The Growing Importance of Social Skills in the Labor Market

David J. Deming
Harvard University and NBER*

August 2016

Abstract

I show that the labor market increasingly rewards *social skills*. Between 1980 and 2012, jobs with high social skill requirements grew by nearly 10 percentage points as a share of the U.S. labor force. In contrast, math-intensive but less social jobs (including many STEM occupations) shrank by about 3 percentage points over the same period. Employment and wage growth was particularly strong for jobs requiring high levels of *both* cognitive 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 trade more efficiently. The model generates predictions about sorting and the relative returns to skill across occupations, which I test and confirm using data from the NLSY79 and the NLSY97. Using a comparable set of skill measures and covariates across survey waves, I show that the labor market return to social skills was much greater in the 2000s than in the mid 1980s and 1990s.

---

*david_deming@gse.harvard.edu. Thanks to Pol Antras, David Autor, Avi Feller, Lawrence Katz, Sandy Jencks, Richard Murnane, and Lowell Taylor for reading early drafts of this paper and for providing insightful feedback. Thanks to Felipe Barrera-Osorio, Amitabh Chandra, Asim Khwaja, Alan Manning, Guy Michaels, Luke Miratrix, Karthik Muralidharan, Devah Pager, Todd Rogers, Doug Staiger, Catherine Weinberger, Marty West and seminar participants at PSE, LSE, CESifo, Yale, Columbia, Harvard, MIT, Michigan State, Northwestern, UBC, Simon Fraser, Cornell, University of Chicago and the NBER Education and Personnel meetings for helpful comments. Madeleine Gelblum, Olivia Chi, Lauren Reisig and Stephen Yen provided superb research assistance. Special thanks to David Autor and Brendan Price for sharing their data and programs. Extra special thanks to Lisa Kahn and Chris Walters for "trading tasks" with me. All errors are my own.

"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)

1 Introduction

A vast literature in economics explains increasing returns to skill over the last several decades as a product of the complementarity between technology and high-skilled labor, or *skill-biased technological change* (SBTC) (e.g. Katz and Murphy 1991, Bound and Johnson 1992, Juhn et al. 1993, Murnane et al. 1995, Grogger and Eide 1995, Heckman and Vytlacil 2001, Taber 2001, Acemoglu and 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 or alternatively, *routine-biased technological change* (RBTC) (Autor et al. 2003, 2006, Goos and Manning 2007, Autor et al. 2008, Acemoglu and Autor 2011, Autor and Dorn 2013, Michaels et al. 2014, Goos et al. 2014, Adermon and Gustavsson 2015).

However, while RBTC 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 and Autor 2011, Autor and Dorn 2013, Liu and Grusky 2013, Beaudry et al. 2014, 2016). Beaudry et al. (2016) show that a "great reversal" in the demand for cognitive skill occurred in the U.S. labor market around 2000, and Castex and Dechter (2014) find that the returns to cognitive skill were substantially smaller in the 2000s than in 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, forthcoming). If technological change is skill-biased, why do the returns to cognitive skill appear to have declined over the last decade?

One possible explanation is that weak growth in high-skilled jobs is caused by a slowdown in technological progress.[1] Beaudry et al. (2016) argue that declining 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 (2014) shows that innovation and U.S. productivity growth slowed down markedly in the early 2000s.

On the other hand, Brynjolfsson and McAfee (2014) discuss advances in computing power

[1] In the long-run, technological progress itself may respond endogenously to changes in the supply of skills (e.g. Acemoglu 1998).

that are rapidly expanding the set of tasks that machines can perform. Many of the tasks they and others highlight - from automated financial management and tax preparation to legal e-discovery to cancer diagnosis and treatment - are typically performed by highly skilled workers (Levy and Murnane 2012, Brynjolfsson and McAfee 2014, Remus and 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).[2] 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 "bust" 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 actually 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 skill*s. 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 extremely 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 2014).[3] 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"

[2] 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 and 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. For ease of presentation, I have grouped occupation codes into larger categories in some cases (e.g. engineers, managers).

[3] Autor (2014) refers to this as "Polanyi's paradox", after the philosopher Michael Polanyi who observed that "we can know more than we can tell". Autor (2014) also notes that computer scientists refer to a similar phenomenon as "Moravec's paradox". Moravec argues that evolution plays an important role in the development of tacit knowledge. Skills such as interpersonal interaction and sensorimotor coordination, while unconscious and apparently effortless, are actually the product of evolutionary design improvements and optimizations over millions of years. In contrast, abstract thought seems difficult because humans have only been doing it for a few thousand years (Moravec 1988).

(Premack and Woodruff 1978, Baron-Cohen 2000, Camerer et al. 2005).

I begin by presenting evidence of growing demand for social skills in the U.S. labor market. Between 1980 and 2012, social skill-intensive occupations grew by 9.3 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. Relative employment and wage growth for social skill-intensive occupations has occurred throughout the wage distribution, not just in low-skilled service work or in management and other top-paying jobs.

I find that employment and wage growth has been particularly strong in occupations with high cognitive skill *and* social skill requirements, which is consistent with growing *complementarity* between cognitive skills and social skills (Weinberger 2014). 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 increased service sector orientation can partially - but not completely - explain the trends described above.[4]

To understand these patterns, I develop 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 skill as a reduction in her *worker-specific* 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 and Kortum (2002).[5]

The model provides a natural explanation for the empirical results described above.

[4]Autor and Dorn (2013) document the rise of low-wage service occupations. In their model, this is explained by non-neutral technological progress - computers replace routine production tasks, which reallocates low-skilled workers to services (which are more difficult to automate because consumers favor variety over specialization). However, this does not explain growth of social skill-intensive jobs at the top of the wage distribution. Moreover, in Table 1 I show that the results are robust to excluding "high-skill" service jobs in sectors such as education and health care. 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 and 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 growth in social skill-intensive jobs.

[5]Acemoglu and 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 a relatively large literature that treats teamwork as a tradeoff between the benefits of increased productivity through specialization and the costs of coordination (Becker and Murphy 1992, Bolton and Dewatripont 1994, Lazear 1999, Garicano 2000, Garicano and Rossi-Hansberg 2004, 2006, Antras et al. 2006)

Workers of all skill levels benefit from trading tasks with each other through horizontal specialization. This contrasts with the literature on "knowledge hierarchies", where vertical specialization leads to less-skilled workers focusing on routine production tasks and managers focusing on nonroutine problem solving (Garicano 2000, Garicano and Rossi-Hansberg 2004, Antras et al. 2006, Garicano and Rossi-Hansberg 2006). These models explain increases in managerial compensation and wage inequality, but do not explain broad-based gains in the labor market returns to social skills.

Moreover, treating social skills as a reduction in coordination costs allows skill complementarity to emerge naturally, because the value of lower trade costs increases in task productivity and thus cognitive skill.[6] The model provides a key link between social skills and routineness through the *variance* of task productivity draws. Nonroutine work requires a more diverse range of tasks (for example, consider the tasks required of management consultants vs. computer programmers), which increases the scope for gains from "task trade" and thus the returns to social skills.

I am aware of only a few other papers that specifically 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 with "relationship" skill, where high levels 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.[7] 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 and Snower 2000, Hackman 2002, Bartel et al. 2007, Edmondson 2012).

The model generates predictions about sorting and the relative returns to skills across occupations, which I test and confirm 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. I also find that

[6] A related literature studies job assignment when workers have multiple skills (Heckman and Sedlacek 1985, Heckman and Scheinkman 1987, Gibbons et al. 2005, Lazear 2009, Sanders and Taber 2012, Yamaguchi 2012, Lindenlaub 2013, Lise and Postel-Vinay 2015). 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.

[7] 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.

workers with higher social skills sort into nonroutine and social skill-intensive occupations. While occupational sorting complicates the interpretation of cross-sectional estimates of the return to skills, I show that the same worker earns a higher wage when she switches into a more social skill-intensive occupation, and that her wage gain is increasing in social skills.[8]

I test for the growing importance of social skills in the labor market by comparing the returns to skills in the NLSY79 and 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.

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. More generally, while social skills may also be important in service jobs, I show that all of the empirical results are robust to including controls (and skill interactions) for the customer service task intensity of a worker's occupation.

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 and Barrington 2006, Jerald 2009).[9] 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 (National Association of Colleges and Employers 2015).

[8]Krueger and 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, this does not explain why firms would be willing to pay more for a worker with higher social skills. 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.

[9]In a 2006 survey of 431 large employers, the five most important skills for four-year college graduates (ranked in order) were 1) oral communications; 2) teamwork/collaboration; 3) professionalism/work ethic; 4) written communications; 5) critical thinking/problem solving. For high school graduates and two-year college graduates, professionalism/work ethic was listed as most important followed by teamwork/collaboration and oral communications, with critical thinking/problem solving listed 7th.

Tests of emotional intelligence and social intelligence have been formally developed and psychometrically validated by psychologists (Salovey and 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.[10]

A growing body of work in economics documents the labor market return to "noncognitive" skills, including social skills and leadership skills (Kuhn and Weinberger 2005, Heckman et al. 2006, Lindqvist and Vestman 2011, Heckman and Kautz 2012, Borghans et al. 2014, Weinberger 2014).[11] This paper builds on the seminal observation of Heckman (1995) that since measured cognitive ability (i.e. g) explains only a small fraction of the variation in earnings, productivity is likely influenced by multiple dimensions of skill. Subsequent work, summarized in Heckman and 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 evidence of growing demand for social skills in the U.S. labor market between 1980 and 2012. Section 3 presents the model and develops specific empirical predictions. Section 4 describes the data. Section 5 presents empirical tests of the model's key predictions using the NLSY79 and NLSY97 panel surveys. Section 6 concludes.

2 Social Skills in the Labor Market

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

[10]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 withthe "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).

[11]Kuhn and Weinberger (2005) find that men who occupied leadership positions in high school had higher earnings as adults, even after controlling for cognitive skill and a wide variety of other covariates. Using more recent data from multiple cohorts, Weinberger (2014) finds an increase in the return to social skills over time, as well as an increase in the complementarity between cognitive skills and social skills. Lindqvist and Vestman (2011) find that Swedish men who scored higher on an interview, which was designed to measure (among other things) social skills and the ability to work in a team, had higher earnings later in life even after conditioning on cognitive skill. Like Weinberger (2014), they also found that cognitive skill and social skill are complements in the earnings regression.

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 and 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 and Dorn (2013) create a balanced and consistent panel of occupation codes that cover the 1980 Census through the 2005 American Community Survey (ACS). I extend their approach 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 four 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?"[12] 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.[13] 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) coordination; 2) negotiation; 3) persuasion; 4) social perceptiveness.[14] Fourth, I define an occupation's *service* task intensity as the average of two O*NET task measures - 1) assisting and caring for others; 2) service orientation.[15]

[12]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 and 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.

[13]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.

[14]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.

[15]Results are extremely similar when I use related measures of service tasks, such as whether the job

While service tasks and social skill tasks both require human interaction, they are important for different types of jobs. Figure 2 shows this by plotting smoothed locally weighted regressions of O*NET occupational task intensities against that occupation's percentile in the 1980 wage distribution. Service tasks are typically oriented around customer service, and are concentrated in the lowest three deciles of the wage distribution. In contrast, jobs that require social skills emphasize teamwork in production, and are relatively high-paying and cognitive skill-intensive.

Figure 3 replicates Figure I of Autor et al. (2003) for the 1980-2012 period using the four key O*NET task measures described above.[16] 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 and 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. Service task inputs grew by about 23 percent over the 1980-2012 period, consistent with Autor and Dorn (2013).

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 extremely 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.

The task measures in Figure 3 are additive, and some of them (such as math and social skills) are highly correlated across occupations. To study changes in the the *bundles* of tasks demanded by employers, I divide occupations into four mutually exclusive categories based on whether they are above or below the median percentile in both nonroutine analytical (math) and social skill task intensity. I then compute the share of all labor supply-weighted employment in each category and year.

requires dealing with external customers.

[16]Many thanks to David Autor and Brendan Price for generously sharing their data and programs.

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 6.5 percentage points as a share of the U.S. labor force between 1980 and 2012. Low math, high social skill jobs grew by about 2.8 percentage points, for a total increase of 9.3 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 percentage points over the same period.

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 8.5 percent between 1980 and 2012, compared to about 27 percent for high math, high social skill occupations. Overall, the results in Figures 4 and 5 are consistent with falling demand for low social skill occupations. The results are robust to choosing cutoffs other than the 50th percentile for each type of task.

Because skilled workers tend to sort into social skill-intensive jobs, Figures 4 and 5 might simply reflect a secular increase in the demand for highly skilled labor. I address this concern first by studying the growth in social skill-intensive occupations throughout the wage distribution. Figure 6 plots smoothed changes in employment shares by occupation between 1980 and 2012 against each occupation's percentile in the 1980 wage distribution. While most occupations with high math and high social skill requirements are relatively high-paying, they have nonetheless grown robustly throughout the wage distribution. In contrast, employment shares for high math, low social skill occupations have declined everywhere except at the very top.[17]

Figure 7 presents the same set of results, but for real median hourly wages. Wages for high math, high social skill occupations have also grown uniformly throughout the skill distribution. Overall, the results in Figures 6 and 7 suggest that the growing importance of social skills is not driven only by high wage jobs.

Despite the fact that employment and wage growth in social skill-intensive occupations appears quite broad-based, the results in Figures 4 through 7 could still be driven by other trends such as changing educational attainment or industry mix. To further separate growing demand for social skills from other contemporaneous trend, I estimate employment and wage

[17] Some examples of high-paying occupations (i.e. above the 60th percentile) with high math and low social skill task intensity include actuaries, mathematicians and statisticians, engineering and chemical technicians, and machinists. Some examples of high-paying occupations with low math and high social skill task intensity include dentists, lawyers, actors/directors/producers, editors and reporters, and physical therapists.

growth for jobs requiring different bundles of tasks in a multivariate framework. Specifically, I collapse the Census and ACS data down to sex-education-industry-occupation-year cells and regress the natural log of employment in each cell on the O*NET task measures, log employment in the base year, and sex-education-industry fixed effects. This approach estimates the relationship between occupational task content and employment growth, controlling for other factors such as general skill upgrading and shifts in demand across industries.

The results are in Table 1. Standard errors are clustered at the occupation level, and there are approximately 340 occupations that are consistently coded across years. For consistency, I restrict the sample to the cells that have positive labor supply weight in all years between 1980 and 2012, although the results are not sensitive to this restriction.[18] Columns 1 through 3 look at employment growth between 1980 and 2012, while Columns 4 through 6 separate the results out by decade.

Column 1 shows results from a simple specification with only math and social skill task intensity included in the regression. Occupations that are 10 percentiles higher in the distribution of social skill intensity grew about 5.4 percent faster between 1980 and 2012, and the coefficient is statistically significant at the less than one percent level. In contrast, I find a 5.3 percent *decline* in occupations that are 10 percent more math-intensive, and the change is statistically significant at the 5 percent level.

Column 2 adds an interaction between math and social skill task intensity, while Column 3 adds a variety of other O*NET task measures as controls.[19] The interaction between math and social skill intensity becomes positive and statistically significant at the 10 percent level after including these controls. The estimates imply that employment growth has been greatest for high math, high social skill occupations, which is consistent with the unadjusted results shown in Figures 4 through 7.

Columns 4 through 6 of Table 1 study employment growth by occupation task content for

[18]This restriction excludes about 5 percent of the labor-supply weighted sample of occupation-industry-sex-education-year cells. While the results are almost identical when I relax this restriction and allow for different sample sizes across years, one concern is that the sparse cell sizes created by industry-occupation combinations throws out important variation such as the growth of new types of jobs. In Appendix Tables 1 and 2 I reestimate the results of Tables 1 and 2, but at the year-occupation-sex-education level (i.e. not creating industry-specific cells). This makes the cell sizes much larger and the data coverage is 99.9 percent. The results are generally similar to Tables 1 and 2, with one key exception. The negative coefficient on routine tasks is much greater without industry fixed effects, which suggests that part of the decline of routine-intensive occupations is due to changing industry mix.

[19]In addition to the routine and service task measures, I also add three alternative measures of cognitive skill intensity (the O*NET variables Number Facility, Inductive and Deductive Reasoning, and Analyzing and Using Information) and three alternative measures of social skill intensity (the O*NET variables Require Social Interaction, Coordinating the Work and Activities of Others, Communicating with Supervisors/Peers/Subordinates). See the Data Appendix for more details on the construction of the O*NET task measures.

the 1980-1990, 1990-2000 and 2000-2012 periods respectively. There are two main takeaways from separating out the results by decade. First, the complementarity between math skills and social skills is driven by changes occurring over the 2000-2012 period. Second, while math-intensive jobs grew relatively rapidly in the 1980s, their growth decelerated sharply beginning in the 1990s. Note that the results in Table 2 show the relationship between occupation task content and *relative* employment growth - while job growth in the 1990s was relatively strong overall, it was significantly weaker for math-intensive occupations.

Even though high math, high social skill jobs tend to have a relatively low customer service component, they are often located in service-oriented sectors of the economy such as education and health care. Moreover, many of these occupations involve the management of people. Thus the results in Table 1 might be driven indirectly by a broader trend toward services rather than manufacturing (e.g. Autor and Dorn 2013). I address this concern by excluding all managerial, health care and education occupations from the sample in column 7.[20] The results actually become much stronger with these occupations excluded. The coefficient on the interaction between math and social skill task intensity increases by more than 50 percent and is now statistically significant at the less than one percent level.

Table 2 presents analogous results for the natural log of hourly wages. The first two columns show results with only the math and social skill measures included, and I find an impact of both task measures on wage growth that is positive and statistically significant at the less than 1 percent level. However, after including the eight other O*NET task measures, only the coefficient on social skills remains statistically significant. The results in Column 3 imply that an increase in social skill task intensity of 10 percentiles is associated with a relative wage gain of 6.15 percent between 1980 and 2012. Unlike the results for employment in Table 1, the relatively greater wage return to social skill-intensive occupations remains constant across decades. In contrast, the coefficient on math task intensity is consistently near zero and never statistically significant in any decade.

Unlike the replication of Autor et al. (2003) in Figure 3, the multivariate results in Tables 1 and 2 do not show a large decline in the relative importance of routine tasks. This is because routine and social skill task intensity are highly negatively correlated in the O*NET data. In fact, if I exclude the social skill measure from the models in Table 1, routine task intensity becomes large, negative and statistically significant.

In Table 3, I directly estimate the correlation between routine task intensity and social skill task intensity, controlling for a variety of other occupation-level characteristics. Column

[20]This sample restriction omits about 20 percent of all the occupation-year-sex-education-industry cells in the data, and about 30 percent of all employment. See the Data Appendix for the full list of excluded occupation titles.

1 controls only for the median log hourly wage and the O*NET service task measure, while Column 2 adds a variety of other task measures from both the O*NET and the DOT.[21] The conditional correlation between an occupation's "routineness" and its social skill intensity moves from -0.68 in Column 1 to -0.56 in Column 2, and both are highly statistically significant.

The bottom line from Table 3 is that an occupation's routine task intensity is a very strong predictor of whether that occupation also has low social skill requirements. Moreover, when the two measures are included together in a multivariate framework, social skills are a relatively more important predictor of changes in employment and wages over the last several decades.[22] Thus when moving to the survey data, I use social skill (rather than routine) task intensity as my key predictor of task variation at the occupation level, although results are broadly similar when I use routineness instead.

In the next section, I develop a model of team production that can explain the empirical patterns described above.

3 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. Beginning with Autor et al. (2003), recent work in labor economics has enriched the standard model by drawing a distinction between skills and job tasks (e.g. Acemoglu and Autor 2011, Autor and Handel 2013). In the spirit of this "task framework", consider the following modification of the standard human capital model:

$$y_j\left(i\right) = A_j \alpha_j\left(i\right) l_j\left(i\right) \tag{1}$$

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

Any job can be separated into an infinite number of discrete tasks that must be performed

[21] The model in Column 2 of Table 1 includes all five DOT measures used in Autor et al. (2003), as well as four alternative measures of cognitive skill and three alternative measures of social skill from the O*NET. Details on these measures are in the Data Appendix.

[22] In results not shown, I estimate models just like Table 1 except with an interaction between math task intensity and routine task intensity also included. These interactions are usually near zero and never statistically significant, and they do not meaningfully diminish the coefficient on the interaction between math and social skills.

jointly to produce a final good Y. Following Acemoglu and Autor (2011), I model this as workers performing a continuum of tasks indexed over the unit interval according to a simple Cobb-Douglas technology:

$$Y_j = \exp[\int_0^1 \ln y_j(i) di]. \tag{2}$$

Assume for simplicity that each worker supplies one unit of labor inelastically:

$$\int_0^1 l_j(i) di = L_j = 1. \tag{3}$$

A key difference between the standard human capital model and equation (1) is that two workers with the same average skill level A_j can vary in their productivity over individual tasks. This suggests that there are gains from workers specializing in the production of particular tasks, an idea that dates back to the *Wealth of Nations* (Smith 1776).

To think about how the productivity gains from specialization can be realized, I develop a model of workers "trading tasks" in the spirit of Ricardo (1891). Workers can increase their total output Y by producing tasks in which they have comparative advantage and then "trading tasks" with other workers for mutual benefit, just as countries trade goods in a standard Ricardian framework.

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.* In Becker and 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. 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 tasks with all other workers. This allows them to earn higher wages because they can specialize more efficiently in their most productive tasks.[23]

The second important feature of the model is that it generates intuitive predictions about

[23]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 and 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.

when social skills will matter. In particular, the returns to social skill and the benefits of task trade will be increasing in the variance of productivity draws (the α_j's). This is 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 - i.e. the standard human capital model. With zero variance in productivity draws, ability (absolute advantage) A_j is the sole determinant of relative productivity and there are no gains from trade.

Finally, note that 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, 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 is that it represents *flexibility*, defined as the extent to which a worker adjusts to changes in their comparative advantage as other factors are introduced to the production process.

3.1 Setup

Consider a competitive market where Y is the unique final good - produced according to (2) - and labor is the only factor of production. Workers seek to maximize output Y_j subject to their labor supply constraint in (3). Here I develop the simple case with bilateral task trade between two workers.[24] Since the two-worker model is isomorphic to the two-country Ricardian trade model of Dornbusch et al. (1977), I keep the presentation of the model brief and refer the reader to the Appendix for proofs and more detailed exposition.[25]

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:

$$\gamma(i) \equiv \frac{\alpha_1(i)}{\alpha_2(i)} \tag{4}$$

with $\gamma'(i) < 0$ by assumption. Without loss of generality, I let the worker- and task-specific productivities take the form:[26]

$$\alpha_1(i) \quad = \quad \exp(\theta(1-i))$$

[24]This is consistent with their being only two workers in the economy, or with their being two *types* of workers - each with unit mass and with only bilateral trade permitted.

[25]An earlier draft of this paper developed a Ricardian model with multiple workers which closely followed Eaton and 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.

[26]In the Model Appendix, I show that the results hold for many distributions (such as exponential and lognormal) that have finite variance and are bounded below by zero.

$$\alpha_2(i) = \exp(\theta i), \tag{5}$$

which yields the comparative advantage schedule:

$$\begin{aligned}\gamma(i) &= \frac{\exp(\theta(1-i))}{\exp(\theta i)} \\ &= \exp(\theta(1-2i)).\end{aligned} \tag{6}$$

The parameter θ indexes the variance of productivity draws and thus the steepness of the comparative advantage schedule. Note that when $\theta = 0$, equation (1) reduces to a standard human capital model where worker j's productivity reduces to A_j for all tasks and there is no comparative advantage.

3.2 Equilibrium with Costless Trade

Each workers maximizes output by obtaining tasks from the lowest-cost producer, including herself. Thus with costless trade, we can define 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 price of task i is clearly decreasing in worker j's overall skill A_j as well as the individual task productivity. The equilibrium price for each task is the lowest 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

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

where $\omega = w_1/w_2$ and $\bar{A} = A_1/A_2$. 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 (2). In equilibrium, the price-adjusted quantity of output for the marginal task i^* must be the same for both workers. This, combined with the constant labor share in tasks implied by the Cobb-Douglas production function, yields the following equilibrium condition for the demand for tasks:[27]

[27]See the Model Appendix for a proof.

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

Equation (9) shows that worker 1's wages are increasing in the demand for tasks that worker 1 has a comparative advantage in producing.[28] We solve for the equilibrium 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 task variance θ.[29]

The relative wage ω is clearly increasing in the task threshold - for example, if $A_1 = A_2$, then $i^* = \frac{1}{2}$ and $\omega = 1$. However, *absolute* wages are increasing in a worker's own skill A 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, the variance of productivity draws.[30]

3.3 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:

$$\begin{aligned} p_1(i) &< p_2^S(i) \\ \frac{w_1}{A_1\alpha_1(i)} &< \frac{w_2}{S^* A_2 \alpha_2(i)} \\ \omega &< \frac{\bar{A}\gamma(i)}{S^*}. \end{aligned} \tag{10}$$

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

$$\gamma(i^H) = \frac{S^*\omega}{\bar{A}} \tag{11}$$

[28] Equation (9) can also be derived by noting that trade must be balanced in equilibrium, i.e. the fraction of worker 1's income spent on tasks produced by worker 2 must be equal to the fraction of worker 2's income spent on tasks produced by worker 1: $w_1(1-i^*) = w_2 i^*$.

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

[30] The Model Appendix shows that equilibrium wages are equal to each worker's output level scaled by the competitive output price. 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 $\exp\left(\int_0^{i^*} \ln\left[\frac{\gamma(i)}{\gamma(i^*)}\right] di\right) = \exp(\theta[i^*-1]^2)$ 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.

$$\gamma(i^L) \quad = \quad \frac{\omega}{S^* \bar{A}}. \tag{12}$$

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 $[i^H, 1]$ 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^* as in the costless trade case in Section 3.2 above. For any values $i^L \leq 0$ and $i^H \geq 1$, workers will maximize output by producing all tasks themselves (i.e. autarky).

Figure 8A provides a visual illustration of the equilibrium task thresholds under two different values of θ. Panel A shows the case where θ is lower and the comparative advantage schedule is flatter, while Figure 8B shows the impact of increasing θ and making the comparative advantage schedule steeper.

Figure 8 shows 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 (11) and (12) for ω, which yields:[31]

$$i^H - i^L = -\frac{\ln S^*}{\theta} \tag{13}$$

Equation (13) 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 (13) 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 (11) and (12) and the demand for tasks, which is given simply by:

$$\omega = \frac{i^L}{1 - i^H}. \tag{14}$$

Combining (11), (12) and (14) 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.

3.4 Empirical Predictions

The model generates severable testable predictions. The first prediction is that *cognitive skill A and social skill S are complements, and both skills have a positive return in the labor*

[31] See the Model Appendix for details.

market. See the Model Appendix for a proof, although the intuition is straightforward. The value of a given increase in social skills (which indexes the gains from task trade) is greater when workers are more productive (i.e. higher cognitive skills).[32] I test this prediction by interacting measures of cognitive skill and social skill in a wage equation. 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 these results.

Additionally, Figure 8 and equation (13) show clearly that *the return to social skill is increasing in the variance of productivity draws (i.e. S^* and θ are complements).* See the Model Appendix for a proof. Intuitively, the gains from trade are greater as the size of the nontraded zone $[i^L, i^H]$ shrinks toward zero, which happens as θ increases and as $S^* \to 1$.

In principle, I can test this prediction by interacting a measure of social skill with the social skill intensity of a worker's occupation, my preferred measure of θ. However, there are at least two problems with this approach. First, the complementarity between S^* and θ implies that workers with higher social skills will sort into jobs with higher task variance and will earn relatively higher wages in those jobs.[33] Second, in the model there is a clear spillover of one worker's skill to the other worker's wages. Thus the wage returns to one worker's skills cannot be identified without information about the skills of the other workers.[34]

I address this empirical limitation in three ways. First, I directly test the sorting prediction by asking whether workers with higher social skills are more likely to work in non-routine and social skill-intensive occupations. Second, I test whether *within-worker* sorting into social skill-intensive 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.

The alternative hypothesis advanced by Krueger and Schkade (2008) is that workers

[32]Consider the special case where workers have equal cognitive skill, that is where $A_1 = A_2 = A$, so $\bar{A} = \omega = 1$. 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 own cognitive skill 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, where we condition on cognitive skill directly.

[33]The baseline model is written with only one sector and a common value of θ. However, it is straightforward to show that if there are two sectors - each employing two workers - the wage return to working in the higher θ sector is *increasing* in social skills. Thus, conditional on cognitive skill, workers with the highest values of S will always sort into the highest θ sectors. The Model Appendix provides a proof of this proposition.

[34]By allowing a worker's productivity to depend on the productivity of her fellow workers, the model speaks to evidence on agglomeration externalities from social interaction and face-to-face contact (Glaeser 1999, Storper and Venables 2004). Bacolod et al. (2009) find that the labor market return to "soft skills" is increasing in city size, and a number of studies have documented higher wages and higher returns to skills in cities (e.g. Glaeser and Mare 2001, Bacolod et al. 2009). The framework of task trade could potentially be applied to studies of social capital and peer effects models, where outcomes are a function of both individual and group characteristics (Glaeser et al. 2002).

sort into interactive jobs because they have a preference for interpersonal interaction. This "compensating differentials" predicts that sorting to a social skill-intensive occupation *lowers* wages, all else equal. Third, because S and θ are complements, any wage gain from switching into a more social skill-intensive occupation should be increasing in the worker's social skills.

I test each of the predictions using data from the National Longitudinal Survey of Youth (NLSY) 1979 and 1997 waves, which give me multiple observations of the same worker. This allows me to address the sorting problem by estimating wage regressions with worker fixed effects and interactions between skills and the task content of occupations.

3.5 The Growing Importance of Social Skills

Section 2 presents evidence of relative employment and wage growth in non-routine and social skill-intensive (i.e. high θ) jobs between 1980 and 2012. The model in Section 3 predicts that the return to social skills is increasing in θ, the variance of productivity draws. Taken together, this suggests that social skills have become more important because the jobs that require them are more numerous and pay relatively higher wages.

While Section 2 presents evidence of shifts in demand *across* occupations, the O*NET data are not well-designed for looking at changes in task content *within* occupations.[35] A growing literature studies how information and communication technology (ICT) has shifted job design within occupations, toward arrangements that favor team production and thus workers with social skills. 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 and Van Reenen 2001, Bresnahan et al. 2002, Autor et al. 2003, Bartel et al. 2007, Akerman et al. 2015).

Autor et al. (2002) discuss how the development of digital check imaging in banks shifted workers away from routine tasks such as reading and proofing check deposits and toward problem solving and customer account management. Caroli and Van Reenen (2001) show that ICT complements workers who are better at analyzing and synthesizing information and who are better communicators. In discussing the impact of ICT on firm organization, Bresnahan et al. (2002) specifically mention both problem-solving ability and "people skills" as possible complements to computerization of the workplace. Bartel et al. (2007) find that valve manufacturing firms who invest in new technology that automates routine tasks are more likely to simultaneously reorganize workers into problem-solving teams; and to introduce regular shop floor meetings.

[35] Although O*NET has been administered multiple times between 1998 and the present, changes in the task content measures as well as the scaling of O*NET variables makes it difficult to compare the task content of occupations longitudinally.

Dessein and 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. They also show how improvements in ICT, broad and flexible job assignments, and intensive employee communication are complements in organization design.

In the context of the model, the rich case study evidence of changes in job design over the last few decades suggests that θ - the variance of productivity draws - may be increasing *within* occupations as well as across them. I can test this directly by comparing the returns to social skills in the 1979 and 1997 waves of the NLSY. I first estimate the unconditional returns to skills across occupations using highly comparable measures of skills for workers in a similar age range. I then ask whether the *within-worker* wage returns to social skill-intensive occupations - which are coded consistently over time - have increased across survey waves. If so, this would imply that θ has increased within occupations. More generally, comparing the return to social skills across NLSY waves provides a direct test of the hypothesis that social skills have become more important in the labor market over time.

4 NLSY Data

4.1 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 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 the log of wages or 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 and 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 are used by the NLSY or (to my knowledge) 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 at age 6 (retrospective)

3. The number of clubs in which the respondent participated in high school[36]

4. Participation in high school sports (yes/no)

I normalize each variable to have a mean of zero and a standard deviation of one. Then I 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 and 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 and Weinberger 2005, Weinberger 2014, Kniffin et al. 2015). These measures 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

[36] Options include community/youth organzations, hobby or subject matter clubs (unspecified), student council/student government, school yearbook or newspaper staff, and band/drama/orchestra.

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 their 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 and 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 and 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.

4.2 NLSY97

I test for 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). The NLSY97 does not ask questions about clubs or participation in high school sports. Following the procedures above, I normalize these two questions, take the average and then re-normalize them. Like the NLSY79, the NLSY97 also includes information on non-cognitive skills (the Big 5 factor conscientiousness), as well as education, occupation and industry.

In the comparison of the return to social skills across waves in Sections 5.4 and 5.5, 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.

5 Empirical Models and Results

To summarize, I test the following five predictions of the model from Sections 3.4 and 3.5:

1. There is a positive return to social skills in the labor market, and cognitive skills and social skills are complements.
2. Workers with higher social skills sort into social skill-intensive occupations.
3. Workers earn a higher wage when they self-select into social skill-intensive occupations, and the wage return to self-sorting is increasing in the worker's own social skills.
4. The return to social skills is higher in the NLSY97 than in the NLSY79.
5. The within-worker wage gain from sorting into a social skill-intensive occupation is higher in the NLSY97, and the gain is increasing in the worker's own social skills.

5.1 Labor Market Returns to Skills and Complementarity

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

$$wage_{ijt} = \alpha + \beta_1 COG_i + \beta_2 SS_i + \beta_3 COG_i * SS_i + \gamma X_{ijt} + \delta_j + \zeta_t + \epsilon_{ijt} \tag{15}$$

The results are in Table 4. 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 \$2.67, relative to baseline mean of about \$16.23. Column 2 adds the AFQT, my measure of cognitive skill. A one standard deviation increase in cognitive skill increase hourly wages by \$4.36. The addition of cognitive skill lowers the coefficient on social skills to \$1.59 but it remains highly statistically significant.

Column 3 tests for complementarity by adding the interaction of cognitive skills and social skills. The interaction is positive, large (1.04) and highly statistically significant, which confirms the first prediction of the model. Column 4 adds controls for non-cognitive skills. The non-cognitive skill measure is highly predictive of wages (1.12, p=0.000) but barely changes the coefficients on cognitive skill and social skill, suggesting that each measure contains independent information about productivity. Finally, Column 5 adds controls for years of completed education. Controlling for education reduces the coefficient on all the skill measures, but has the biggest marginal impact on cognitive skills (a reduction of about 40 percent). Nonetheless, all of the skill measures remain highly statistically significant predictors of wages.

Overall, social skills appear to be a very strong predictor of wages even after conditioning on a wide variety of individual characteristics, including completed education and measures of cognitive and non-cognitive skills. Moreover, like Weinberger (2014) I find strong evidence of complementarity between cognitive skills and social skills. Table A3 shows that the labor market return to social skills is positive and statistically significant for all race, gender and education subgroups. 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).

5.2 Occupational Sorting on Skills

I next test the prediction of the model that workers with higher levels of social skill will sort into social skill-intensive occupations. I estimate regressions like equation (15) above but with the task content of occupations (measured using O*NET) as the dependent variable. The baseline model and set of covariates is identical to equation (15).

The results are in Table 5. Column 1 shows that a one standard deviation increase in social skills increases the social skill task intensity of a worker's occupation by 2.35 percentiles, and the coefficient is highly statistically significant. I also find a positive coefficient on cognitive skills. Column 2 adds industry fixed effects, which yields very similar results.

Column 3 adds controls for math task intensity as well as three other related O*NET cognitive task measures. Conditional on overall cognitive task intensity, workers in social skill-intensive occupations have somewhat lower cognitive skills (-0.044, p=0.021) and significantly higher social skills (0.119, p=0.000). This finding is robust to controlling for non-cognitive skills as well (Column 4).

Column 5 estimates a parallel specification to Column 4 except with math task intensity as the outcome and with controls for social skill task intensity as well as two other O*NET measures related to social interaction. I find that workers in math-intensive occupations are strongly selected on cognitive skill (0.285, p=0.000) but negatively selected on social skill and on skill complementarity. This suggests that workers with high cognitive skill and low social skill are particularly likely to sort into high math, low social skill occupations.

Finally, Column 6 estimates the impact of skills on sorting into customer service-intensive occupations. In contrast with the results in Columns 1 through 4, I find that workers with higher social skills are *less* likely to sort into jobs with high service intensity. The coefficients on the other skill measures are also negative, which reinforces the finding that customer service occupations require lower levels of skill and are distinct from occupations that require coordination between workers.

Overall, the results in Table 5 strongly confirm the predictions of the model related to occupational sorting. However, the implication is that estimates of the return to skill within occupations should be interpreted with caution. I address this difficulty by estimating the return to skill controlling for worker fixed effects, which looks at changes in the returns to skill when the same worker switches jobs.

5.3 Returns to Skills by Occupation Task Intensity

As discussed in Section 3.4, the model predicts that the return to social skills is increasing in the variance of productivity draws (i.e. θ). This suggests that workers will earn more when they sort into social skill-intensive occupations, and that the wage gain from sorting will be increasing in the worker's social skills. Using the social skill intensity of an occupation as a proxy for θ, I estimate:

$$\begin{aligned} wage_{ijt} &= \beta_1 COG_i * T_{ijt} + \beta_2 SS_i * T_{ijt} + \beta_3 COG_i * SS_i * T_{ijt} \\ &+ \gamma X_{ijt} + \eta_i + \delta_j + \zeta_t + \epsilon_{ijt} \end{aligned} \tag{16}$$

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. The results are in Table 6. The baseline specification in Column 1 shows that workers earn significantly higher wages in social skill-intensive occupations and that the wage gain is increasing in social skills, cognitive skills and their interaction. All four coefficients are statistically significant at the less than one percent level.

The magnitude of the main effect on social skill intensity suggests that a worker of average skill level earns about 19 cents more per hour when she switches to an occupation that is 10 percentiles higher in social skill intensity. In contrast, a worker with cognitive skill and social skill that is one standard deviation above average earns a wage gain of about 87 cents for a 10 percentile increase in social skill intensity.

Column 2 adds controls for a wide variety of other O*NET task measures. Accounting for a wide variety of other measures job task content leaves these results nearly unchanged. Moreover, the main effect of social skill intensity more than doubles to 0.473 and remains highly statistically significant.

One possible interpretation of the positive coefficients on social skills is that they reflect the promotion of employees to management positions. Column 3 controls for an indicator variable for any occupation with the word "manager" or "supervisor" in the title, which includes about 11.8 percent of the employed sample. Column 4 adds industry fixed effects. In both cases, the results are nearly unchanged.

Column 5 adds interactions between skills and math task intensity, while Column 6 does the same for customer service. Strikingly, the pattern of results does not replicate for math-intensive occupations. While the main effect is positive and statistically significant (0.210, p=0.021), none of the interactions between skills and math task intensity are statistically distinguishable from zero. Moreover, they do very little to attenuate the coefficients on the interaction between skills and social skill task intensity.

Column 6 shows *negative* interactions between skills and customer service task intensity, although none are statistically distinguishable from zero. Moreover, all of the main effects on customer service task intensity in Columns 2 through 6 are negative and statistically significant.

This is broadly consistent with Krueger and Schkade (2008), where workers sort to customer service jobs because of preferences for social interaction. While Krueger and 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, and the results in Column 6 are consistent with that story. However, the wage *gains* from switching into a social skill-intensive occupation show in Table 6 are not consistent with a compensating differentials story. Instead, the results in Table 6 strongly 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".

5.4 Returns to Skills Across NLSY Waves

Overall, the empirical results from the NLSY79 strongly confirm the key predictions of the model. Additionally, the relative employment and wage gains for social skill-intensive occupations presented in Section 2 - combined with the case study evidence discussed in Section 3.5 - provide circumstantial evidence that social skills are becoming more important over time.

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, and I restrict the age range and covariate set across waves to maximize comparability. I compare the returns to skills across waves by estimating:

$$y_{ijt} = \alpha + \sum_{s=1}^{S} \left[\beta_s SKILL_i + \gamma_s \left(SKILL_i * NLSY97_i\right)\right] + \zeta X_{ijt} + \delta_j + \zeta_t + \epsilon_{ijt} \tag{17}$$

where 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, as well as 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 real hourly wage (conditional on employment). As a reminder, I restrict the age range to 25-33 to maximize comparability across waves, although age and year fixed effects are included in all specifications.

The results are in Table 7. 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 6.9 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. In the NLSY79, 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), compared to 3 percentage points in the NLSY97 sample (p=0.000).

Importantly, 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 2. 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 cognitive skill overall but has almost no impact on the change in returns to skills over time. Column 3 adds a measure of 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 0.7 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.[37]

Interestingly, I find that the wage return to cognitive skills appears to have *declined* over time. This is consistent with Castex and Dechter (2014), who also study the changing returns to cognitive skill using the NLSY. In contrast, the returns to social skill appear to have increased slightly, although the coefficients are somewhat small (around \$0.30 for a one standard deviation increase in social skill) and only statistically significant at the 10 percent level in Columns 5 and 6. Overall, the results in Table 7 are broadly consistent with social skills becoming more important in the labor market over time.

5.5 Changes in the Relative Returns to Skill Across Occupations

As a final test, I study 1) whether the wage gain from sorting into a social skill-intensive occupation has changed across survey waves; and 2) whether this wage gain (if any) is increasing in a worker's social skills. I test both hypotheses by estimating:

$$\begin{aligned} wage_{ijt} &= \sum_{s=1}^{S}\left[\beta_s\left(SKILL_i * T_{ijt}\right) + \vartheta_s\left(T_{ijt} * NLSY97_i\right) + \gamma_s\left(SKILL_i * T_{ijt} * NLSY97_i\right)\right] \\ &\quad + \zeta X_{ijt} + \eta_i + \delta_j + \phi_t + \epsilon_{ijt} \qquad (18) \end{aligned}$$

Equation (18) takes the same general form as equation (16), 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 8. Columns 1 through 3 include only the two-way interactions between the task measures T_{ijt} and the NLSY97 indicator. In Column 1, I find that the wage 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 only 2 cents per hour in the late 1980s and early 1990s, compared

[37] Table A4 shows that occupational sorting on skills is very similar across waves. Since the impact of skills on the probability of full-time employmentt has increased sharply, this suggests that the change in wage returns to skills across NLSY waves estimated in Table 5 are likely a lower bound.

to about 41 cents per hour in the 2004-2012 period.[38] In contrast, the wage return to math-intensive occupations appears to have declined from about 0.14 to close to zero, and the difference across waves is statistically significant. The results become smore pronounced when I add controls for other O*NET task measures (Column 2) and industry fixed effects (Column 3).

Columns 4 through 6 add the three-way interactions with skills shown in equation (18). I add summary tests of statistical significance across multiple coefficients on skills at the bottom of Table 8. Overall, I find modest evidence that the wage gain from switching to a social skill-intensive occupation is increasing in worker skills to a greater extent in the NLSY97 sample. While none of the three-way interactions are statistically significant on their own, they are always positive and relatively large. Moreover, a joint test for whether the relative returns to skill are greater in the NLSY97 can reject at the 10 percent level in the basic model (Column 4), although those results are no longer significant once other controls are added (p=0.222 and p=0.241 in Columns 5 and 6). In sum, comparing the returns to skills and the impact of job changes across survey waves yields results that are broadly consistent with the growing importance of social skills in the labor market.

6 Conclusion

This paper presents evidence of growing demand for social skills in the U.S. labor market over the last several decades. I show that social skill-intensive occupations have grown by nearly 10 percentage points as a share of the U.S. labor force, and that wage growth has also been particularly strong for social skill-intensive occupations. 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. This finding is robust to controlling for overall shifts in educational attainment and industry mix, and to excluding occupations that are in high-skilled but service-intensive sectors such as education and health care.

Why are social skills so important in the modern 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

[38]Note that this estimate differs from the worker fixed effects models in Table 6, 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.)

over thousands of years. Human interaction in the workplace involves team production, 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 and better realize the gains from specialization.

The model generates intuitive predictions about sorting and the relative returns to skills across occupations, which I test 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.

Finally, I study changes in the returns to skills 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. The NLSY results closely match the broad labor market trends by occupational task content documented in Section 2.

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 then 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 tend to 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.

References

Acemoglu, D.: 1998, Why do new technologies complement skills? directed technical change and wage inequality, *Quarterly journal of economics* pp. 1055–1089.

Acemoglu, D. and Autor, D.: 2011, Skills, tasks and technologies: Implications for employment and earnings, *Handbook of Labor Economics* **4**, 1043–1171.

Adermon, A. and Gustavsson, M.: 2015, Job polarization and task-biased technological change: Evidence from sweden, 1975–2005, *The Scandinavian Journal of Economics* **117**(3), 878–917.

Akerman, A., Gaarder, I. and Mogstad, M.: 2015, The skill complementarity of broadband internet, *The Quarterly Journal of Economics* **130**(4), 1781–1824.

Altonji, J. G., Bharadwaj, P. and Lange, F.: 2012, Changes in the characteristics of american youth: Implications for adult outcomes, *Journal of Labor Economics* **30**(4), 783–828.

Antras, P., Garicano, L. and Rossi-Hansberg, E.: 2006, Offshoring in a knowledge economy, *The Quarterly Journal of Economics* **121**(1), 31–77.

Autor, D.: 2014, Polanyi's paradox and the shape of employment growth, *Working Paper 20485*, National Bureau of Economic Research.

Autor, D.: 2015, Why are there still so many jobs? the history and future of workplace automation, *The Journal of Economic Perspectives* **29**(3), 3–30.

Autor, D. and Dorn, D.: 2013, The growth of low-skill service jobs and the polarization of the us labor market, *The American Economic Review* **103**(5), 1553–1597.

Autor, D., Dorn, D. and Hanson, G. H.: 2015, Untangling trade and technology: Evidence from local labour markets, *The Economic Journal* **125**(584), 621–646.

Autor, D. H. and Handel, M. J.: 2013, Putting tasks to the test: Human capital, job tasks, and wages, *Journal of Labor Economics* **31**(2 Part 2), S59–S96.

Autor, D., Katz, L. F. and Kearney, M. S.: 2006, The polarization of the us labor market, *The American Economic Review* **96**(2), 189–194.

Autor, D., Katz, L. F. and Kearney, M. S.: 2008, Trends in us wage inequality: Revising the revisionists, *The Review of Economics and Statistics* **90**(2), 300–323.

Autor, D., Levy, F. and Murnane, R. J.: 2002, Upstairs, downstairs: Computers and skills on two floors of a large bank, *Industrial & Labor Relations Review* **55**(3), 432–447.

Autor, D., Levy, F. and Murnane, R. J.: 2003, The skill content of recent technological change: An empirical exploration, *The Quarterly Journal of Economics* **118**(4), 1279—1333.

Autor, D. and Price, B.: 2013, The changing task composition of the us labor market: An update of autor, levy, and murnane (2003), *Working paper*, Massachusetts Institute of Technology.

Bacolod, M., Blum, B. S. and Strange, W. C.: 2009, Skills in the city, *Journal of Urban Economics* **65**(2), 136–153.

Baker, C. A., Peterson, E., Pulos, S. and Kirkland, R. A.: 2014, Eyes and iq: A meta-analysis of the relationship between intelligence and reading the mind in the eyes, *Intelligence* **44**, 78–92.

Baron-Cohen, S.: 2000, Theory of mind and autism: A fifteen year review., *in* S. Baron-Cohen, H. Tager-Flusberg and D. Cohen (eds), *Understanding other minds: Perspectives from developmental cognitive neuroscience*, 2 edn, Oxford University Press, New York, NY.

Baron-Cohen, S., Wheelwright, S., Hill, J., Raste, Y. and Plumb, I.: 2001, The reading the mind in the eyes test revised version: A study with normal adults, and adults with asperger syndrome or high-functioning autism, *Journal of Child Psychology and Psychiatry* **42**(2), 241–251.

Barron, J. M., Ewing, B. T. and Waddell, G. R.: 2000, The effects of high school athletic participation on education and labor market outcomes, *The Review of Economics and Statistics* **82**(3), 409–421.

Bartel, A., Ichniowski, C. and Shaw, K.: 2007, How does information technology affect productivity? plant-level comparisons of product innovation, process improvement, and worker skills, *The Quarterly Journal of Economics* **122**(4), 1721–1758.

Beaudry, P., Green, D. A. and Sand, B. M.: 2014, The declining fortunes of the young since 2000, *The American Economic Review* **104**(5), 381–386.

Beaudry, P., Green, D. A. and Sand, B. M.: 2016, The great reversal in the demand for skill and cognitive tasks, *Journal of Labor Economics* **34**(1), 199–247.

Becker, G. S. and Murphy, K. M.: 1992, The division of labor, coordination costs, and knowledge, *The Quarterly Journal of Economics* **107**(4), 1137–1160.

Bolton, P. and Dewatripont, M.: 1994, The firm as a communication network, *The Quarterly Journal of Economics* **104**(4), 809–839.

Borghans, L., Ter Weel, B. and Weinberg, B. A.: 2014, People skills and the labor-market outcomes of underrepresented groups, *Industrial & Labor Relations Review* **67**(2), 287–334.

Bound, J. and Johnson, G. E.: 1992, Changes in the structure of wages in the 1980's: An evaluation of alternative explanations, *The American Economic Review* **82**(3), 371–92.

Bresnahan, T. F., Brynjolfsson, E. and Hitt, L. M.: 2002, Information technology, workplace organization, and the demand for skilled labor: Firm-level evidence, *The Quarterly Journal of Economics* **117**(1), 339–376.

Brynjolfsson, E. and McAfee, A.: 2014, *The second machine age: Work, progress and prosperity in a time of brilliant technologies*, W. W. Norton & Company, New York, NY.

Camerer, C., Loewenstein, G. and Prelec, D.: 2005, Neuroeconomics: How neuroscience can inform economics, *Journal of Economic Literature* **43**(1), 9–64.

Card, D., Cardoso, A. R. and Kline, P.: forthcoming, Bargaining, sorting and the gender wage gap: Quantifying the impact of firms on the relative pay of women, *The Quarterly Journal of Economics* .

Card, D., Heining, J. and Kline, P.: 2013, Workplace heterogeneity and the rise of west german wage inequality, *The Quarterly Journal of Economics* **128**(3), 967–1015.

Caroli, E. and Van Reenen, J.: 2001, Skill-biased organizational change? evidence from a panel of british and french establishments, *The Quarterly Journal of Economics* **116**(4), 1449–1492.

Casner-Lotto, J. and Barrington, L.: 2006, Are they really ready to work? employers' perspectives on the basic knowledge and applied skills of new entrants to the 21st century us workforce., *Report*, Partnership for 21st Century Skills.

Castex, G. and Dechter, E. K.: 2014, The changing roles of education and ability in wage determination, *Journal of Labor Economics* **32**(4), 685–710.

Chetty, R., Friedman, J. N., Hilger, N., Saez, E., Schanzenbach, D. W. and Yagan, D.: 2011, How does your kindergarten classroom affect your earnings? evidence from project star, *The Quarterly Journal of Economics* **126**(4), 1593–1660.

Declerck, C. H. and Bogaert, S.: 2008, Social value orientation: Related to empathy and the ability to read the mind in the eyes, *The Journal of Social Psychology* **148**(6), 711–726.

Deming, D.: 2009, Early childhood intervention and life-cycle skill development: Evidence from head start, *American Economic Journal: Applied Economics* **1**(3), 111–134.

Dessein, W. and Santos, T.: 2006, Adaptive organizations, *Journal of Political Economy* **114**(5), 956–995.

Dodge, K. A., Bierman, K. L., Coie, J. D., Greenberg, M. T., Lochman, J. E., McMahon, R. J. and Pinderhughes, E. E.: 2014, Impact of early intervention on psychopathology, crime, and well-being at age 25, *American Journal of Psychiatry* **172**(1), 59–70.

Dornbusch, R., Fischer, S. and Samuelson, P. A.: 1977, Comparative advantage, trade, and payments in a ricardian model with a continuum of goods, *The American Economic Review* **67**(5), 823–839.

Eaton, J. and Kortum, S.: 2002, Technology, geography, and trade, *Econometrica* **70**(5), 1741–1779.

Edmondson, A. C.: 2012, *Teaming: How organizations learn, innovate, and compete in the knowledge economy*, John Wiley & Sons, San Francisco, CA.

Garicano, L.: 2000, Hierarchies and the organization of knowledge in production, *Journal of Political Economy* **108**(5), 874–904.

Garicano, L. and Rossi-Hansberg, E.: 2004, Inequality and the organization of knowledge, *The American Economic Review* **94**(2), 197–202.

Garicano, L. and Rossi-Hansberg, E.: 2006, Organization and inequality in a knowledge economy, *The Quarterly Journal of Economics* **121**(4), 1383–1435.

Gibbons, R., Katz, L. F., Lemieux, T. and Parent, D.: 2005, Comparative advantage, learning, and sectoral wage determination, *Journal of Labor Economics* **23**(4), 681–724.

Glaeser, E. L.: 1999, Learning in cities, *Journal of Urban Economics* **46**(2), 254–277.

Glaeser, E. L., Laibson, D. and Sacerdote, B.: 2002, An economic approach to social capital, *The Economic Journal* **112**(483), 437–458.

Glaeser, E. and Mare, D.: 2001, Cities and skills, *Journal of Labor Economics* **19**(2), 316–42.

Goldberg, L. R.: 1993, The structure of phenotypic personality traits., *American psychologist* **48**(1), 26.

Goleman, D.: 2006, *Emotional intelligence*, Bantam, New York, NY.

Goos, M. and Manning, A.: 2007, Lousy and lovely jobs: The rising polarization of work in britain, *The Review of Economics and Statistics* **89**(1), 118–133.

Goos, M., Manning, A. and Salomons, A.: 2014, Explaining job polarization: Routine-biased technological change and offshoring, *The American Economic Review* **104**(8), 2509–2526.

Gordon, R. J.: 2014, The demise of u.s. economic growth: Restatement, rebuttal, and reflections, *Working Paper 19895*, National Bureau of Economic Research.

Grogger, J. and Eide, E.: 1995, Changes in college skills and the rise in the college wage premium, *Journal of Human Resources* **30**(2), 280–310.

Hackman, J. R.: 2002, *Leading teams: Setting the stage for great performances*, Harvard Business Press, Boston, MA.

Heckman, J. J.: 1995, Lessons from the bell curve, *Journal of Political Economy* **103**(5), 1091–1120.

Heckman, J. J. and Kautz, T.: 2012, Hard evidence on soft skills, *Labour Economics* **19**(4), 451–464.

Heckman, J. J. and Sedlacek, G.: 1985, Heterogeneity, aggregation, and market wage functions: an empirical model of self-selection in the labor market, *The Journal of Political Economy* **93**(6), 1077–1125.

Heckman, J. J., Stixrud, J. and Urzua, S.: 2006, The effects of cognitive and noncognitive abilities on labor market outcomes and social behavior, *Journal of Labor Economics* **24**(3), 411–482.

Heckman, J., Pinto, R. and Savelyev, P.: 2013, Understanding the mechanisms through which an influential early childhood program boosted adult outcomes, *The American Economic Review* **103**(6), 1–35.

Heckman, J. and Scheinkman, J.: 1987, The importance of bundling in a gorman-lancaster model of earnings, *The Review of Economic Studies* **54**(2), 243–255.

Heckman, J. and Vytlacil, E.: 2001, Identifying the role of cognitive ability in explaining the level of and change in the return to schooling, *The Review of Economics and Statistics* **83**(1), 1–12.

Jerald, C. D.: 2009, Defining a 21st century education, *Report*, Center for Public Education.

Jones, D. E., Greenberg, M. and Crowley, M.: 2015, Early social-emotional functioning and public health: The relationship between kindergarten social competence and future wellness, *American Journal of Public Health* **105**(11), 2283–2290.

Juhn, C., Murphy, K. M. and Pierce, B.: 1993, Wage inequality and the rise in returns to skill, *Journal of Political Economy* **101**(3), 410–442.

Kambourov, G., Siow, A. and Turner, L.: 2013, Relationship skills in the labor and marriage markets, *Working paper*, University of Toronto.

Karabarbounis, L. and Neiman, B.: 2014, The global decline of the labor share, *The Quarterly Journal of Economics* **129**(1), 61–103.

Katz, L.: 2014, Get a liberal arts b.a., not a business b.a., for the coming artisan economy, *PBS NewsHour* . Retrieved from http://www.pbs.org/newshour/making-sense/get-a-liberal-arts-b-a-not-a-business-b-a-for-the-coming-artisan-economy/.

Katz, L. F. and Murphy, K. M.: 1991, Changes in relative wages, 1963-1987: Supply and demand factors, *Working Paper 3927*, National Bureau of Economic Research.

Kniffin, K. M., Wansink, B. and Shimizu, M.: 2015, Sports at work: Anticipated and persistent correlates of participation in high school athletics, *Journal of Leadership & Organizational Studies* **22**(2), 217–230.

Krueger, A. B. and Schkade, D.: 2008, Sorting in the labor market: Do gregarious workers flock to interactive jobs?, *Journal of Human Resources* **43**(4), 859–883.

Kuhn, P. and Weinberger, C.: 2005, Leadership skills and wages, *Journal of Labor Economics* **23**(3), 395–436.

Lawrence, E., Shaw, P., Baker, D., Baron-Cohen, S. and David, A.: 2004, Measuring empathy: reliability and validity of the empathy quotient, *Psychological Medicine* **34**(5), 911–920.

Lazear, E. P.: 1999, Globalisation and the market for team-mates, *The Economic Journal* **109**(454), 15–40.

Lazear, E. P.: 2009, Firm-specific human capital: A skill-weights approach, *Journal of Political Economy* **117**(5), 914–940.

Levy, F. and Murnane, R. J.: 2012, *The new division of labor: How computers are creating the next job market*, Princeton University Press.

Lindbeck, A. and Snower, D. J.: 2000, Multitask learning and the reorganization of work: From tayloristic to holistic organization, *Journal of Labor Economics* **18**(3), 353–376.

Lindenlaub, I.: 2013, Sorting multidimensional types: Theory and application, *Working paper*, European University Institute.

Lindqvist, E. and Vestman, R.: 2011, The labor market returns to cognitive and noncognitive ability: Evidence from the swedish enlistment, *American Economic Journal: Applied Economics* **3**(1), 101–128.

Lise, J. and Postel-Vinay, F.: 2015, Multidimensional skills, sorting, and human capital accumulation, *Working paper*, University College London.

Liu, Y. and Grusky, D.: 2013, The payoff to skill in the third industrial revolution, *The American Journal of Sociology* **118**(5), 1330–1374.

Lu, Q.: 2015, The end of polarization? technological change and employment in the us labor market, *Working paper*, University of Texas at Austin.

Mayer, J. D., Caruso, D. R. and Salovey, P.: 1999, Emotional intelligence meets traditional standards for an intelligence, *Intelligence* **27**(4), 267–298.

Mayer, J. D., Roberts, R. D. and Barsade, S. G.: 2008, Human abilities: Emotional intelligence, *Annual Review of Psychology* **59**, 507–536.

McCann, R. J., Shi, X., Siow, A. and Wolthoff, R.: 2014, Becker meets ricardo: Multisector matching with communication and cognitive skills, *IZA Discussion Paper 6533*, Institute for the Study of Labor.

Michaels, G., Natraj, A. and Van Reenen, J.: 2014, Has ict polarized skill demand? evidence from eleven countries over twenty-five years, *Review of Economics and Statistics* **96**(1), 60–77.

Moravec, H.: 1988, *Mind children: The future of robot and human intelligence*, Harvard University Press, Cambridge, MA.

Murnane, R. J., Willett, J. B. and Levy, F.: 1995, The growing importance of cognitive skills in wage determination, *The Review of Economics and Statistics* **77**(2), 251–266.

National Association of Colleges and Employers: 2015, 2015 job outlook, *Report*. Retrieved from https://www.umuc.edu/upload/NACE-Job-Outlook-2015.pdf.

Neal, D. A. and Johnson, W. R.: 1996, The role of premarket factors in black-white wage differences, *The Journal of Political Economy* **104**(5), 869–895.

Oldenski, L.: 2012, Export versus fdi and the communication of complex information, *Journal of International Economics* **87**(2), 312–322.

Premack, D. and Woodruff, G.: 1978, Does the chimpanzee have a theory of mind?, *Behavioral and Brain Sciences* **1**(4), 515–526.

Remus, D. and Levy, F. S.: 2015, Can robots be lawyers? computers, lawyers, and the practice of law, *Computers, Lawyers, and the Practice of Law (December 30, 2015)* .

Ricardo, D.: 1891, *Principles of political economy and taxation*, G. Bell, London.

Salovey, P. and Mayer, J. D.: 1990, Emotional intelligence, *Imagination, Cognition and Personality* **9**(3), 185–211.

Sanders, C. and Taber, C.: 2012, Life-cycle wage growth and heterogeneous human capital, *Annual Review of Economics* **4**(1), 399–425.

Smith, A.: 1776, The wealth ofnations, *New York: The Modern Library* .

Storper, M. and Venables, A. J.: 2004, Buzz: Face-to-face contact and the urban economy, *Journal of Economic Geography* **4**(4), 351–370.

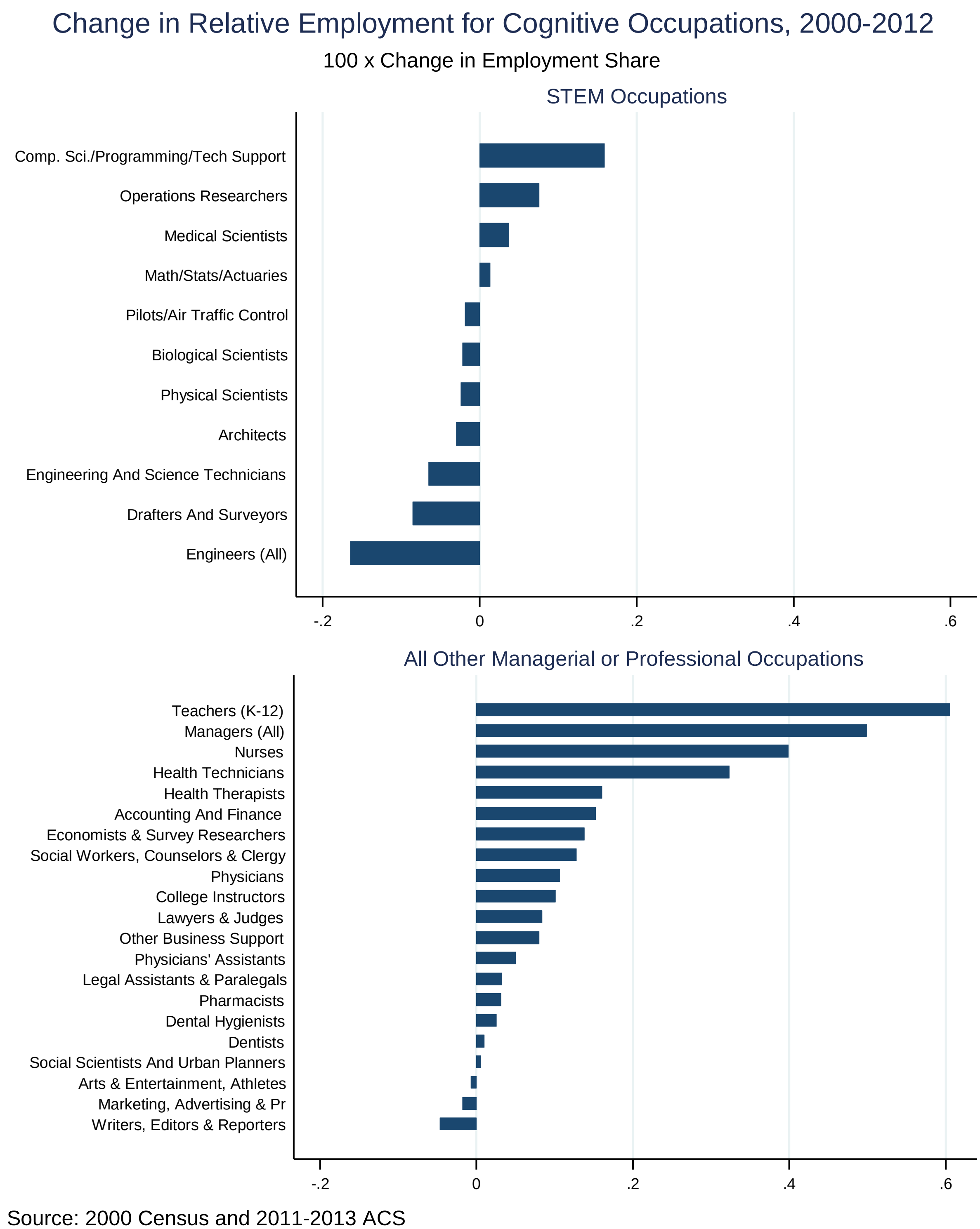
Taber, C. R.: 2001, The rising college premium in the eighties: Return to college or return to unobserved ability?, *Review of Economic Studies* **68**(236), 665–691.

Weinberger, C. J.: 2014, The increasing complementarity between cognitive and social skills, *Review of Economics and Statistics* **96**(4), 849–861.

Woolley, A. W., Chabris, C. F., Pentland, A., Hashmi, N. and Malone, T. W.: 2010, Evidence for a collective intelligence factor in the performance of human groups, *Science* **330**(6004), 686–688.

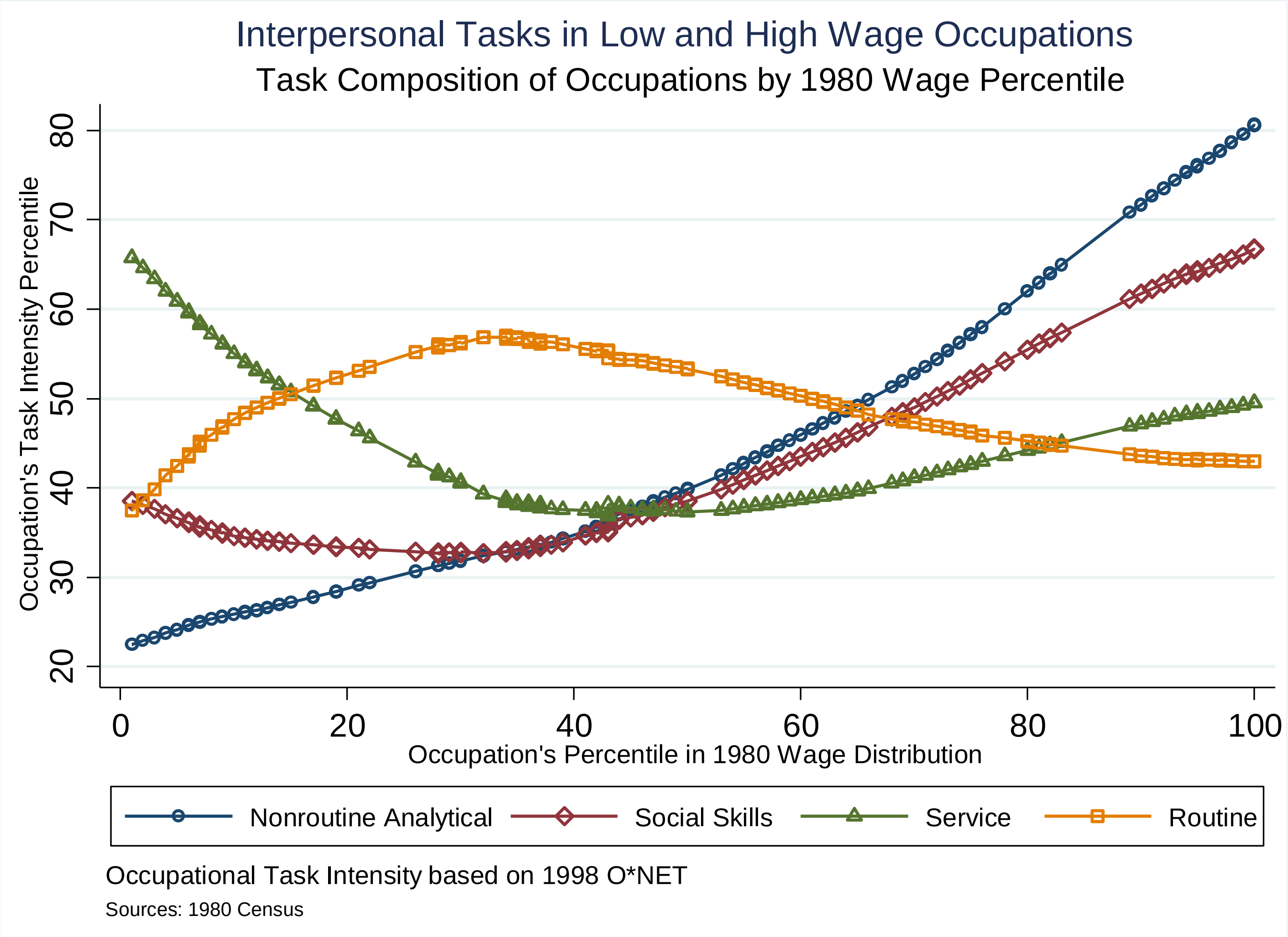
Yamaguchi, S.: 2012, Tasks and heterogeneous human capital, *Journal of Labor Economics* **30**(1), 1–53.

Figure 1



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 2



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 1980-2012 are updated from Autor and Dorn (2013) and Autor and Price (2013).

Figure 3

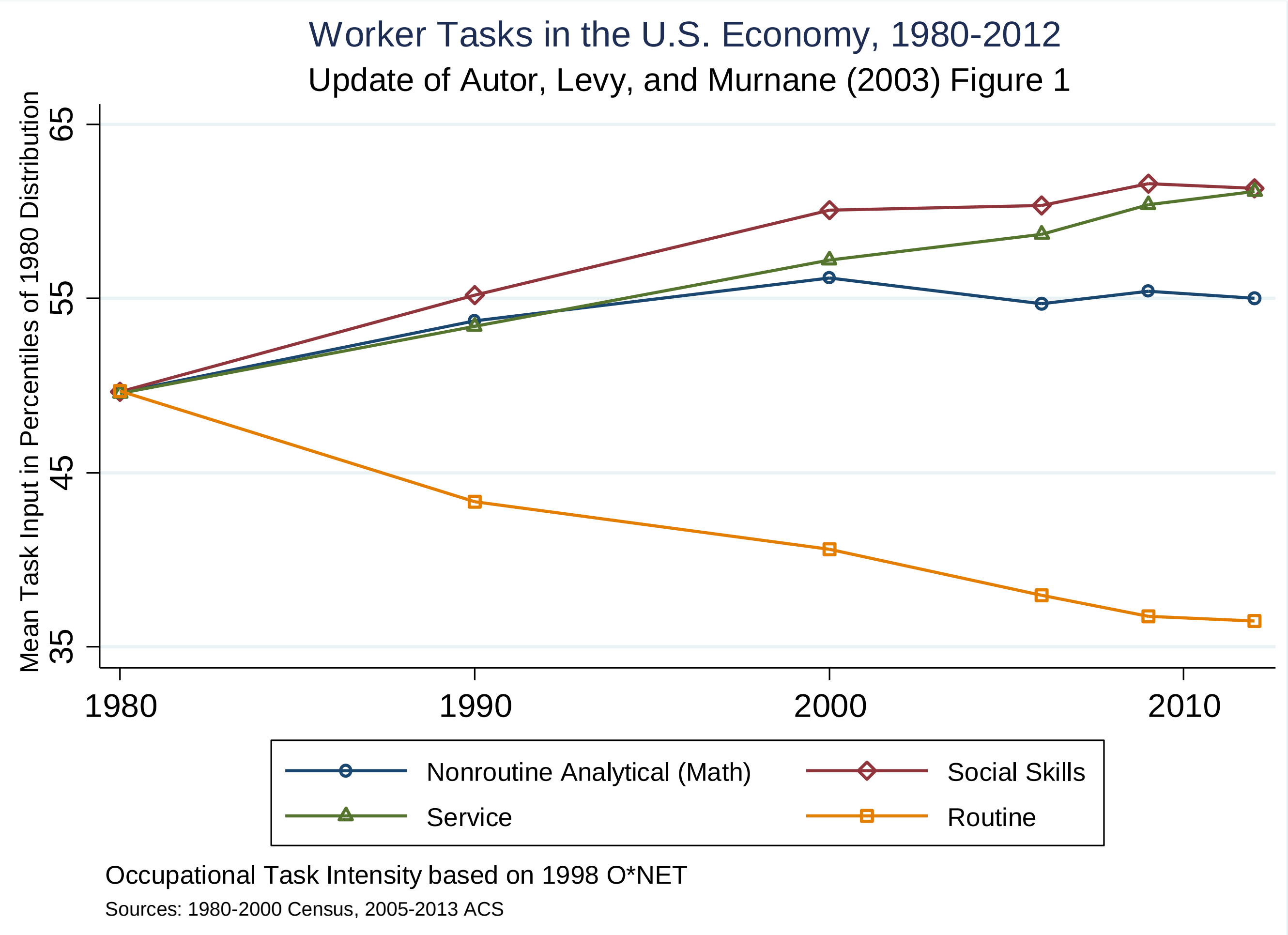
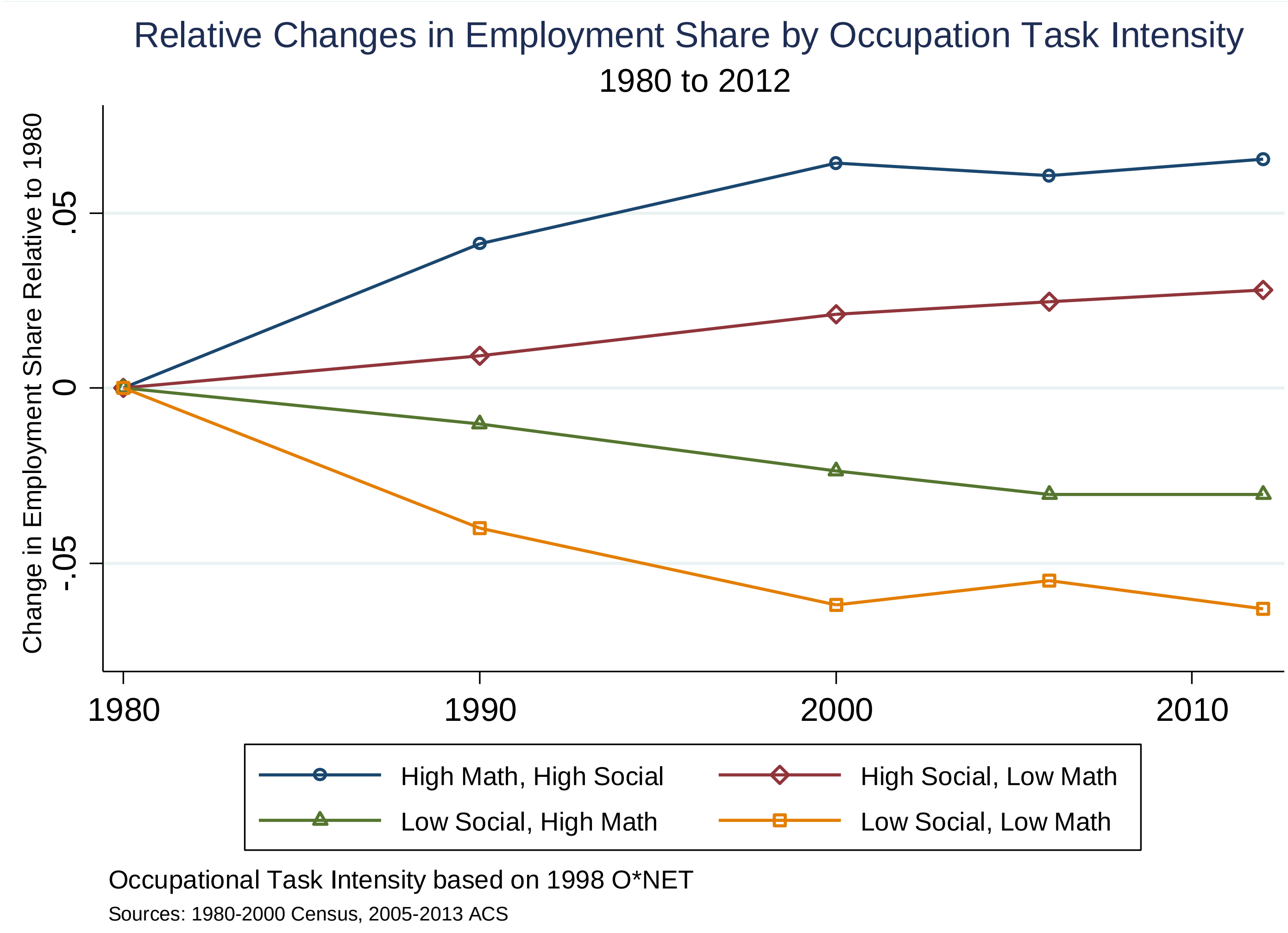


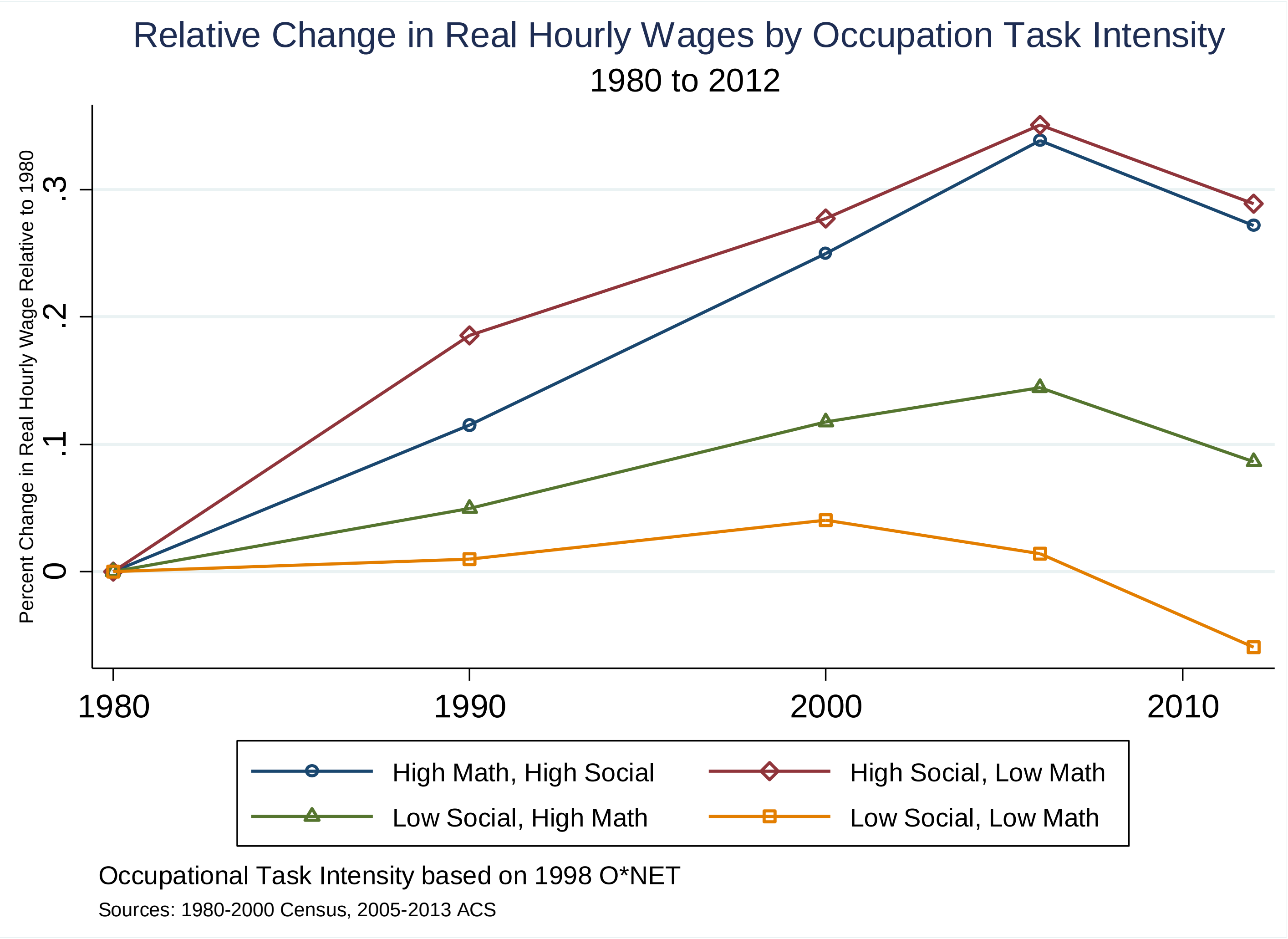
Figure 3 is constructed to parallel Figure I of Autor, Levy and Murnane (2003). O*NET 1998 task measures by occupation are paired with data from the IPUMS 1980-2000 Censuses and the 2005-2013 American Community Survey samples. Consistent occupation codes for 1980-2012 are from Autor and Dorn (2013) and 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 4



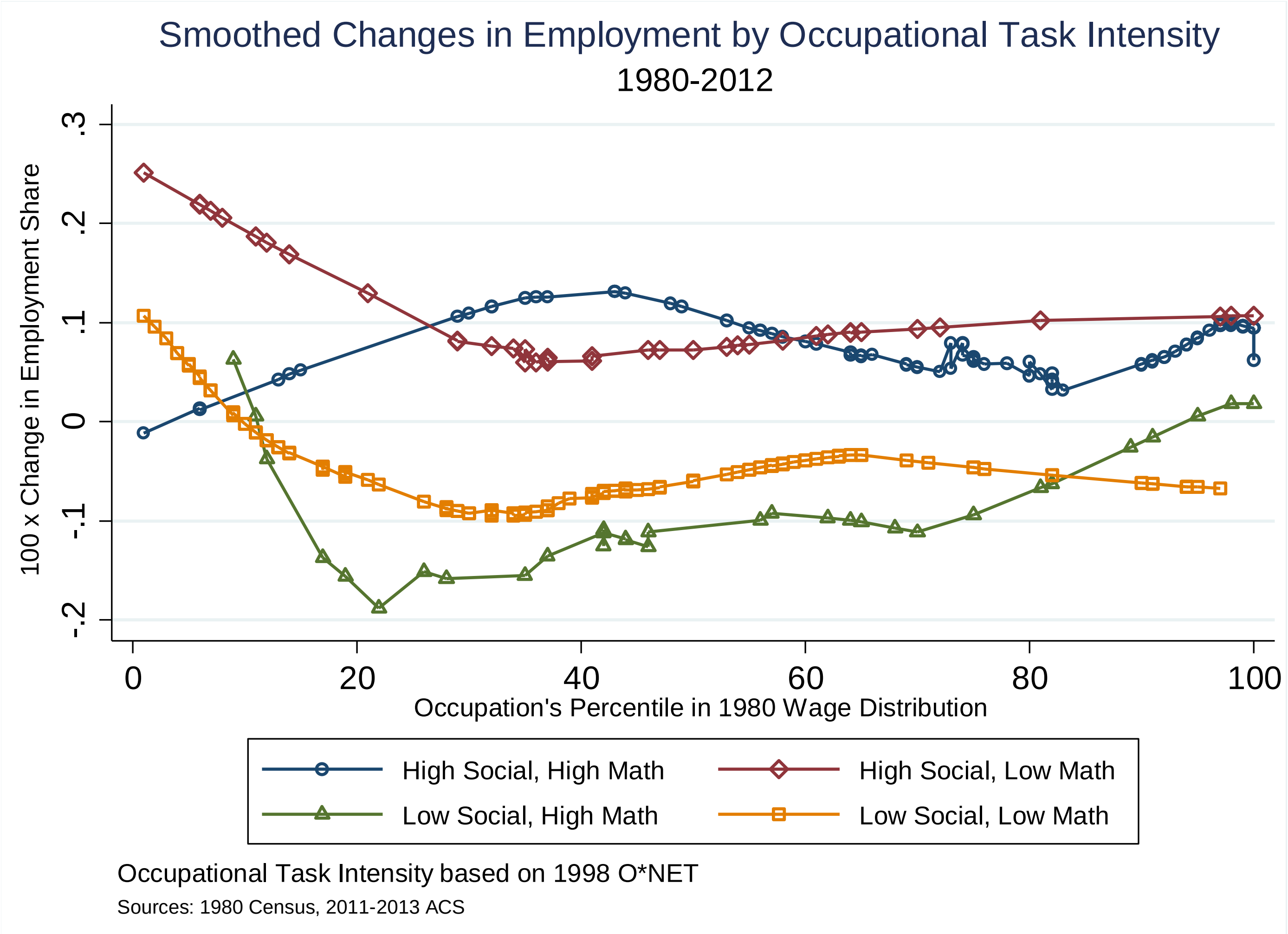
Each line plots 100 times the change in employment share – relative to a 1980 baseline - between 1990 and 2012 for occupations that are above and/or below the 50th percentile in nonroutine analytical and social skill task intensity as measured by the 1998 O*NET. Consistent occupation codes for 1980-2012 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 5



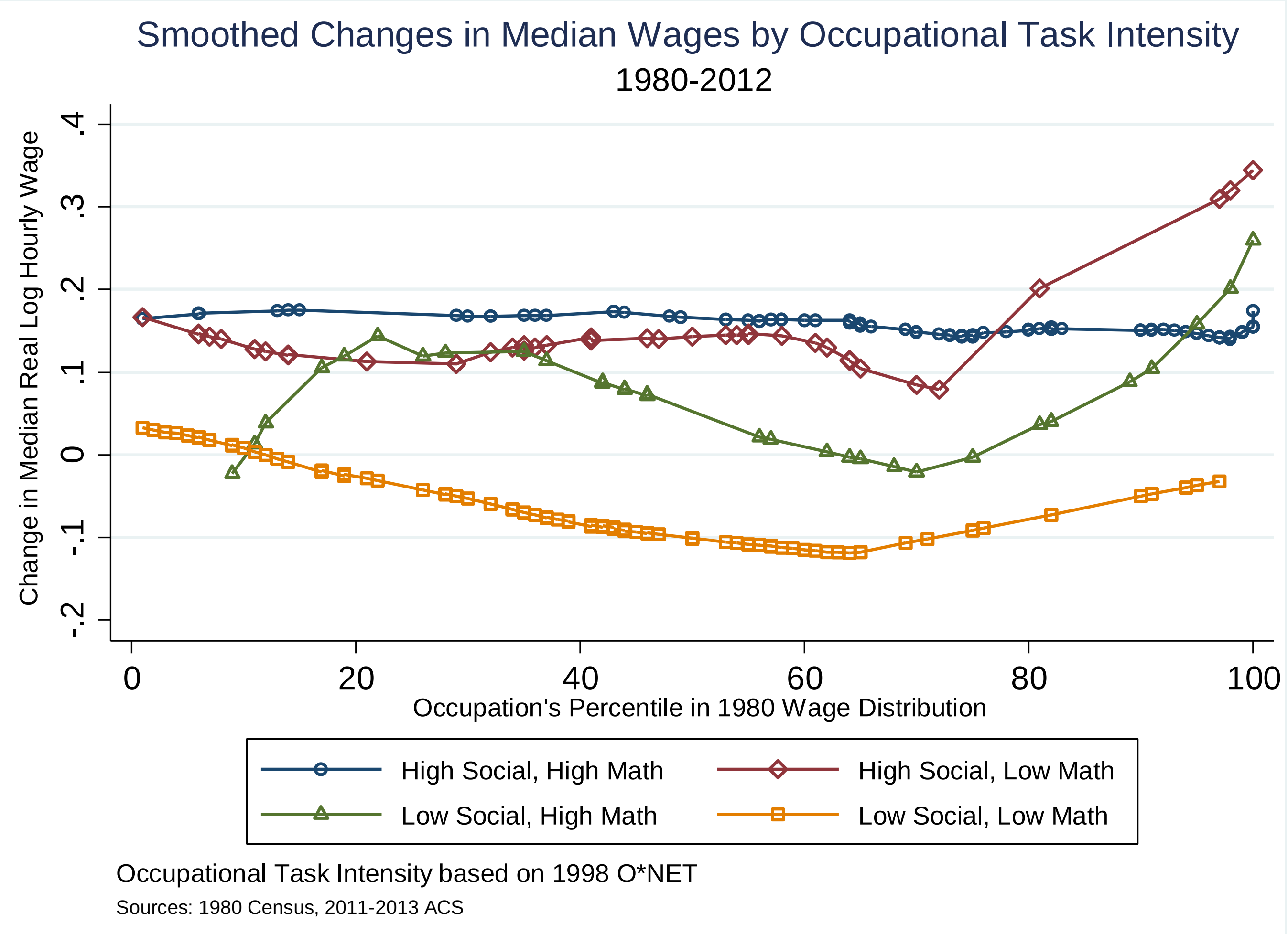
Each line plots the percent change in median hourly wages – relative to a 1980 baseline and in constant 2012 dollars - between 1990 and 2012 for occupations that are above and/or below the 50th percentile in nonroutine analytical and social skill task intensity as measured by the 1998 O*NET. Consistent 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.

Figure 6



Each line plots 100 times the change in employment share between 1980 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. 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 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.

Figure 7



Each line plots 100 times the change in median log hourly real wages between 1980 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. 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 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.

Figure 8A

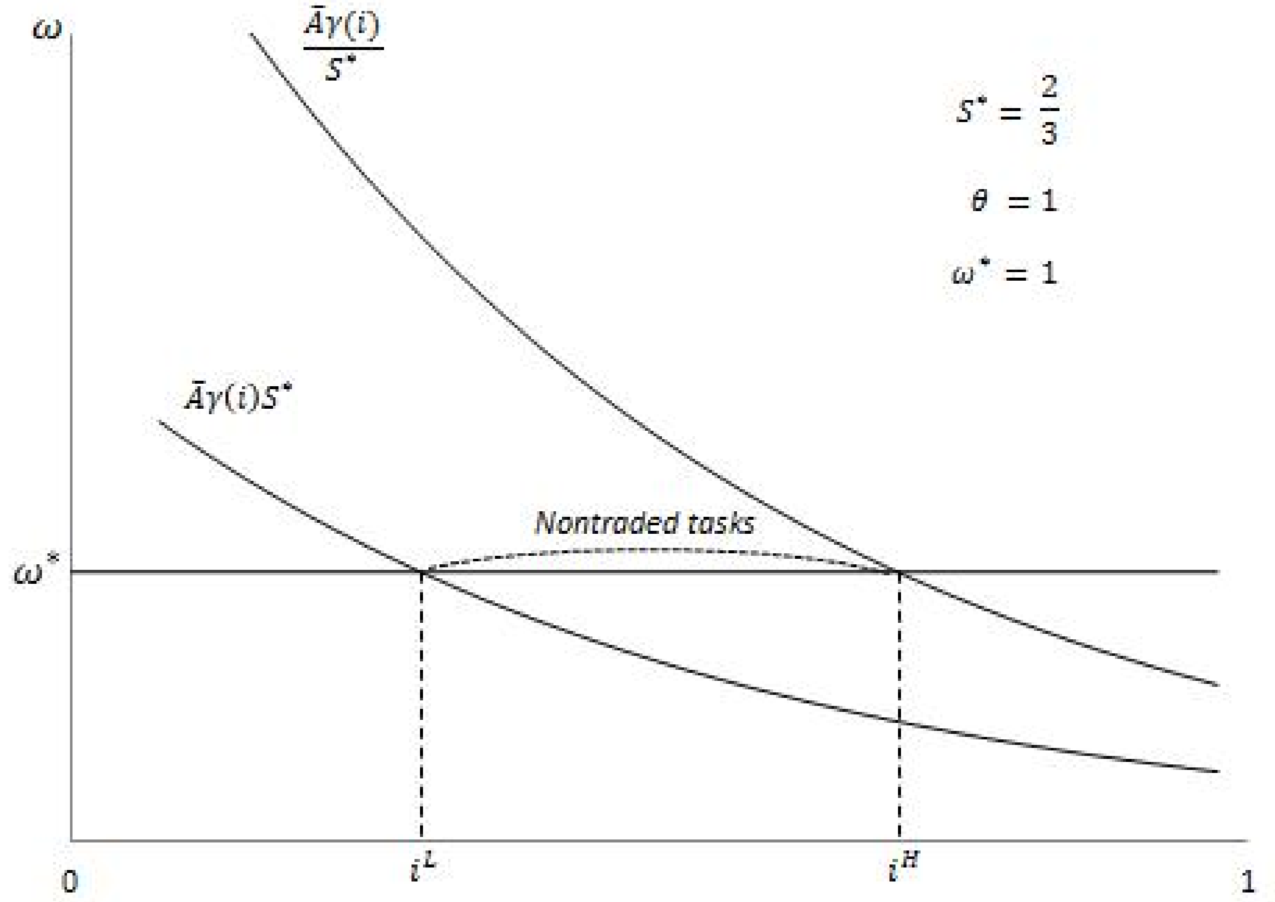


Figure 8A illustrates the equilibrium task thresholds i^L and i^H from the Model in Section 3 of the paper when $S^* = \frac{2}{3}$, $\theta = 1$ and $\omega^* = 1$ – see the text for details.

Figure 8B

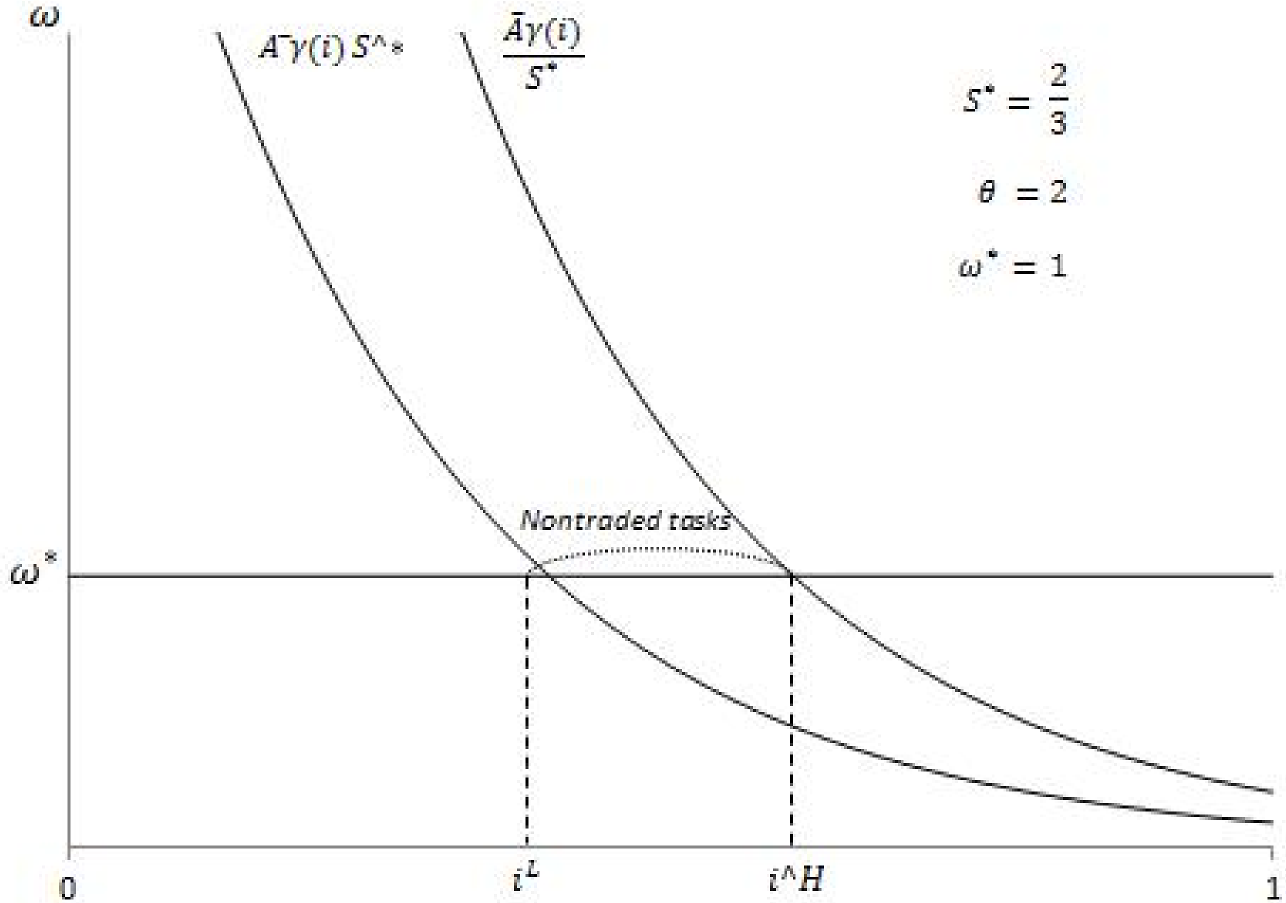


Figure 8B illustrates the equilibrium task thresholds i^L and i^H from the Model in Section 3 of the paper when $S^* = \frac{2}{3}$, $\theta = 2$ and $\omega^* = 1$ – see the text for details.

Table 1 - Changes in Employment by Occupation Task Intensity

	1980-2012			1980-1990	1990-2000	2000-2012	2000-2012
Outcome is Log Employment (LS Weighted)	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Math Task Intensity	-0.053**	-0.075*	-0.127	0.130**	-0.196**	-0.054	-0.117**
	[0.024]	[0.042]	[0.099]	[0.058]	[0.089]	[0.048]	[0.056]
Social Skill Task Intensity	0.054***	0.029	-0.025	0.003	0.052	-0.050	-0.069*
	[0.019]	[0.038]	[0.071]	[0.045]	[0.049]	[0.036]	[0.036]
Math * Social		0.006	0.018*	0.002	0.001	0.012*	0.019***
		[0.008]	[0.010]	[0.007]	[0.009]	[0.007]	[0.007]
Routine Task Intensity			-0.049	-0.012	-0.018	-0.024	-0.019
			[0.039]	[0.020]	[0.031]	[0.017]	[0.019]
Service Task Intensity			0.036	-0.019	0.023	0.034**	0.028
			[0.040]	[0.024]	[0.029]	[0.016]	[0.020]
Sex-Education-Industry Fixed Effects	X	X	X	X	X	X	X
Controls for other O*NET Task Measures			X	X	X	X	X
Exclude Managers, Health Care and Education							X
R-squared	0.516	0.516	0.521	0.714	0.663	0.716	0.698
Observations	74,212	74,212	74,212	74,212	74,212	74,212	60,739

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 2005-2013 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 and are weighted by labor supply to conform to the 1980 occupation distribution. The additional O*NET task measures not included in the table rows are three alternative measures of cognitive skill intensity (the O*NET variables Number Facility, Inductive and Deductive Reasoning, and Analyzing and Using Information) and three alternative measures of social skill intensity (the O*NET variables Require Social Interaction, Coordinating the Work and Activities of Others, Communicating with Supervisors/Peers/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 2 - Changes in Wages by Occupation Task Intensity

	1980-2012			1980-1990	1990-2000	2000-2012	2000-2012
Outcome is the Log Hourly Wage	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Math Task Intensity	0.0451***	0.0418***	0.0007	0.0044	0.0046	0.0003	-0.0060
	[0.0069]	[0.0101]	[0.0230]	[0.0165]	[0.0162]	[0.0207]	[0.0250]
Social Skill Task Intensity	0.0492***	0.0453***	0.0615***	0.0532***	0.0434***	0.0564***	0.0675***
	[0.0059]	[0.0124]	[0.0159]	[0.0117]	[0.0113]	[0.0143]	[0.0157]
Math * Social		0.0009	-0.0029	-0.0020	-0.0012	-0.0028	-0.0032
		[0.0024]	[0.0023]	[0.0018]	[0.0016]	[0.0021]	[0.0025]
Routine Task Intensity			0.0034	0.0038	0.0027	0.0028	0.0049
			[0.0057]	[0.0046]	[0.0042]	[0.0051]	[0.0052]
Service Task Intensity			-0.0126	-0.0216***	-0.0150***	-0.0118	-0.0255***
			[0.0085]	[0.0063]	[0.0058]	[0.0077]	[0.0097]
Sex-Education-Industry Fixed Effects	X	X	X	X	X	X	X
Controls for other O*NET Task Measures			X	X	X	X	X
Exclude Managers, Health Care and Education							X
R-squared	0.501	0.501	0.516	0.564	0.557	0.525	0.501
Observations	74,212	74,212	74,212	74,212	74,212	74,212	60,739

Notes: Each column reports results from a regression of the natural log of real (indexed to 2012) 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 2005-2013 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 and are weighted by labor supply to conform to the 1980 occupation distribution. The additional O*NET task measures not included in the table rows are three alternative measures of cognitive skill intensity (the O*NET variables Number Facility, Inductive and Deductive Reasoning, and Analyzing and Using Information) and three alternative measures of social skill intensity (the O*NET variables Require Social Interaction, Coordinating the Work and Activities of Others, Communicating with Supervisors/Peers/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 3 - Correlation between Routine and Social Skill Task Intensity

Outcome is the Routine Task Intensity of an Occupation	(1)	(2)
Social Skill Intensity of Occupation	-0.679***	-0.560***
	[0.113]	[0.155]
Add Other O*NET and DOT tasks		X
Observations	337	337
R-squared	0.439	0.662

Notes: Data from the 1980-2000 Census, 2006-2013 ACS, 1991 DOT, and 1998-2013 O*NET. Observations are at the occupation level. Additional DOT task measures are nonroutine analytical, nonroutine interactive, routine cognitive, routine manual and nonroutine manual. Additional O*NET task measures are Number Facility, Inductive/Deductive Reasoning, Use/Analyze Information, the Service task composite and Require Social Interaction. See text and Appendix for details on all O*NET task measures. All models also control for median log hourly wage and are weighted by total labor supply in each cell. Standard errors are clustered at the occupation level. *** p<0.01, ** p<0.05, * p<0.10

Table 4 - Labor Market Returns to Cognitive Skills and Social Skills

Outcome is Hourly Wage (in 2012 dollars)	(1)	(2)	(3)	(4)	(5)
Cognitive Skills (AQT, standardized)		4.36***	4.35***	3.95***	2.32***
		[0.17]	[0.16]	[0.17]	[0.18]
Social Skills (standardized)	2.67***	1.59***	1.20***	1.07***	0.75***
	[0.16]	[0.15]	[0.12]	[0.12]	[0.12]
Cognitive * Social			1.04***	1.04***	0.74***
			[0.17]	[0.16]	[0.16]
Non-cognitive Skills (standardized)				1.12***	0.89***
				[0.15]	[0.15]
Demographics and Age / Year Fixed Effects		X	X	X	X
Years of completed education					X
R-squared	0.132	0.171	0.173	0.176	0.195
Observations	133,603	133,603	133,603	133,539	133,539

Notes: Each column reports results from an estimate of equation (15) in the paper, with real hourly wages as the outcome and person-year as the unit of observation. 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 5 - Sorting into Occupations by Cognitive and Social Skills

	Social Skills				Math	Service
*Outcomes are O*NET Task Measures*	(1)	(2)	(3)	(4)	(5)	(6)
Cognitive Skills (AQT, standardized)	0.404***	0.345***	-0.044**	-0.056***	0.285***	-0.018
	[0.031]	[0.028]	[0.019]	[0.020]	[0.025]	[0.016]
Social Skills (standardized)	0.235***	0.209***	0.119***	0.115***	-0.018	-0.023**
	[0.022]	[0.020]	[0.014]	[0.014]	[0.018]	[0.012]
Cognitive * Social	0.008	0.013	0.012	0.012	-0.064***	-0.021*
	[0.020]	[0.019]	[0.014]	[0.014]	[0.020]	[0.012]
Non-cognitive Skills (standardized)				0.043***	0.027	-0.005
				[0.015]	[0.021]	[0.013]
Demogs, Age / Year, Education Fixed Effects	X	X	X	X	X	X
Industry Fixed Effects		X	X	X	X	X
Controls for O*NET Cognitive Tasks			X	X		X
Controls for O*NET Interactive Tasks					X	X
Observations	133,603	133,603	133,603	133,539	133,539	133,539
R-squared	0.236	0.305	0.668	0.668	0.530	0.796

Notes: Each column reports results from an estimate of equation (15) 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 interactive task measures are Social Skills, Service Tasks, and Require Social Interaction. 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. 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 6 - Returns to Skills by Occupation Task Intensity - Worker Fixed Effects Models

Outcome is Hourly Wage (in 2012 dollars)	(1)	(2)	(3)	(4)	(5)	(6)
Social Skill Task Intensity	0.193***	0.473***	0.281***	0.154*	0.176**	0.141
	[0.032]	[0.086]	[0.087]	[0.089]	[0.088]	[0.089]
Cognitive * Social Skill Task Intensity	0.365***	0.324***	0.313***	0.301***	0.269***	0.338***
	[0.039]	[0.039]	[0.039]	[0.039]	[0.043]	[0.054]
Social Skills * Social Skill Task Intensity	0.143***	0.121***	0.116***	0.117***	0.085**	0.128***
	[0.035]	[0.034]	[0.034]	[0.034]	[0.034]	[0.045]
Cognitive * Social * Social Skill Task Intensity	0.173***	0.170***	0.166***	0.158***	0.143***	0.156***
	[0.041]	[0.041]	[0.041]	[0.040]	[0.043]	[0.053]
Math Task Intensity		0.375***	0.275***	0.256***	0.210**	0.261***
		[0.094]	[0.095]	[0.093]	[0.091]	[0.093]
Cognitive * Math Task Intensity					0.056	
					[0.040]	
Social Skills * Math Task Intensity					0.052	
					[0.032]	
Cognitive * Social * Math Task Intensity					0.030	
					[0.043]	
Service Task Intensity		-0.280***	-0.217***	-0.141**	-0.150**	-0.123*
		[0.066]	[0.067]	[0.071]	[0.070]	[0.067]
Cognitive * Service Task Intensity						-0.056
						[0.044]
Social Skills * Service Task Intensity						-0.018
						[0.037]
Cognitive * Social * Service Task Intensity						-0.001
						[0.045]
O*NET Task Measures		X	X	X	X	X
Control for Management Occupations			X	X	X	X
Industry Fixed Effects				X	X	X
Observations	133,603	133,603	133,603	133,603	133,603	133,603
Number of individuals	11,141	11,141	11,141	11,141	11,141	11,141

Notes: Each column reports results from an estimate of equation (16) in the paper, with real hourly wages as the outcome and person-year as the unit of observation. 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. The additional O*NET task measures not listed are Require Social Interaction, 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. Standard errors are in brackets and clustered at the individual level. *** p<0.01, ** p<0.05, * p<0.10

Table 7 - Labor Market Returns to Skills Across NLSY Waves

	Full-Time Employment			Real Hourly Wage		
	(1)	(2)	(3)	(4)	(5)	(6)
Cognitive Skills (AQT, standardized)	0.069***	0.045***	0.043***	3.256***	2.129***	1.905***
	[0.003]	[0.003]	[0.003]	[0.098]	[0.113]	[0.117]
Cognitive Skills * NLSY97	0.006	0.004	0.007	-0.590***	-0.649***	-0.368*
	[0.004]	[0.004]	[0.005]	[0.200]	[0.197]	[0.199]
Social Skills (standardized)	0.007***	0.005**	0.004*	0.379***	0.305***	0.233***
	[0.002]	[0.002]	[0.002]	[0.087]	[0.087]	[0.087]
Social Skills * NLSY97	0.023***	0.021***	0.019***	0.298	0.365*	0.339*
	[0.004]	[0.004]	[0.004]	[0.197]	[0.193]	[0.194]
Cognitive * Social	-0.007***	-0.006**	-0.007**	0.256***	0.211**	0.188**
	[0.003]	[0.003]	[0.003]	[0.085]	[0.084]	[0.083]
Cognitive * Social * NLSY97	-0.006	-0.007	-0.006	-0.084	-0.135	-0.107
	[0.004]	[0.004]	[0.004]	[0.199]	[0.195]	[0.195]
Non-cognitive Skills (standardized)			0.007**			0.719***
			[0.003]			[0.092]
Non-cognitive Skills * NLSY97			0.014***			0.043
			[0.005]			[0.195]
Demographics and Age / Year Fixed Effects	X	X	X	X	X	X
Years of completed education		X	X		X	X
R-squared	0.081	0.094	0.095	0.090	0.104	0.106
Observations	104,603	104,252	104,206	84,971	84,712	84,678

Notes : Each column reports results from an estimate of equation (17) in the paper, with an indicator for being employed full-time as the outcome in Columns 1 through 3, real 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. 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 8 - Returns to Skills by Occupation Task Intensity - Worker Fixed Effects Models

Outcome is Hourly Wage (in 2012 dollars)	(1)	(2)	(3)	(4)	(5)	(6)
Social Skill Task Intensity	0.018	0.203***	0.068	0.013	0.200***	0.066
	[0.033]	[0.072]	[0.073]	[0.033]	[0.072]	[0.072]
Social Skill Task Intensity * NLSY97	0.391***	0.532***	0.514***	0.326***	0.461**	0.446**
	[0.102]	[0.194]	[0.193]	[0.103]	[0.195]	[0.194]
Math Task Intensity	0.139***	0.184**	0.167*	0.141***	0.172*	0.157*
	[0.030]	[0.089]	[0.090]	[0.029]	[0.088]	[0.090]
Math Task Intensity * NLSY97	-0.156*	-0.383*	-0.407**	-0.191**	-0.444**	-0.452**
	[0.083]	[0.199]	[0.200]	[0.078]	[0.196]	[0.197]
Cognitive Skill * Social Skill Task Intensity				0.117***	0.088***	0.081**
				[0.032]	[0.032]	[0.033]
Cognitive Skill * Social Skill Task Intensity * NLSY97				0.137	0.105	0.101
				[0.122]	[0.124]	[0.122]
Social Skill * Social Skill Task Intensity				0.046	0.038	0.037
				[0.036]	[0.036]	[0.036]
Social Skill * Social Skill Task Intensity * NLSY97				0.098	0.072	0.067
				[0.094]	[0.095]	[0.093]
Cognitive Skill * Math Task Intensity				0.027	0.040	0.040
				[0.034]	[0.034]	[0.034]
Cognitive Skill * Math Task Intensity * NLSY97				0.115	0.112	0.085
				[0.099]	[0.101]	[0.099]
Social Skill * Math Task Intensity				-0.045	-0.043	-0.038
				[0.031]	[0.031]	[0.031]
Social Skill * Math Task Intensity * NLSY97				-0.036	-0.018	-0.030
				[0.087]	[0.087]	[0.086]
O*NET Task Measures		X	X		X	X
Industry Fixed Effects			X			X
P (Social Skill * Social Skill Intensity in NLSY97 >0)				0.098	0.211	0.229
P (All Skills * Social Skill Intensity in NLSY97 >0)				0.011	0.085	0.107
P (All Skills in NLSY97 > All Skills in NLSY79)				0.096	0.222	0.241
Observations	85,233	85,233	85,233	85,233	85,233	85,233
Number of individuals	15,205	15,205	15,205	15,205	15,205	15,205

Notes: Each column reports results from an estimate of equation (18) in the paper, with real hourly wages as the outcome 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. 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. The additional O*NET task measures not listed are Require Social Interaction, 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. Standard errors are in brackets and clustered at the individual level. *** p<0.01, ** p<0.05, * p<0.10