform all tasks in the interval $[0, i^*]$ and worker 2 will perform all tasks in the interval $[i^*, 1]$.

The equilibrium wage w_j is also determined by the demand for tasks, which comes out of the production function for the final good Y in equation (3). In equilibrium, the price-adjusted quantity of output for the marginal task i^* must be the same for both workers. This, combined with the fact that the Cobb-Douglas production function implies that the same share of output is paid to each task, yields the following equilibrium condition for the demand for tasks:

$$\omega = \frac{i^*}{1 - i^*} \tag{9}$$

[10] Specifically, imagine that worker j's productivity is task t is a random variable with a log-normal distribution: $a_j(t) \sim \ln\mathcal{N}(\mu_j, \sigma^2)$. Then the ratio of worker 1 to worker 2's productivity in task t, $G(t) \equiv a_1(t)/a_2(t)$, also takes on a log-normal distribution: $G(t) \sim \ln\mathcal{N}(\mu_G, \sigma_G^2)$, with $\mu_G = \mu_1 - \mu_2$ and $\sigma_G^2 = 2\sigma^2$. It can be shown that the quantile function for $G(t)$ evaluated at $(1 - i)$ corresponds closely to the chosen functional form for $\gamma(i)$, with $\bar{A} \approx \exp(\mu_1 - \mu_2)$ and $\theta \approx 2\sigma$. See Section 1.3 of the Model Appendix for details.

Equilibrium is found by setting the downward-sloping comparative advantage condition in equation (8) equal to the upward-sloping labor demand condition in equation (9), which yields a unique marginal task as a function of worker skills and the variance of productivity θ.[11]

The relative wage ω is clearly increasing in the task threshold - for example, if $A_1 = A_2$, then $i^* = \frac{1}{2}$ and $\omega = 1$. Equilibrium wages for worker 1 are given by:

$$w_1 = P^* A_1^{i^*} (A_2\omega)^{1-i^*} \exp[\int_0^{i^*} \ln\alpha_1(i)di + \int_{i^*}^1 \ln\alpha_2(i)di] \tag{10}$$

The expression for worker 2 is very similar. Thus wages are increasing in a worker's own skill A_j as well as the skill of her co-worker. Moreover, the gains from trade are also priced into absolute wages and are increasing in θ.[12]

II..C Equilibrium with Social Skills

With only two workers, we can define $S^* = S_1 * S_2$ as the (symmetric) cost of trading tasks between the two workers, with self-trade normalized to one as above. Thus worker 1 will produce her own tasks rather than trading if:

$$\begin{aligned} p_1(i) &< p_2^S(i) \\ \frac{w_1}{A_1\alpha_1(i)} &< \frac{w_2}{S^* A_2 \alpha_2(i)} \\ \omega &< \frac{\gamma(i)}{S^*}. \end{aligned} \tag{11}$$

Likewise, worker 2 will produce her own tasks if $\omega > S^*\gamma(i)$. Thus in equilibrium there will be two task thresholds, defined by:

$$\gamma(i^H) = S^*\omega \tag{12}$$

$$\gamma(i^L) = \frac{\omega}{S^*}. \tag{13}$$

Since $\gamma'(i) < 0$, it is clear that $i^H > i^* > i^L$ when $S^* < 1$.

Tasks in the interval $[0, i^L]$ will be produced exclusively by worker 1, tasks in the interval

[11]The marginal task is equal to $i^* = \frac{A_1}{A_1 + A_2 \exp(\theta(2i^*-1))}$

[12]The gains from trade can be expressed as $\Delta Y = \frac{Y^T}{Y^A}$, the ratio of worker output under trade to worker output under autarky. This is equal to $\exp\left(\int_{i^*}^1 \ln\left[\frac{\gamma(i^*)}{\gamma(i)}\right]di\right) = \exp(\theta[i^* - 1]^2)$ for worker 1 and $\exp\left(\int_0^{i^*} \ln\left[\frac{\gamma(i)}{\gamma(i^*)}\right]di\right) = \exp(\theta i^{*2})$ for worker 2.

$[i^H, 1]$ will be produced exclusively by worker 2, and tasks in the interval $[i^L, i^H]$ will be non-traded (produced by both workers for their own use).

As $S^* \to 1$, i^L and i^H converge to a single value i^*. For any values $i^L \leq 0$ and $i^H \geq 1$, workers will maximize output by producing all tasks themselves (i.e. autarky).

Figures 2A and 2B provides a visual illustration of the equilibrium task thresholds under two different values of θ. Figure 2A shows the case where θ is lower and the comparative advantage schedule is flatter, while Figure 2B shows the impact of increasing θ and making the comparative advantage schedule steeper.

Figures 2A and 2B show that - all else equal - the size of the nontraded zone $[i^L, i^H]$ is decreasing in θ. This can also be demonstrated by solving equations (12) and (13) for ω, which yields:

$$i^H - i^L = -\frac{\ln S^*}{\theta} \tag{14}$$

Equation (14) shows that the size of the range of nontraded tasks (inversely) scales the gains from trade. When trade is costless (i.e. $S^* = 1$), $i^L = i^H$. On the other hand, equation (14) also shows that there are many values of S^* and θ for which autarky is preferable (i.e. whenever $i^H - i^L > 1$).

As in the case of costless trade, equilibrium can be obtained by solving for the intersection between the two comparative advantage schedules in (12) and (13) and the demand for tasks, which is given simply by:

$$\omega = \frac{i^L}{1 - i^H}. \tag{15}$$

Combining (12), (13) and (15) gives two functions with two unknowns (i^H and i^L) and three parameters ($\bar{A}$, S^* and θ). Plotting these two implicit functions in the (i^L, i^H) space shows that their intersection defines the unique equilibrium values of i^H and i^L.

Finally, equilibrium wages for workers 1 and 2 are given by:

$$w_1 = P^* A_1^{i^H} (S^* A_2 \omega)^{1-i^H} \exp[\int_0^{i^H} \ln \alpha_1(i) di + \int_{i^H}^1 \ln \alpha_2(i) di] \tag{16}$$

$$w_2 = P^* A_2^{1-i^L} (S^* A_1 \omega^{-1})^{i^L} \exp[\int_0^{i^L} \ln \alpha_1(i) di + \int_{i^L}^1 \ln \alpha_2(i) di] \tag{17}$$

II..D Interpreting θ

The variance parameter θ admits at least two interpretations. The first concerns the task content of occupations. What kinds of jobs are characterized by greater productivity dispersion over tasks? One can interpret θ as a measure of predictability. Some jobs require workers to perform the same set of tasks repeatedly, while others are unpredictable or require a wide range of tasks depending on the situation.

While existing data do not allow me to directly measure the variance of tasks for a particular occupation, the closest analog is routineness. Autor *et al.* (2003) define a task as "routine" if it can be accomplished by following explicit programmed rules. Relatedly, Bresnahan (1999) argues that computers change the workplace by "organizing, routinizing and regularizing tasks that people- and paper-based systems did more intuitively but more haphazardly". The idea behind both of these statements is that there is a well-established, correct way to perform some tasks. For example, tasks such as complex mathematical calculations require high levels of cognitive skill but are also routine according to this definition.

Thus one interpretation of θ is that it indexes the share of tasks for which there is no single best approach. As θ increases, a lower share of tasks are routine. Thus the return to social skills should be decreasing in the routineness of an occupation. I examine this prediction in Section 4 by estimating variation in the returns to social skill across occupations at a particular point in time.

A second interpretation is that θ is a general production technology parameter that applies to all occupations, but is changing over time. Autor *et al.* (2003) show that the U.S. has experienced relative employment declines in routine-intensive occupations since the 1970s, and Goos *et al.* (2014) document this same pattern over a number of Western European countries.

One empirical limitation of this line of work is that it only measures shifts in the distribution of employment across occupations, not within them. Yet it is likely that all occupations are becoming less routine. Indeed the driving causal force in Autor *et al.* (2003) is an exogenous decline in the price of computer capital, a phenomenon that presumably affects all occupations to some degree. Case studies that accompany quantitative work on SBTC focus on how occupations such as bank tellers and machinists have changed in response to computerization (Autor *et al.* 2002; Bresnahan *et al.* 2002; Bartel *et al.* 2007).

In the model, any general increase in the variance of job tasks θ will lead to an increase in the return to social skills. Thus increases in the variability of workplace tasks should accompany increases in team production. The organizational economics literature strongly supports this conclusion. Studies of the impact of information and communication technology (ICT) suggest that job design has shifted away from unbundling of discrete tasks and toward increased job rotation and worker "multi-tasking" (e.g. Bresnahan 1999; Lindbeck & Snower 2000; Bloom & Van Reenen 2011).

A key theme in studies of ICT and organizational change is the reallocation of skilled workers into flexible, team-based settings that facilitate group problem-solving (e.g. Caroli & Van Reenen 2001; Autor *et al.* 2002; Bresnahan *et al.* 2002; Bartel *et al.* 2007). Dessein & Santos (2006) develop a model where organizations optimally choose the extent to which employees are allowed to use discretion in response to local information - whether to follow a rigid script or to be "adaptive". They show that when the business environment is more uncertain - which could be interpreted as a measure of θ - organizations endogenously allow for more ex post coordination among employees.

This literature suggests that the variance of job tasks has increased greatly over time, even within occupations. Thus if we interpret θ as a measure of nonroutineness, the return to social skills should have grown over time for workers in all occupations. Additionally, we should be able to observe increases over time in the importance of jobs that require social interaction.

II..E Empirical Predictions

The model generates severable predictions, which I summarize here. The first four predictions concern variation in the returns to social skill across workers and occupations at a particular point in time:

1. *There is a positive labor market return to both cognitive skill and social skill.* This is evident from the expressions for equilibrium wages in (16) and (17). I examine this prediction using data from the National Longitudinal Survey of Youth 1979 (NLSY79), which contains direct measures of worker skills.

2. *Cognitive skill and social skill are complements.* This is true because the second derivatives of w_1 and w_2 with respect to A and S^* are positive.[13] Intuitively, social skills are relatively more valuable when a worker is more productive overall, because she has more of value to "trade" with her fellow worker. I examine this prediction by interacting measures of cognitive skill and social skill from the NLSY79 in a

[13] For simplicity, assume workers have equal cognitive skill, i.e. $A_1 = A_2 = A$ and thus $\bar{A} = \omega = 1$. Then worker 1's production is $Y_1^S = A(S^*)^{1-i^H}\exp(\int_0^{i^H}\ln[\alpha_1(i)]di + \int_{i^H}^1 \ln[\alpha_2(i)]di)$. The second derivative with respect to A and S^* is $\frac{d^2Y_1^S}{dAdS^*} = (1-i^H)(S^*)^{-i^H}\exp(\int_0^{i^H}\ln[\alpha_1(i)]di + \int_{i^H}^1 \ln[\alpha_2(i)]di)$, which is always positive. Note that the special case of equal ability matches the empirical work in section 4, which explicitly conditions on cognitive skill. See Section 3.5 of the Model Appendix for a proof.

Mincerian earnings regression, with a positive interaction indicating complementarity. Weinberger (2014) finds evidence for growing complementarity between cognitive skills and social skills across two cohorts of young men. The model provides a theoretical foundation for those results. This prediction contrasts with existing models of job assignment where workers have multiple skills. Such models typically feature matching of workers to firms according to Roy-type selection, and skills are assumed to be additively separable for tractability (e.g. Heckman & Scheinkman 1987; Lindenlaub 2014; Lise & Postel-Vinay 2014). While one could certainly write down a model which simply asserts that cognitive skill and social skill are complements, the model above develops complementarity from first principles.

3. *Workers with higher social skill sort into non-routine occupations.* This follows because S^* and θ are complements - i.e. the second derivative of wages with respect to S^* and θ is positive.[14] Thus an increase in θ will yield a *relatively* greater gain for workers with higher social skills, leading to a greater incentive (among both workers and firms) for high S workers to sort into non-routine occupations. To see this, consider a simple extension of the model where there are two occupations (1 and 2) that differ in the variance of productivity, $\theta_1 > \theta_2$. All workers earn higher wages in higher θ occupations, and thus in the absence of labor market frictions all workers will sort into occupation 1.[15] However, if jobs in 1 are limited, workers with higher social skills will obtain them first because they earn *relatively* higher wages in occupation 1 due to complementarity between S^* and θ.[16] The NLSY79 includes multiple observations of the same worker, which allows me to estimate changes in the returns to skill when workers switch occupations. I estimate models with worker fixed effects and interactions between skills and the task content of occupations.

4. *Workers earn more when they switch into non-routine occupations, and their relative wage gain is increasing in social skill.* This follows from the logic of prediction 3

[14]The second derivative of wages with respect to θ and S^* is positive because S^* and θ are complements in the gains from trade. See Section 3.6 of the Model Appendix for a formal proof of this proposition. Since production under task trade is equal to production under autarky times the gains from trade, and since wages are equal to output times the exogenous output price P^*, S^* and θ are complements in output (and thus in wages) when S^* and θ are complements in the gains from trade.

[15]Section 3.7 of the Model Appendix (equations (78) and (84)) shows that $\frac{dY}{d\theta} > 0$ for all workers when $\bar{A} = 1$.

[16]Section 3.7 of the Model Appendix provides a formal proof of this proposition by assuming that there are two occupations characterized by different values of θ ($\theta_1 > \theta_2$). The setup of the model is the same as above, except that each firm hires two workers into a single occupation - i.e. firms are either type 1 or type 2. Workers maximize wages and can switch occupations. I show that in the simplified case where all workers have equal cognitive ability, the set of two workers with the highest combined S^* will always sort into θ_1. Since wages are increasing in S^* and increasing in θ, and since S^* and θ are complements, workers with higher social skills will earn relatively higher wages in high θ occupations.

above. While the prediction for occupational sorting on social skills is clear, the impact of sorting on wages is less clear, for two reasons. First, in the absence of frictions, occupational sorting implies that wages will adjust until the marginal worker is indifferent between occupations. Second, the wage equations in (16) and (17) show a clear spillover of one worker's skill to the other worker's wages. Thus wage returns cannot be identified without information about labor market frictions and about the skills of the other workers. My solution is to study whether *within-worker* sorting into non-routine occupations increases wages. While the magnitude of the coefficient will not have an economic interpretation because of the issues raised above, a positive sign is consistent with the predictions of the model.[17] Moreover, because S and θ are complements, any wage gain from switching into a less routine occupation should be increasing in the worker's social skills.

In addition, the model yields two predictions about changes in the return to social skills over time:

1. *Growth in the relative importance of jobs requiring social skills.* The decline of routine employment is widely known (e.g. Autor *et al.* 2003). However, I show that jobs requiring social skills have also experienced relative employment and wage growth in the U.S. over the last several decades. Indeed, these are largely the same types of jobs. I show that there is a strong negative correlation between measures of an occupation's routineness and its social skill intensity. Thus the decline of routine employment can also be understood as growth in social-skill intensive employment. Importantly, this is not due to growth of higher-skill jobs more generally - in fact, employment and wage growth for high math, low social jobs (including many STEM ocucpations) has been relatively slow.

2. *Increasing returns to social skills over time.* I explore this prediction by comparing the returns to social skills across the 1979 and 1997 waves of the NLSY. This compares youth entering the labor market in the 1980s and early 1990s to their counterparts in the early 2000s. I construct comparable age cohorts and include an identical set of covariates, which allows me to estimate changes in the returns to skills over time holding other factors constant. I also study whether the wage returns from sorting into social skill-intensive occupations have increased with time.

[17] An alternative hypothesis - advanced by Krueger & Schkade (2008) - is that gregarious workers have a preference for social interaction, and thus will accept a *lower* wage to work in a non-routine occupation.

III. Data

*III..A O*NET and Census/ACS Data*

I study changes in the the task content of work using data from the Occupational Information Network (O*NET). O*NET is a survey administered by the U.S. Department of Labor to a random sample of U.S. workers in each occupation. The O*NET survey began in 1998 and is updated periodically. I use the 1998 O*NET to most accurately reflect the task content of occupations in earlier years, although results with later versions of O*NET are generally similar.

The O*NET survey asks many different questions about the abilities, skills, knowledge and work activities required in an occupation. The questions are rated on an ordinal scale, with specific examples that illustrate the value of each number to help workers answer the question accurately. Because the scale values have no natural cardinal meaning, I follow Autor *et al.* (2003) and convert average scores by occupation on O*NET questions to a 0-10 scale that reflects their weighted percentile rank in the 1980 distribution of task inputs.

Autor & Dorn (2013) create a balanced and consistent panel of occupation codes that cover the 1980-2000 Censuses and the 2005 American Community Survey (ACS). I extend their approach with the ACS data through 2012, updating the occupation crosswalk to reflect changes made in 2010 and making a few minor edits for consistency - see the Data Appendix for details.

I focus on changes in three key indicators of task content. First, I measure an occupation's routine task intensity as the average of the following two questions - 1) "how automated is the job?" and 2) "how important is repeating the same physical activities (e.g. key entry) or mental activities (e.g. checking entries in a ledger) over and over, without stopping, to performing this job?"[18] Second, I closely follow Autor *et al.* (2003) and define nonroutine analytical (math) task intensity as the average of three O*NET variables that capture an occupation's mathematical reasoning requirements.[19] Third, I define an occupation's social skill intensity as the average of the four items in the O*NET module on "social skills" - 1)

[18]This definition of routineness differs from the task measures used by Autor *et al.* (2003), who use the 1977 Dictionary of Occupational Titles (DOT) measures "set limits, tolerances or standards" (STS) and "finger dexterity" (FINGER). They call these task measures "routine cognitive" and "routine manual" respectively. Autor & Dorn (2013) and other subsequent work combine these two measures into an index of routine task intensity (RTI). Occupations that are at least 50 percentiles higher on the RTI measure compared to my O*NET-based measure include telecom and line installers, masons, tilers and carpet installers, pharmacists, and dental assistants. Occupations that rank as much more routine according to the O*NET measure include taxi drivers and chauffeurs, bus drivers, garbage collectors and computer scientists.

[19]The three O*NET variables are 1) the extent to which an occupation requires mathematical reasoning; 2) whether the occupation requires using mathematics to solve problems; and 3) whether the occupation requires knowledge of mathematics. See the Data Appendix for details.

coordination; 2) negotiation; 3) persuasion; and 4) social perceptiveness.[20]

The measures of routiness and social skill intensity are strongly negatively correlated. Appendix Table A1 shows that the occupation-level correlation between routine task intensity and social skill task intensity is -0.68. This strong negative correlation drops only slightly (-0.56) after adding controls for ten other widely used O*NET task measures. This suggests that a strong predictor of whether or not an occupation is routine is whether it requires social skills.

O*NET is the successor of the Dictionary of Occupational Titles (DOT), which was used by Autor *et al.* (2003) and many others to study the changing task content of work. Appendix Figure A2 shows that the two data sources yield similar results for analogous task measures. I use the O*NET in this paper because it is a more recent data source that is updated regularly, and because it contains many more measures of the task content of work than the DOT.

III..B NLSY79

My main data source for worker skills and wages is the 1979 National Longitudinal Survey of Youth (NLSY79). The NLSY79 is a nationally representative sample of youth ages 14 to 22 in 1979. The survey was conducted yearly from 1979 to 1993 and then biannually from 1994 through 2012, and includes detailed measures of pre-market skills, schooling experience, employment and wages. My main outcome is the real log hourly wage (indexed to 2013 dollars), excluding respondents under the age of 23 or who are enrolled in school. Following Altonji *et al.* (2012), I trim values of the real hourly wage that are below 3 and above 200. The results are robust to alternative outcomes and sample restrictions such as using log annual earnings or conditioning on 20 or more weeks of full-time work.

I use respondents' standardized scores on the Armed Forces Qualifying Test (AFQT) to proxy for cognitive skill, following many other studies (e.g. Neal & Johnson 1996; Altonji *et al.* 2012). Altonji *et al.* (2012) construct a mapping of the AFQT score across NLSY waves that is designed to account for differences in age-at-test, test format and other idiosyncracies. I take the raw scores from Altonji *et al.* (2012) and normalize them to have mean zero and standard deviation one.

Several psychometrically valid and field-tested measures of social skills exist, but none

[20]O*NET gives the following definitions for the four items designed to measure social skills: 1) Coordination - "adjusting actions in relation to others' actions"; 2) Negotiation - "bringing others together and trying to reconcile differences"; 3) Persuasion - "persuading others to change their minds or behavior"; 4) Social Perceptiveness - "being aware of others' reactions and understanding why they react as they do". Appendix Figure A1 demonstrates that my preferred measure of social skills is strongly correlated with other similar O*NET variables that capture coordination, interaction and team production. See the Data Appendix for details.

are used by the NLSY or other panel surveys of adult workers. As an alternative, I construct a pre-market measure of social skills using the following four variables:

1. Self-reported sociability in 1981 (extremely shy, somewhat shy, somewhat outgoing, extremely outgoing)
2. Self-reported sociability in 1981 at age 6 (retrospective)
3. The number of clubs in which the respondent participated in high school
4. Participation in high school sports (yes/no)

I normalize each variable to have a mean of zero and a standard deviation of one. I then take the average across all 4 variables and re-standardize so that cognitive skills and social skills have the same distribution. The results are not sensitive to other reasonable choices, such as dropping any one of the four measures or constructing a composite using principal component analysis.

The first three questions measure behavioral extraversion and prosocial orientation - both of which have been shown in meta-analyses to be positively correlated with measures of social and emotional intelligence (Lawrence *et al.* 2004; Declerck & Bogaert 2008; Mayer *et al.* 2008). Participation in team sports in high school has been associated with leadership, prosocial orientation and teamwork ability, and has been shown to positively predict labor market outcomes in adulthood (Barron *et al.* 2000; Kuhn & Weinberger 2005; Weinberger 2014). The measures of participation in sports and clubs used here are very similar to those used in Weinberger (2014).

A key concern is that this measure of social skills may simply be a proxy for unmeasured cognitive or "non-cognitive" skills. The correlation between AFQT and social skills is about 0.26 in the analysis sample, which is consistent with the modest positive correlations (between 0.25 and 0.35) found between IQ and social and emotional intelligence across a variety of meta-analyses and independent studies (Mayer *et al.* 2008; Baker *et al.* 2014).

To account for possible bias from unmeasured ability differences, I control for completed years of education in addition to AFQT in some specifications. I also construct a measure of "non-cognitive" skills using the normalized average of the Rotter Locus of Control and the Rosenberg Self-Esteem Scale - which are also used by Heckman *et al.* (2006). This "non-cognitive" skill measure is modestly positively correlated with both AFQT (0.30) and the social skills composite (0.20). To the extent that my measure of social skills is an imperfect or even poor proxy for the underlying construct, the results may understate its relative importance.

The NLSY79 includes information on each respondent's occupation, which I match to the O*NET and DOT codes using the Census occupation crosswalks developed by Autor & Dorn (2013). The NLSY also includes Census industry codes, and I control for industry fixed effects in some specifications.

Mean self-reported sociability is 2.32 at age 6 and 2.88 as an adult, so on average respondents viewed themselves as less sociable in childhood than as adults. About 39 percent of respondents participated in athletics in high school, and the mean number of clubs was just above 1. Kuhn & Weinberger (2005) and Weinberger (2014) study the returns to leadership skills among a sample of white males who begin as high school seniors, leading to college-going rates that are about three times higher than in the NLSY79. Compared to those samples, the NLSY79 respondents are more disadvantaged and more representative of the U.S. population.

III..C NLSY97

I investigate the growing importance of social skills by comparing the return to skills in the NLSY79 to the NLSY97. The NLSY97 is a nationally representative panel survey of youth age 12-16 in 1997 that follows a nearly identical structure to the NLSY79. My measure of social skills in the NLSY97 is two questions that capture the extraversion factor from the commonly-used Big 5 personality inventory (e.g. Goldberg 1993). Following the procedures above, I normalize these two questions, take the average and then re-normalize them. The NLSY97 does not ask questions about clubs or participation in high school sports. Like the NLSY79, the NLSY97 also includes information on non-cognitive skills (the Big 5 factor conscientiousness), as well as education, occupation and industry.

When estimating changes in the return to skills over time in Section 5.2, I modify the construction of the social skills measure from the NLSY79 so that it only uses the first two items on sociability. This maximizes the comparability of the two measures of social skills across NLSY waves. Finally, when comparing NLSY waves I restrict the sample to ages 25-33 to exploit the overlap in ages across surveys. This means I am comparing the returns to social skills for youth of similar ages during the late 1980s and early 1990s, compared to the more recent 2004-2012 period.

IV. NLSY79 Results

IV..A Labor Market Returns to Skills and Complementarity

The first two predictions of the model are that there will be a positive return to skills in the labor market, and that cognitive skill and social skill are complements. I regress log hourly wages on both measures of skill and their interaction, controlling for a variety of other covariates:[21]

$$\ln\left(wage_{ijt}\right) = \alpha + \beta_1 COG_i + \beta_2 SS_i + \beta_3 COG_i * SS_i + \gamma X_{ijt} + \delta_j + \zeta_t + \epsilon_{ijt} \tag{18}$$

The results are in Table 1. The baseline model includes controls for race-by-gender indicators, indicators for region and urbanicity, and age (indexed by j) and year (indexed by t) fixed effects. Each observation is a person-year, and I cluster standard errors at the individual level.

Column 1 shows that the return to social skills is positive and statistically significant. A one standard deviation increase in social skills increases real hourly wages by 10.7 percent. Column 2 adds the AFQT, my measure of cognitive skill. A one standard deviation increase in cognitive skill increase hourly wages by 20.6 percent. The addition of cognitive skill lowers the coefficient on social skills to 5.5 percent but it remains highly statistically significant.

Column 3 tests for complementarity by adding the interaction of cognitive skills and social skills, following the results in Weinberger (2014). The interaction is positive, large (0.019) and statistically significant at the less than one percent level. Column 4 adds controls for non-cognitive skills. Non-cognitive skills are highly predictive of wages (0.048, p<0.001), but their inclusion barely changes the coefficients on cognitive skill and social skill, suggesting that each measure contains independent information about productivity. Column 5 adds controls for years of completed education. Controlling for education reduces the coefficient on all the skill measures, yet they remain statistically significant predictors of wages.

One concern is that cognitive skill and social skill are noisy measures of the same underlying ability. In that case, the estimated complementarity between cognitive skills and social skills reflects measurement error. I test this in Column 6 by adding an interaction

[21]The formal model is written in levels. However, taking logs in equations (16) and (17) would lead to a regression with the natural log of wages as the outcome and additive separability of cognitive skills and social skills. This implies that cognitive skills and social skills are complements in levels, but not in logs. However, I present main results using log wages to follow standard practice in the literature. Table 1 shows results for log wages, while Appendix Table A2 presents analogous results with hourly wages in levels. I find complementarity in both specifications, although it is stronger in levels than in logs.

between cognitive skill and non-cognitive skill. If wages are determined by a single ability that is measured by all three skills with error, all of the interaction terms will be positive. Yet Column 6 shows that the interaction between cognitive skills and non-cognitive skills is not statistically significant. Moreover, it drops to zero after adding controls for education, even as the coefficient on the cognitive skill and social skill interaction remains statistically significant (Column 7). Complementarity holds only for cognitive skills and social skills.

Appendix Tables A3 and A4 show that the labor market return to social skills is positive and statistically significant for all race, gender and education subgroups, in both logs and levels respectively. I find some evidence of greater returns to skills and greater skill complementarity among respondents who have at least some college education, which is consistent again with Weinberger (2014).

IV..B Occupational Sorting on Skills

I next examine the third prediction of the model - workers with higher levels of social skill will sort into non-routine and social skill-intensive occupations. I estimate regressions like equation (18) above but with the task content of occupations (measured using O*NET) as the dependent variable. The baseline model is identical to equation (18), and I control for the covariates in Table 1 plus years of completed education and industry fixed effects.

The results are in Table 2. Column 1 shows that a one standard deviation increase in social skills decreases the routine task intensity of a worker's occupation by 1.88 percentiles, and the coefficient is highly statistically significant. I also find a negative coefficient on cognitive skills and the interaction between cognitive skills and social skills. Column 2 adds controls for math task intensity as well as three other related O*NET cognitive task measures. This causes the sign on cognitive skills to flip but has little impact on the other coefficients. Conditional on overall cognitive task intensity, workers in routine occupations have higher cognitive skills (0.161, $p<0.001$) and significantly lower social skills (-0.149, $p<0.001$). Combined with the negative coefficient on the interaction, these results imply that workers with high cognitive skills and low social skills sort into routine occupations.

Columns 3 and 4 estimate parallel specifications but with the social skill intensity of a worker's occupation as the outcome. The results are generally similar but opposite in sign. Overall, the results in Table 2 confirm the prediction that workers with higher social skills sort into non-routine and social skill-intensive occupations. This suggests that estimates of the return to skills within occupations should be interpreted with caution.

IV..C Returns to Skills by Occupation Task Intensity

Table 2 shows clearly that workers sort into occupations where their skills are more rewarded. This makes it difficult to estimate the returns to worker skills controlling for occupation. However, if we are willing to assume that labor market frictions prevent perfect sorting of workers to occupations, we can estimate how the return to skills changes when the same worker switches occupations. Labor market frictions may be particularly important early in one's career, when skills are imperfectly observed by employers (e.g. Altonji *et al.* 2001).

The model predicts that workers will earn more when they switch into non-routine and social skill-intensive occupations, and that the wage gain from switching will be increasing in social skill. I explore these predictions by estimating:

$$\begin{aligned} \ln\left(wage_{ijt}\right) &= \beta_1 COG_i * T_{ijt} + \beta_2 SS_i * T_{ijt} + \beta_3 COG_i * SS_i * T_{ijt} \\ &\quad + \gamma X_{ijt} + \eta_i + \delta_j + \zeta_t + \epsilon_{ijt} \end{aligned} \tag{19}$$

where T_{ijt} indexes the task content of a worker's occupation (with the main effect included in the X_{ijt} vector), η_i is a worker fixed effect and the rest of the terms are defined as above. Note that with worker fixed effects only the interactions between skills and T_{ijt} are identified, not the returns to skills themselves.

The results are in Table 3. The baseline specification in Column 1 shows that workers earn significantly *higher* wages when they sort into routine occupations. However I do find that the wage return from sorting into non-routine occupations is increasing in social skills, which is consistent with the predictions of the model. Column 2 replaces routine with social skill task intensity. Workers who switch into a job that is 10 percentiles higher in the O*NET measure of social skill intensity earn about 3.9 percent higher wages. Moreover, the worker's wage gain is significantly increasing her social skills. For example, the estimates imply a wage gain of 3.9 percent for a worker of average social skills but 8.9 percent when the worker has social skills that are one standard deviation above the mean.

Column 3 includes both the routine and social skill measures together. This causes the interactions between skills and routine task intensity to fade to near zero, while the coefficients on the social skill interactions remain statistically significant and even increase slightly. Thus the social skill O*NET task measure is a better predictor of the returns to social skills when both measures are included together. The results in Table 3 are robust to including industry fixed effects as well as other specific job attributes such as union status or whether a position involves supervising workers. Additionally, in results not reported I find that interactions between skills and math task intensity are not statistically significant. This shows that relatively higher returns to skill in social skill-intensive occupations are not simply a proxy for job complexity or overall skill requirements.

While Krueger & Schkade (2008) do not estimate within-worker wage changes, their compensating differentials explanation implies that workers are willing to accept a wage penalty for a job with more social interaction. However, the wage gains from switching into a social skill-intensive occupation show in Table 3 are not consistent with a compensating differentials story. Instead, the results support the predictions of the model, which suggest that higher social skills are more beneficial in occupations where there is more potential gain from "task trade".

V. The Growing Importance of Social Skills

V..A Employment and Wage Growth in Social Skill-Intensive Occupations

I begin by presenting trends in employment and wage growth in the U.S. between 1980 and 2012. Figure 3 replicates Figure I of Autor *et al.* (2003) for the 1980-2012 period using the three O*NET task measures described above. By construction, each task variable has a mean of 50 centiles in 1980. Thus subsequent movement should be interpreted as changes in the employment-weighted mean of each task relative to its importance in 1980. The data are aggregated to the industry-education-sex level, which implicitly controls for changes in task inputs that are due to changes in the industry and skill mix of the U.S. economy over time. There is no adding-up constraint for tasks in a given year, and so changes over time can also reflect changes in total labor supply.

Like Autor & Price (2013), I find that the labor input of routine tasks has continued to decline, and that nonroutine analytical (math) task inputs stopped growing and even declined modestly after 2000. However, social skill task inputs grew by 24 percent from 1980 to 2012, compared to only about 11 percent for nonroutine analytical tasks. Moreover, while nonroutine analytical task inputs have declined since 2000, social skills task inputs held steady (growing by about 2 percent) through the 2000s. Not surprisingly, the decline in routine tasks mirrors the growing importance of social skills between 1980 and 2012.

Since the math and social skill task measures are highly correlated, growth in the importance of social skills could simply reflect general skill upgrading. I address this by dividing occupations into four mutually exclusive categories based on whether they are above or below the median percentile in both math and social skill task intensity. I then compute the share of all labor supply-weighted employment in each category and year.

Figure 4 plots the growth of employment shares - relative to a 1980 baseline - in each category. Jobs with high math and high social skill intensity grew by about 7.2 percentage points as a share of the U.S. labor force between 1980 and 2012. Low math, high social skill jobs grew by about 4.6 percentage points, for a total increase of 11.8 percentage points in the employment share of social skill-intensive occupations since 1980. In contrast, the employment share of jobs with high math but low social skill intensity shrank by about 3.3 percentage points over the same period. This includes many of the STEM jobs shown in Figure 1. The basic pattern in Figure 4 is robust to choosing cutoffs other than the 50th percentile for each type of task.

One possible explanation for the slow growth of high math, low social skill jobs is that employers cannot find workers to fill technical and math-intensive positions. In that case, we would expect relatively greater wage growth for these occupations. Figure 5 plots the change since 1980 in real hourly wages for occupations in each of the four categories. I find that wages for high math, low social skill jobs grew by only about 5.9 percent between 1980 and 2012, compared to about 26 percent for high math, high social skill occupations.

Appendix Figures A3 and A4 show that employment and wage growth for social skill-intensive occupations has occurred throughout the skill distribution and is not concentrated in particularly low- or high-paying jobs.

Appendix Tables A5 and A6 estimate employment and wage growth for jobs requiring different bundles of tasks in a multivariate framework. The results generally support the growing importance of social skills after controlling for changes in sex, education and industry mix. I find particularly strong employment growth for jobs that are high in both math and social skills. This pattern has accelerated since 2000. Finally, I note that the strong growth of social skill-intensive jobs is robust to excluding all managerial, health care and education occupations from the sample, although these jobs are important drivers of the overall trend.

Overall, the evidence from aggregate labor market data suggests that jobs requiring social skills have experience strong relative employment and wage growth since 1980.

V..B Increasing Returns to Social Skill Across NLSY Waves

Here I present direct evidence on the growing importance of social skills by studying changes in the returns to skills across the 1979 and 1997 waves of the NLSY. The cognitive skill and social skill measures are designed to be closely comparable across waves. As a reminder, I restrict the age range to 25-33 and use an alternative definition of social skills for this analysis to maximize comparability across waves - see Section 3 for details. I estimate:

$$(20) \qquad y_{ijt} = \alpha + \sum_{s=1}^{S} \left[\beta_s SKILL_i + \gamma_s (SKILL_i * NLSY97_i) \right] + \zeta X_{ijt} + \delta_j + \zeta_t + \epsilon_{ijt}$$

The skill vector includes cognitive skills, social skills and their interaction, as well as non-cognitive skills in some specifications. The interaction between skills and an indicator for being in the NLSY97 sample allows me to directly test the hypothesis that the returns to skills have changed over time. The X_{ijt} vector includes a standard set of demographic controls, age and year fixed effects, and an indicator variable for whether the respondent is in the NLSY97 sample. In order to study changing selection into the labor force, I allow y_{ijt} to be either an indicator for full-time employment or the log real hourly wage (conditional on employment).

The results are in Table 4. Columns 1 through 3 show results for full-time employment. Column 1 shows that a one standard deviation increase in cognitive skills increases the probability of full-time employment by 6.8 percentage points, relative to a baseline mean of about 85 percent. However, the interaction with the NLSY97 sample indicator is not statistically significant, suggesting that the returns to cognitive skill in terms of full-time work have not changed very much across survey waves.

In contrast, the association between social skills and the probability of full-time work has increased more than fourfold. A one standard deviation increase in social skills is associated with an increase in the probability of full-time employment of only about 0.7 percentage points ($p=0.006$) in the NLSY79 sample, compared to 3.0 percentage points in the NLSY97 sample ($p<0.001$).

The NLSY97 sample was in the 25-33 age range between 2004 and 2012, which matches up closely to the labor market trends shown in Section 5.1. In results not shown, I find that the difference in returns to skills across NLSY waves is slightly larger for males, which suggests that differences in female labor force participation across the last few decades are not directly driving the results.

Column 2 adds controls for years of completed education, which reduces the impact of skills overall but has almost no impact on the change in returns to skills over time. Column 3 adds controls for non-cognitive skills. Interestingly, I find that the impact of a one standard deviation gain in non-cognitive skills on the probability of full-time work has increased from 0.8 to 2.1 percentage points. However, the coefficients on social skills are qualitatively unchanged.

Columns 4 through 6 study changes in the impact of skills on wages, among workers who are employed full-time. The large change in the impact of skills on full-time work in Columns 1 through 3 suggests that these results should be interpreted with caution, although under reasonable assumptions about labor market sorting they provide a lower bound estimate of the changing returrn to skills.

Interestingly, the wage return to cognitive skills appears to have declined modestly over time. The estimates in Column 4 imply that a one standard deviation increase in cognitive skills increased wages by 20.3 percent in the NLSY79 but only 15.1 percent in the NLSY97.[22] This is consistent with Castex & Dechter (2014), who also study the changing returns to cognitive skill using the NLSY79 and NLSY97.

In contrast, the returns to social skill among full-time workers have grown significantly across NLSY waves. The estimates in Column 4 imply that a one standard deviation increase in social skills yields a wage gain of 2.0 percent in the NLSY79, compared to 3.7 percent in the NLSY97. Adding controls for years of completed education and non-cognitive skills has little impact on the estimates. Overall, the results in Table 4 show that social skills are a significantly more important predictor of labor market success for youth in the 2004 to 2012 period, compared to the late 1980s and 1990s.

V..C Changes in the Relative Returns to Skill Across Occupations

Finally, I study 1) whether the wage gain from sorting into social skill-intensive occupations has changed across survey waves; and 2) whether this wage gain (if any) is increasing in a worker's social skills. I estimate:

$$\begin{aligned}\ln\left(wage_{ijt}\right) &= \sum_{s=1}^{S}\left[\beta_s\left(SKILL_i * T_{ijt}\right) + \vartheta_s\left(T_{ijt} * NLSY97_i\right) + \gamma_s\left(SKILL_i * T_{ijt} * NLSY97_i\right)\right] \\ &\quad + \zeta X_{ijt} + \eta_i + \delta_j + \phi_t + \epsilon_{ijt} \qquad (21)\end{aligned}$$

Equation (21) takes the same general form as equation (19), with worker fixed effects and interactions between skills and occupation task intensities from O*NET. The key difference is that I also include three-way interactions between skills, task measures and an indicator for being in the NLSY97 panel.

The results are in Table 5. Columns 1 and 2 include only the two-way interactions between the task measures T_{ijt} and the NLSY97 indicator. In Column 1, I find that the wage

[22]Unlike Table 1, the results in Columns 4 through 6 show little evidence of complementarity between cognitive skills and social skills. The results are different for two reasons. First, the sample in Table 4 is restricted to ages 25-33, whereas Table 1 estimates returns to skills for prime-age workers. Skill complementarity is about 30 percent smaller when I restrict to ages 25-33 in Table 1. Second, the definition of social skills in Table 4 only includes self-reported sociability, whereas the measurement of social skills in Table 1 also includes participation in clubs and sports. Complementarity is about 50 percent smaller (but still statistically significant at the 5 percent level) when I use only survey responses to measure social skills in Table 1.

gain for a worker who switches into a more social skill-intensive occupation is significantly greater in more recent years. The within-worker wage return to a 10 percentile increase in skill intensity is equal to zero in the NLSY79 wave, compared to about 2.1 percent in the NLSY97 wave.[23] Column 2 adds the math task measure plus an interaction with the NLSY97 indicator. In contrast to the results for social skills, the wage return to math-intensive occupations declined from about 1.7 percent to 0.8 percent between the 1979 and 1997 NLSY cohorts. Thus the evidence in Table 5 suggests that the wage gain from sorting into social skill-intensive jobs has increased over time.

Columns 3 and 4 add the three-way interactions with skills shown in equation (22). I add summary tests of statistical significance across multiple coefficients on skills at the bottom of Table 5. The complementarity between social skills and jobs requiring social interaction has increased in the NLSY97 sample. The coefficient on the triple interaction in Column 3 is positive but not statistically significant, and the sum of the coefficients barely fails to reject at the 10 percent level (p=0.108). Column 4 adds interactions between skills, the NLSY97 indicator, and math task intensity. To conserve space, I do not show these coefficients. However, adding math task intensity makes the triple interaction between social skills, social skill task intensity and the NLSY97 indicator larger and more precise, and it is now statistically significant at the 10 percent level (0.0069, p=0.071). In contrast, the triple interaction with math task intensity (not shown) is negative and not statistically different from zero.

In sum, comparing the returns to skills and the impact of job changes across survey waves suggests that social skills have become more important over time, and that growth in the return to social skills has been greater for workers who sort into social skill-intensive occupations.

VI. Conclusion

This paper presents evidence of growing demand for social skills over the last several decades. What explains the growing importance of social skills in the labor market? One reason is that computers are still very poor at simulating human interaction. Reading the minds of others and reacting is an unconscious process, and skill in social settings has evolved in humans over thousands of years. Human interaction in the workplace involves team pro-

[23]Note that this estimate differs from the worker fixed effects models in Table 3, because those are estimated using a much larger age range. This suggests that the wage gain from switching to a social skill-intensive occupation was greater for older workers in the NLSY79 survey. Unfortunately, the panel design of the NLSY does not allow me to distinguish between age effects and cohort effects (i.e. whether the larger return for older workers is because the return to social skills increased over time or whether the return is constant but larger for later-career workers.)

duction, with workers playing off of each other's strengths and adapting flexibly to changing circumstances. Such nonroutine interaction is at the heart of the human advantage over machines.

I formalize the importance of social skills with a model of team production in the workplace. Because workers naturally vary in their ability to perform the great variety of workplace tasks, teamwork increases productivity through comparative advantage. I model social skills as reducing the worker-specific cost of coordination, or "trading tasks" with others. Workers with high social skills can trade tasks at a lower cost, enabling them to work with others more efficiently.

The model generates intuitive predictions about sorting and the relative returns to skills across occupations, which I investigate using two panel surveys - the NLSY79 and NLSY97 - that contain comparable measures of worker skills and repeated observations of occupational choice and wages. I find that the wage return to social skills is positive even after conditioning on cognitive skill, non-cognitive skill, and a wide variety of other covariates, and that cognitive skill and social skill are complements. I also find that workers with higher social skills are more likely to work in social skill-intensive occupations, and that they earn a relatively higher wage return when they sort into these occupations.

I show evidence of strong relative employment and wage growth for social skill-intensive occupations between 1980 and 2012. Jobs that require high levels of cognitive skill *and* social skill have fared particularly well, while high math, low social skill jobs (including many STEM occupations) have fared especially poorly. I also study changes in the returns to social skill between the NLSY79 and NLSY97, using nearly identical measures of skills and other covariates across survey waves. I find that social skills were a much stronger predictor of employment and wages for young adults age 25 to 33 in the mid 2000s, compared to the 1980s and 1990s. In contrast, the importance of cognitive skills has declined modestly.

This paper argues for the importance of social skills, yet it is silent about where social skills come from and whether they can be affected by education or public policy. A robust finding in the literature on early childhood interventions is that long-run impacts on adult outcomes can persist can even when short-run impacts on test scores "fade out" (e.g. Deming 2009; Chetty *et al.* 2011).

It is possible that increases in social skills are a key mechanism for long-run impacts of early childhood interventions. Heckman *et al.* (2013) find that the long-run impacts of the Perry Preschool project on employment, earnings and criminal activity were mediated primarily by program-induced increases in social skills. The Perry Preschool curriculum placed special emphasis on developing children's skills in cooperation, resolution of interpersonal conflicts and self-control. Recent longitudinal studies have found strong correlations between a measure of socio-emotional skills in kindergarten and important young adult outcomes such as employment, earnings, health and criminal activity (Dodge *et al.* 2014; Jones *et al.* 2015).

If social skills are learned early in life, not expressed in academic outcomes such as reading and math achievement, but important for adult outcomes such as employment and earnings, this would generate the "fade out" pattern that is commonly observed for early life interventions. Indeed, preschool classrooms focus much more on the development of social and emotional skills than elementary school classrooms, which emphasize "hard" academic skills such as literacy and mathematics. Still, these conclusions are clearly speculative, and the impact of social skill development on adult labor market outcomes is an important question for future work.

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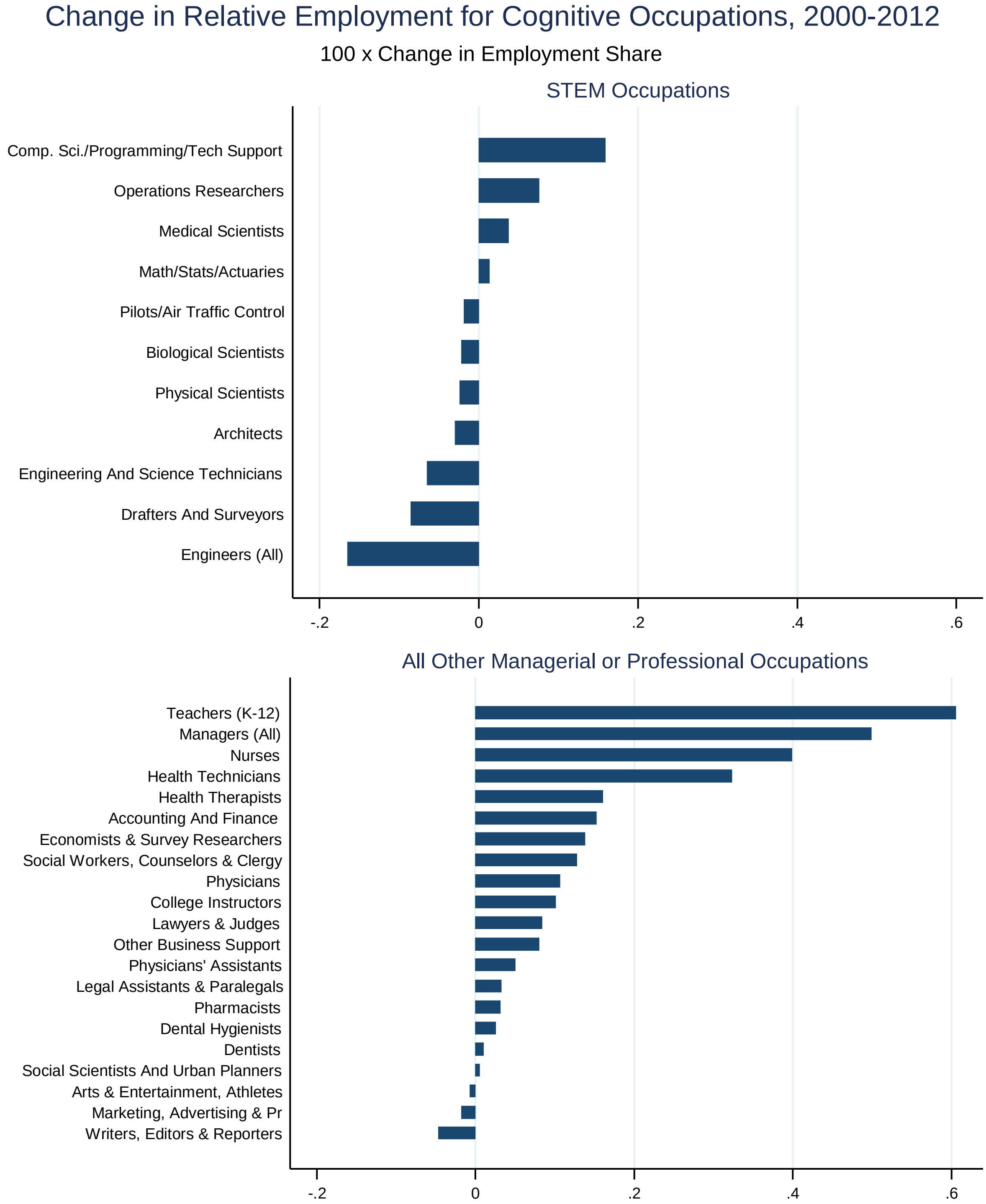
FIGURE I



Source: 2000 Census and 2011-2013 ACS

Each row presents 100 times the change in employment share between 2000 and 2012 for the indicated occupation. Consistent occupation codes for 1980-2012 are updated from Autor and Dorn (2013) and Autor and Price (2013) and consolidated to conserve space – see the Data Appendix for details.

FIGURE II.A

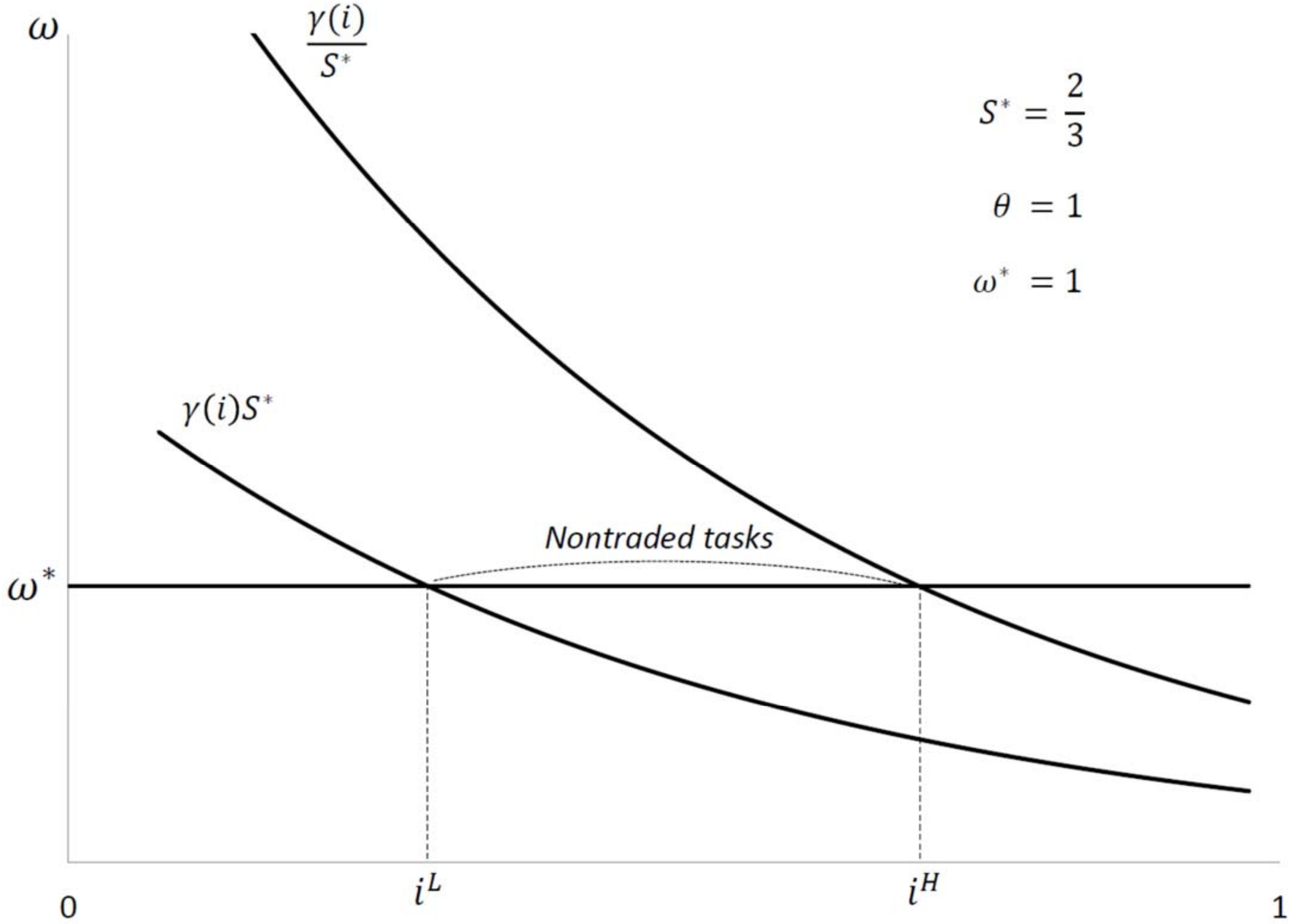


Figure 2A illustrates the equilibrium task thresholds i^L and i^H from the Model in Section 2 of the paper when $S^* = \frac{2}{3}$, $\theta = 1$ and $\omega^* = 1$ – see the text for details.

FIGURE II.B

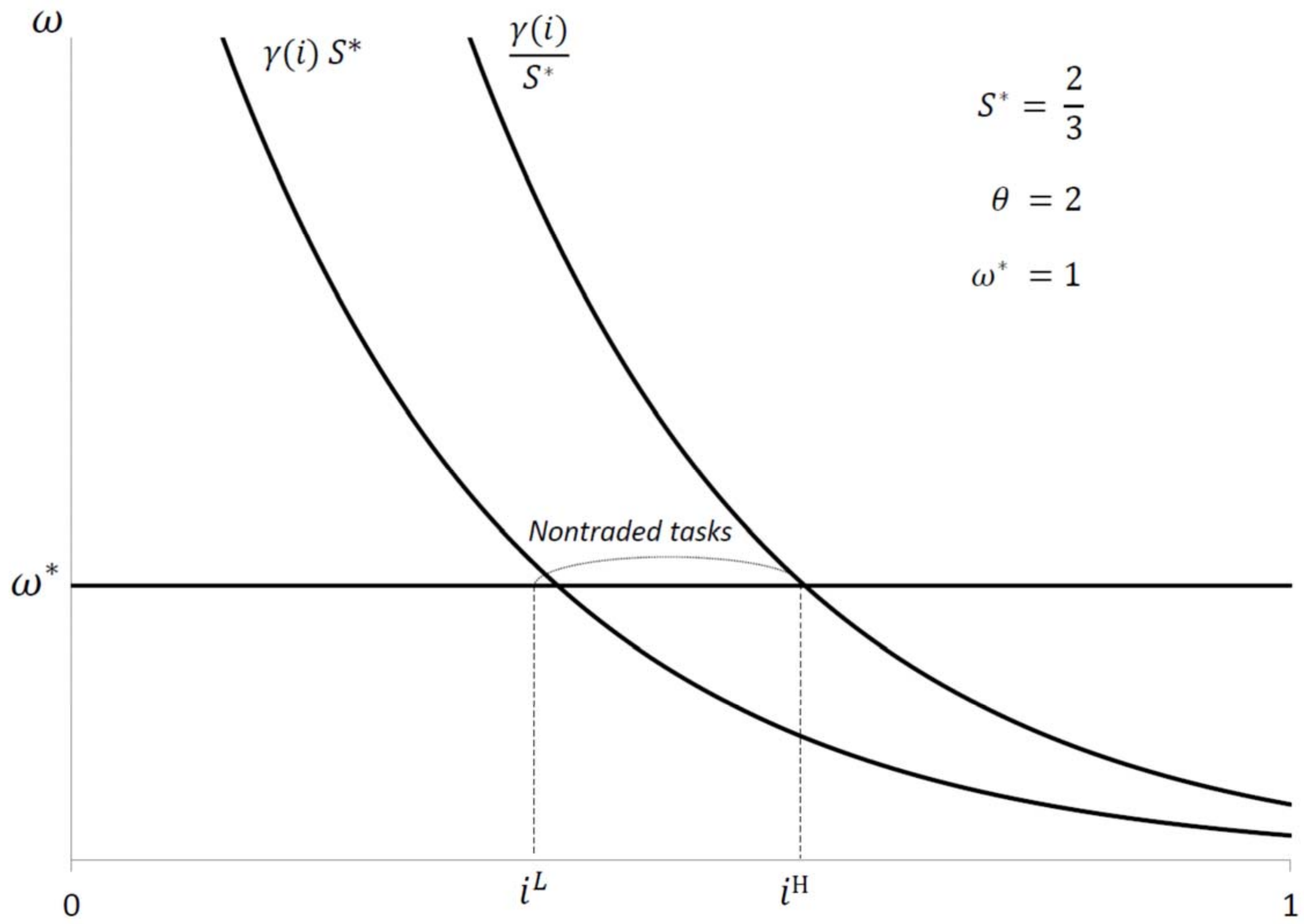


Figure 2B illustrates the equilibrium task thresholds i^L and i^H from the Model in Section 2 of the paper when $S^* = \frac{2}{3}$, $\theta = 2$ and $\omega^* = 1$ – see the text for details.

FIGURE III

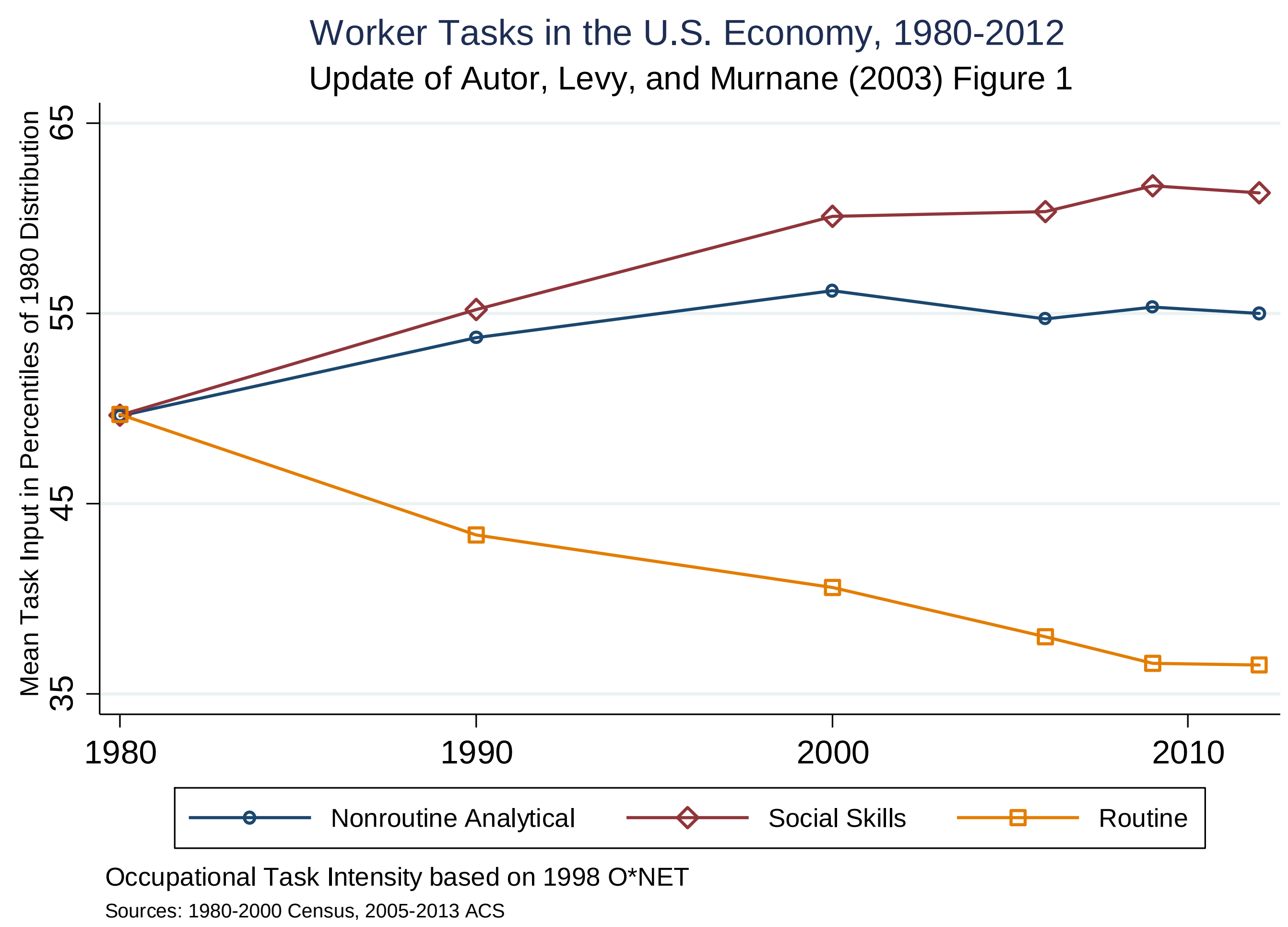
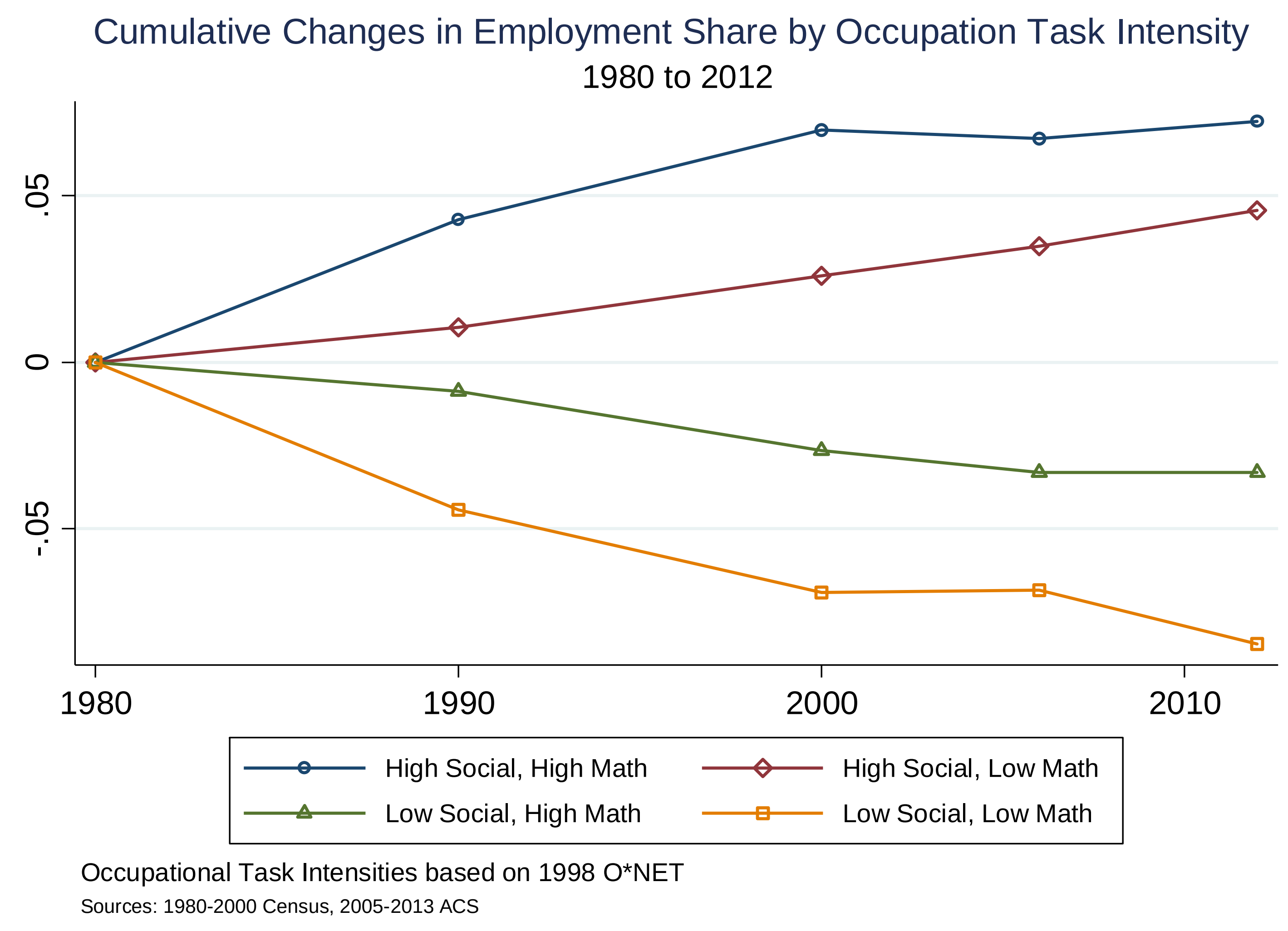


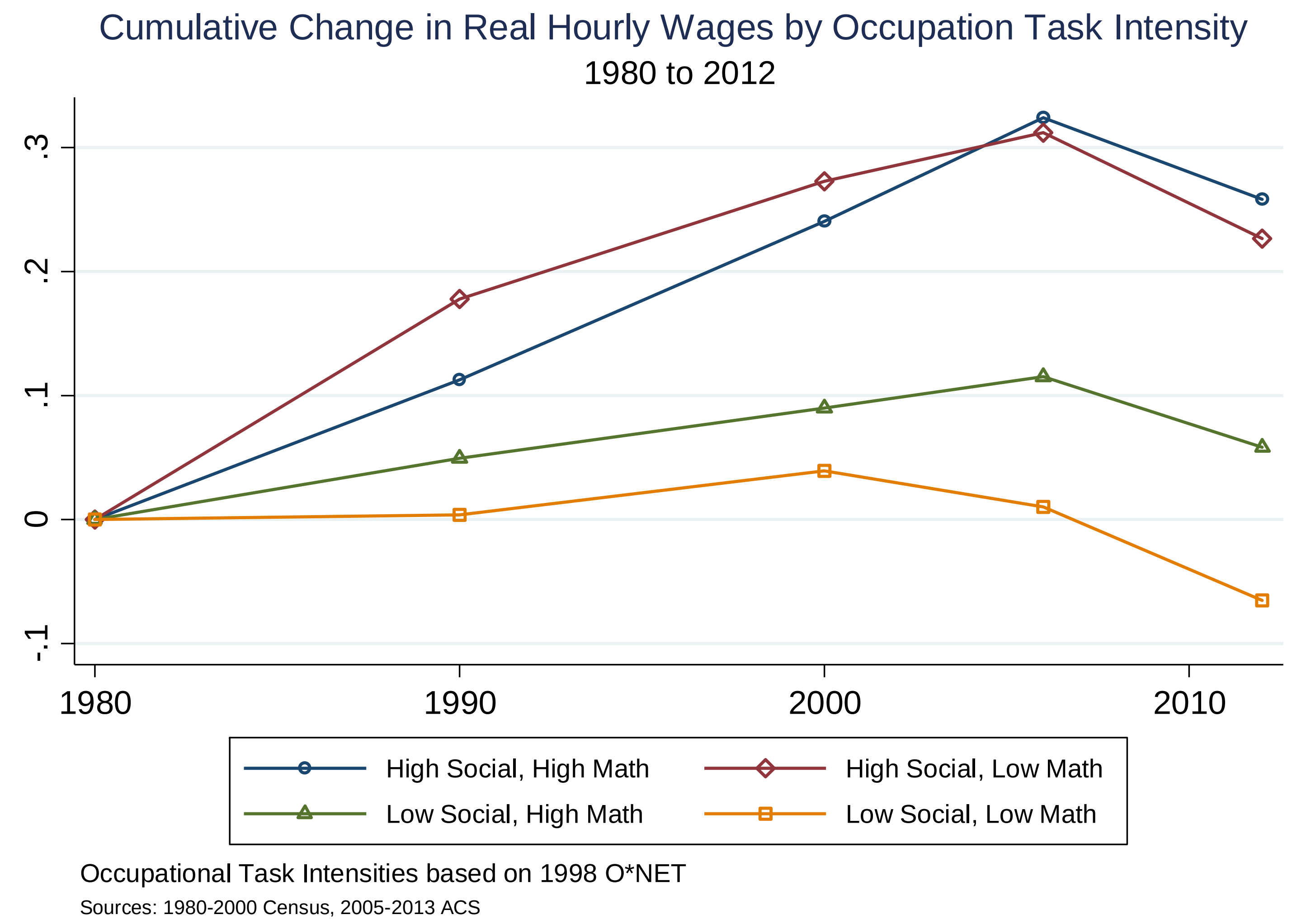
Figure 3 is constructed to parallel Figure I of Autor, Levy and Murnane (2003). O*NET 1998 task measures by occupation are paired with data from the IPUMS 1980-2000 Censuses and the 2005-2013 American Community Survey samples. Consistent occupation codes for 1980-2012 are from Autor and Dorn (2013) and Autor and Price (2013). Data are aggregated to industry-education-sex cells by year, and each cell is assigned a value corresponding to its rank in the 1980 distribution of task input. Plotted values depict the employment-weighted mean of each assigned percentile in the indicated year. See the text and Appendix for details on the construction of O*NET task measures.

FIGURE IV



Each line plots 100 times the change in employment share – relative to a 1980 baseline - between 1990 and 2012 for occupations that are above and/or below the 50th percentile in nonroutine analytical and social skill task intensity as measured by the 1998 O*NET. Consistent occupation codes for 1980-2012 are updated from Autor and Dorn (2013) and Autor and Price (2013). See the text and Appendix for details on the construction of O*NET task measures and for examples of occupations in each of the four categories.

FIGURE V



Each line plots the percent change in mean hourly wages – relative to a 1980 baseline and in constant 2012 dollars - between 1990 and 2012 for occupations that are above and/or below the 50th percentile in nonroutine analytical and social skill task intensity as measured by the 1998 O*NET. Consistent occupation codes for 1980-2012 are updated from Autor and Dorn (2013) and Autor and Price (2013). See the text and Appendix for details on the construction of O*NET task measures and for examples of occupations in each of the categories.

TABLE I

LABOR MARKET RETURNS TO COGNITIVE SKILLS AND SOCIAL SKILLS IN THE NLSY79

Outcome is Log Hourly Wage (in 2012 dollars)	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Cognitive Skills (AQT, standardized)		0.206***	0.206***	0.189***	0.126***	0.190***	0.126***
		[0.007]	[0.007]	[0.007]	[0.008]	[0.007]	[0.008]
Social Skills (standardized)	0.107***	0.055***	0.049***	0.043***	0.029***	0.044***	0.029***
	[0.006]	[0.006]	[0.006]	[0.006]	[0.006]	[0.006]	[0.006]
Cognitive * Social			0.019***	0.019***	0.011*	0.017***	0.010*
			[0.006]	[0.006]	[0.006]	[0.006]	[0.006]
Non-cognitive Skills (standardized)				0.048***	0.040***	0.046***	0.040***
				[0.006]	[0.006]	[0.006]	[0.006]
Cognitive * Noncognitive						0.008	0.001
						[0.006]	[0.006]
Demographics and Age / Year Fixed Effects		X	X	X	X	X	X
Years of completed education					X		X
R-squared	0.300	0.343	0.344	0.347	0.359	0.347	0.359
Observations	126,251	126,251	126,251	126,191	126,191	126,191	126,191

Notes: Each column reports results from an estimate of equation (18) in the paper, with real log hourly wages as the outcome and person-year as the unit of observation. The data source is the National Longitudinal Survey of Youth 1979 cohort (NLSY79). Cognitive skills are measured by each NLSY79 respondent's score on the Armed Forces Qualifying Test (AFQT), and are normalized to have a mean of zero and a standard deviation of one. I use the AFQT score crosswalk developed by Altonji, Bharadwaj and Lange (2012). Social skills is a standardized composite of four variables - 1) sociability in childhood; 2) sociability in adulthood; 3) participation in high school clubs; and 4) participation in team sports - see the text for details on construction of the social skills measure. My measure of "non-cognitive" skills is the normalized average of the Rotter and Rosenberg scores in the NLSY. The regression also controls for race-by-gender indicator variables, age, year, census region, and urbanicity fixed effects - plus additional controls as indicated. Standard errors are in brackets and clustered at the individual level. *** p<0.01, ** p<0.05, * p<0.10

TABLE II

OCCUPATIONAL SORTING ON SKILLS IN THE NLSY79

	Routine		Social Skills	
*Outcomes are O*NET Task Measures*	(1)	(2)	(3)	(4)
Cognitive Skills (AQT, standardized)	-0.055*	0.161***	0.345***	-0.044**
	[0.030]	[0.032]	[0.028]	[0.019]
Social Skills (standardized)	-0.188***	-0.149***	0.208***	0.119***
	[0.022]	[0.024]	[0.020]	[0.014]
Cognitive * Social	-0.058***	-0.054**	0.014	0.013
	[0.021]	[0.023]	[0.019]	[0.014]
Demogs, Age / Year, Education Fixed Effects	X	X	X	X
Controls for O*NET Cognitive Tasks		X		X
Observations	133,599	133,599	133,599	133,599
R-squared	0.204	0.237	0.305	0.668

Notes: Each column reports results from an estimate of equation (18) in the paper, with the indicated 1998 O*NET task intensity of an occupation as the outcome and person-year as the unit of observation. The task measures are percentiles that range from 0 to 10 and are weighted by labor supply to conform to the 1980 occupation distribution. The additional O*NET cognitive task measures are Nonroutine Analytical, Number Facility, Inductive/Deductive Reasoning, and Analyze/Use Information. See the text and Appendix for details on the construction of each O*NET task measure. The data source is the National Longitudinal Survey of Youth 1979 cohort (NLSY79). Cognitive skills are measured by each NLSY79 respondent's score on the Armed Forces Qualifying Test (AFQT), and are normalized to have a mean of zero and a standard deviation of one. I use the AFQT score crosswalk developed by Altonji, Bharadwaj and Lange (2012). Social skills is a standardized composite of four variables - 1) sociability in childhood; 2) sociability in adulthood; 3) participation in high school clubs; and 4) participation in team sports - see the text for details on construction of the social skills measure. My measure of "non-cognitive" skills is the normalized average of the Rotter and Rosenberg scores in the NLSY. The regression also controls for race-by-gender indicator variables, age, year, census region, and urbanicity fixed effects - plus additional controls as indicated. Standard errors are in brackets and clustered at the individual level. *** $p<0.01$, ** $p<0.05$, * $p<0.10$

TABLE III

RETURNS TO SKILLS BY OCCUPATION TASK INTENSITY IN THE NLSY79

Outcome is Log Hourly Wage (in 2012 dollars)	(1)	(2)	(3)
Routine Task Intensity	0.0136***		0.0212***
	[0.0012]		[0.0014]
Cognitive * Routine Task Intensity	-0.0034***		0.0005
	[0.0013]		[0.0015]
Social Skills * Routine Task Intensity	-0.0025**		-0.0008
	[0.0013]		[0.0015]
Cognitive * Social * Routine Task Intensity	-0.0008		-0.0011
	[0.0012]		[0.0014]
Social Skill Task Intensity		0.0039***	0.0176***
		[0.0013]	[0.0016]
Cognitive * Social Skill Task Intensity		0.0113***	0.0112***
		[0.0015]	[0.0018]
Social Skills * Social Skill Task Intensity		0.0050***	0.0041**
		[0.0015]	[0.0018]
Cognitive * Social * Social Skill Task Intensity		0.0021	0.0011
		[0.0015]	[0.0023]
Worker Fixed Effects	X	X	X
Observations	126,251	126,251	126,251
Number of individuals	11,050	11,050	11,050

Notes: Each column reports results from an estimate of equation (19) in the paper, with real log hourly wages as the outcome and person-year as the unit of observation. The data source is the National Longitudinal Survey of Youth 1979 cohort (NLSY79). Cognitive skills are measured by each NLSY79 respondent's score on the Armed Forces Qualifying Test (AFQT), and are normalized to have a mean of zero and a standard deviation of one. I use the AFQT score crosswalk developed by Altonji, Bharadwaj and Lange (2012). Social skills is a standardized composite of four variables - 1) sociability in childhood; 2) sociability in adulthood; 3) participation in high school clubs; and 4) participation in team sports - see the text for details on construction of the social skills measure. My measure of "non-cognitive" skills is the normalized average of the Rotter and Rosenberg scores in the NLSY. All models control for worker fixed effects, age, year, census region, and urbanicity fixed effects - plus additional controls as indicated. The interactions between cognitive/social skills and 1998 O*NET task intensities measure whether the returns to skills vary with the task content of the worker's occupation. The task measures are percentiles that range from 0 to 10 and are weighted by labor supply to conform to the 1980 occupation distribution. See the text and Appendix for details on the construction of each O*NET task measure. Standard errors are in brackets and clustered at the individual level. *** p<0.01, ** p<0.05, * p<0.10

TABLE IV

LABOR MARKET RETURNS TO SKILLS IN THE NLSY79 VS. NLSY97

	Full-Time Employment			Log Real Hourly Wage		
	(1)	(2)	(3)	(4)	(5)	(6)
Cognitive Skills (AQT, standardized)	0.068***	0.042***	0.040***	0.203***	0.129***	0.116***
	[0.003]	[0.003]	[0.003]	[0.005]	[0.006]	[0.006]
Cognitive Skills * NLSY97	0.008*	0.005	0.009*	-0.052***	-0.061***	-0.045***
	[0.004]	[0.004]	[0.005]	[0.008]	[0.008]	[0.008]
Social Skills (standardized)	0.007***	0.005**	0.004*	0.020***	0.015***	0.011**
	[0.002]	[0.002]	[0.002]	[0.004]	[0.004]	[0.004]
Social Skills * NLSY97	0.023***	0.021***	0.019***	0.017**	0.019**	0.016**
	[0.004]	[0.004]	[0.004]	[0.008]	[0.008]	[0.008]
Cognitive * Social	-0.007***	-0.006**	-0.007**	0.006	0.003	0.002
	[0.003]	[0.003]	[0.003]	[0.004]	[0.004]	[0.004]
Cognitive * Social * NLSY97	-0.006	-0.006	-0.006	-0.004	-0.004	-0.002
	[0.004]	[0.004]	[0.004]	[0.008]	[0.008]	[0.008]
Non-cognitive Skills (standardized)			0.008**			0.041***
			[0.003]			[0.005]
Non-cognitive Skills * NLSY97			0.013***			0.016*
			[0.005]			[0.009]
Demographics and Age / Year FE	X	X	X	X	X	X
Years of completed education		X	X		X	X
R-squared	0.081	0.096	0.097	0.309	0.333	0.337
Observations	104,613	104,252	104,206	77,845	77,631	77,599

Notes: Each column reports results from an estimate of equation (20) in the paper, with an indicator for being employed full-time as the outcome in Columns 1 through 3, real log hourly wages as the outcome in Columns 4 through 6, and person-year as the unit of observation. The data are a pooled sample of two cohorts of youth - the National Longitudinal Survey of Youth 1979 (NLSY79) and 1997 (NLSY97) waves. I restrict the age range to 25-33, which allows for a comparison of NLSY respondents at similar ages across survey waves. Cognitive skills are measured by each NLSY respondent's score on the Armed Forces Qualifying Test (AFQT), and are normalized to have a mean of zero and a standard deviation of one. I use the AFQT score crosswalk developed by Altonji, Bharadwaj and Lange (2012) which adjusts for differences across survey waves in age-at-test and test format. Social skills is a standardized composite of two variables that measure extraversion in both the NLSY79 (sociability in childhood and sociability in adulthood) and in the NLSY97 (two items from the Big 5 personality inventory that measure extraversion). The "non-cognitive" skill measures are a normalized average of the Rotter and Rosenberg scores in the NLSY79, and two items from the NLSY97 that measure the Big 5 personality factor Conscientiousness. The regression also controls for an indicator for whether the respondent was in the NLSY97 wave, race-by-gender indicator variables, age, year, census region, and urbanicity fixed effects - plus additional controls as indicated. Standard errors are in brackets and clustered at the individual level. *** $p<0.01$, ** $p<0.05$, * $p<0.10$

TABLE V

RETURNS TO SKILLS BY OCCUPATION TASK INTENSITY IN THE NLSY79 VS. NLSY97

Outcome is Log Hourly Wage (in 2012 dollars)	(1)	(2)	(3)	(4)
Social Skill Task Intensity	0.0004	-0.0096***	-0.0095***	-0.0096***
	[0.0013]	[0.0015]	[0.0015]	[0.0015]
Social Skill Task Intensity * NLSY97	0.0210***	0.0253***	0.0217***	0.0225***
	[0.0036]	[0.0041]	[0.0040]	[0.0040]
Math Task Intensity		0.0175***	0.0177***	0.0177***
		[0.0015]	[0.0015]	[0.0015]
Math Task Intensity * NLSY97		-0.0082**	-0.0085**	-0.0099***
		[0.0035]	[0.0034]	[0.0034]
Cognitive Skill * Social Skill Task Intensity			0.0069***	0.0074***
			[0.0013]	[0.0016]
Cognitive Skill * Social Skill Task Intensity * NLSY97			0.0114***	0.0047
			[0.0036]	[0.0044]
Social Skill * Social Skill Task Intensity			0.00008	0.0011
			[0.0013]	[0.0016]
Social Skill * Social Skill Task Intensity * NLSY97			0.0040	0.0069*
			[0.0032]	[0.0038]
P (Social Skill * Social Skill Intensity in NLSY97 >0)			0.108	0.023
P (All Skills * Social Skill Intensity in NLSY97 >0)			0.000	0.001
P (All Skills in NLSY97 > All Skills in NLSY79)				0.000
Observations	77,845	77,845	77,845	77,845
Number of individuals	14,998	14,998	14,998	14,998

Notes: Each column reports results from an estimate of equation (21) in the paper, with real log hourly wages as the outcome and person-year as the unit of observation. The data are a pooled sample of two cohorts of youth - the National Longitudinal Survey of Youth 1979 (NLSY79) and 1997 (NLSY97) waves. I restrict the age range to 25-33, which allows for a comparison of NLSY respondents at similar ages across survey waves. Cognitive skills are measured by each NLSY respondent's score on the Armed Forces Qualifying Test (AFQT), and are normalized to have a mean of zero and a standard deviation of one. I use the AFQT score crosswalk developed by Altonji, Bharadwaj and Lange (2012) which adjusts for differences across survey waves in age-at-test and test format. Social skills is a standardized composite of two variables that measure extraversion in both the NLSY79 (sociability in childhood and sociability in adulthood) and in the NLSY97 (two items from the Big 5 personality inventory that measure extraversion). The regression also controls for age, year, census region, and urbanicity fixed effects - plus additional controls as indicated. The interactions between cognitive/social skills and 1998 O*NET task intensities measure whether the returns to skills vary with the task content of the worker's occupation. The task measures are percentiles that range from 0 to 10 and are weighted by labor supply to conform to the 1980 occupation distribution. See the text and Appendix for details on the construction of each O*NET task measure. Standard errors are in brackets and clustered at the individual level. *** p<0.01, ** p<0.05, * p<0.10