NBER WORKING PAPER SERIES

THE GROWING IMPORTANCE OF SOCIAL SKILLS IN THE LABOR MARKET

David J. Deming

Working Paper 21473
http://www.nber.org/papers/w21473

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
August 2015

Thanks to Pol Antras, David Autor, Avi Feller, Lawrence Katz, Sandy Jencks, Richard Murnane, Doug Staiger 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, Todd Rogers, Marty West and seminar participants at LSE and PSE for helpful comments. Olivia Chi, Madeleine Gelblum, 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. The views expressed herein are those of the author and do not necessarily reflect the views of the National Bureau of Economic Research.

The Growing Importance of Social Skills in the Labor Market
David J. Deming
NBER Working Paper No. 21473
August 2015
JEL No. J24,J31

ABSTRACT

The slow growth of high-paying jobs in the U.S. since 2000 and rapid advances in computer technology have sparked fears that human labor will eventually be rendered obsolete. Yet while computers perform cognitive tasks of rapidly increasing complexity, simple human interaction has proven difficult to automate. In this paper, I show that the labor market increasingly rewards social skills. Since 1980, jobs with high social skill requirements have experienced greater relative growth throughout the wage distribution. Moreover, employment and wage growth has been strongest in jobs that require 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. The female advantage in social skills may have played some role in the narrowing of gender gaps in labor market outcomes since 1980.

David J. Deming
Harvard Graduate School of Education
Gutman 411
Appian Way
Cambridge, MA 02139
and NBER
david_deming@gse.harvard.edu

An online appendix is available at:
http://www.nber.org/data-appendix/w21473

"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 increases in the 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) (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 highly-skilled labor, there has been little or no employment growth in high-paying jobs since 2000 (Acemoglu and Autor 2011, Autor and Dorn 2013, Beaudry et al. 2013, 2014).[1] Beaudry et al. (2013) argue 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 labor market return to cognitive skill was 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, Heining and Kline 2013, Card, Cardoso and Kline 2013).

One possible explanation is that computer capital is substituting for labor higher up in the skill distribution, as advances in computerization redefine what it means for work to be "routine" (Lu 2015). This view implies that polarization is an intermediate phase, with the shape of employment growth eventually looking more like a "downward ramp" (Autor

[1] Acemoglu and Autor (2011) and Beaudry et al. (2013) show that shrinking employment in high-wage occupations occurred between 2000 and 2007, predating the Great Recession. Acemoglu et al. (2014) find that import competition from China led to declines in U.S. manufacturing employment over the 2000-2007 period, with some indirect impacts on downstream industries. Beaudry et al. (2013) argue that this "great reversal" in the 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.

2014). Figure 1 plots decadal changes in employment growth in routine occupations, ranked by their percentile in the 1980 education distribution.[2]

Figure 1 shows clearly that routine jobs are disappearing further up the skill distribution. Routine employment shrank for low-skilled production and trade jobs in the 1980s, and middle-skilled clerical jobs in the 1990s. Between 2000 and 2012, employment in routine occupations declined all the way up through the 80th percentile of the skill distribution, and even above that job growth was much slower than in the 1990s.[3] New technologies such as machine learning have dramatically improved the ability of computers to automate "cognitive" tasks, leading to fears that the labor share is in permanent decline as computers replace even the most highly skilled workers (Brynjolfsson and McAfee 2012, Frey and Osborne 2013, Autor 2014, Karabarbounis and Neiman 2014).

In this paper, I show that high-skilled, difficult-to-automate jobs increasingly require *social skill*s. The reason is that skill in human interaction is largely based on tacit knowledge and, as argued by Autor (2014), computers are still very poor substitutes for tasks where programmers don't know "the rules".[4] Human interaction requires a capacity that psychologists call "theory of mind" - the ability to attribute mental states to others based on their behavior, or more colloquially to "put oneself into another's shoes" (Premack and Woodruff 1978, Baron-Cohen 2000, Camerer et al. 2005). Progress in automating social interaction is best exemplified by the continued failure of the Turing test, which measures a machine's ability to imitate human conversation for five minutes in a highly controlled setting.[5] Based

[2]I measure an occupation's routine task intensity as the average of the following two questions from the 1998 Occupational Information Network (O*NET) - 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?". Section 2 provides more detail on the O*NET data and the construction of task measures by occupation.

[3]I restrict the sample to occupations with above-median routine task intensity based on the 1998 O*NET. The results are not sensitive to other reasonable cutoffs such as the 66th percentile. See Section 2 and the Data Appendix for details on the construction of the routine task measure. Routine occupations above the 75th percentile of the 1980 education distribution that either lost jobs between 2000 and 2012 or grew much more slowly than in the previous decade include engineers, computer software developers, computer scientists, financial managers and airline pilots. Jaimovich and Siu (2012) show that most of the decline in routine employment has occurred over the last several recessions, and that declines in routine employment are largely responsible for the recent pattern of post-recession "jobless recoveries".

[4]Autor (2014) refers to this as "Polyani'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 "Morevec'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 design improvements and optimizations over millions of years. Abstract thought appears difficult, but only because humans have only been doing it for a few thousand years (Moravec 1988).

[5]Alan Turing proposed the following test for machine intelligence - an interviewer asks written questions of two respondents, and is given the task of determining which respondent is human and which is a computer. Turing proposed that a machine would pass the test once it could convince a human 70 percent of

on poor performance in the Turing test and the inability of computers to even recognize (much less replicate) human emotion, Frey and Osborne (2013) identify social intelligence tasks as a key bottleneck to computerization.

I begin by presenting evidence for three important facts about the U.S. labor market. First, I show that employment growth in social skill-intensive occupations has occurred throughout the wage distribution, not just in management and other top-paying jobs.[6] Second, consistent with Weinberger (2014), I find a growing complementarity between cognitive skills and social skills. Since 1980, employment and wage growth has been particularly strong in occupations with high cognitive *and* social skill requirements. In contrast, employment has fallen in occupations with high math but low social skill requirements, suggesting that cognitive skills are increasingly a necessary but not sufficient condition for obtaining a high-paying job. Third, I show that measures of an occupation's social skill intensity and its routineness are strongly negatively correlated.

To understand these patterns, I develop a model of team production where workers "trade tasks" to exploit their comparative advantage. Following existing models, teamwork increases productivity through specialization but requires costly coordination (Becker and Murphy 1992, Bolton and Dewatripont 1994, Lazear 1999, Garicano 2000, Garicano and Rossi-Hansberg 2004, 2006, Antras et al. 2006).

However, I depart from prior work by treating social skills as reducing *worker-specific* coordination costs. Workers draw individual task productivities from a distribution, and cognitive skill is the mean of the distribution. Thus two workers with the same cognitive skill differ in their productivity over individual tasks. Social skills act as a kind of social anti-gravity, reducing the cost of task trade and allowing workers to specialize and co-produce more efficiently. This approach takes on the structure of a Ricardian trade model, with workers as countries and social skills acting as inverse "iceberg" trade costs as in Dornbusch et al. (1977) and Eaton and Kortum (2002).[7]

---

the time after five minutes of conversation. Since 1990, the Loebner prize has been awarded annually to software programs that come closest to passing the Turing test. In 2014, a "chatbot" program called Eugene Goostman convinced 33 percent of the contest's judges that it was human, arguably passing the Turing test for the first time. However, like other programs before it, Goostman passed the Turing test through trickery, posing as a 13-year-old Ukrainian with a poor grasp of the English language. Cognitive psychologist Gary Marcus writes in the New Yorker that "the winners aren't genuinely intelligent...It has turned out, in fact, that the winners tend to use bluster and misdirection far more than anything approximating true intelligence." http://www.newyorker.com/tech/elements/why-cant-my-computer-understand-me, last accessed June 15, 2015.

[6]Autor et al. (2003) separately show trends in nonroutine "analytical" and "interpersonal" task inputs. Subsequent work on routine-biased technological change (RBTC) and job polarization has grouped these two categories together as "abstract" or "cognitive" tasks, and implicitly or explicitly assumed that proxies such as education are a sufficient statistic for both types of skill (e.g. Acemoglu and Autor 2011, Autor and Dorn 2013, Goos et al. 2014).

[7]Acemoglu and Autor (2011) develop a Ricardian model of the labor market with three skill groups, a

The model provides a natural explanation for the empirical patterns described above. 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 is increasing in task productivity (i.e. cognitive skill).[8]

The model provides a key link between social skills and routine task intensity through the *variance* of task productivity draws. Occupations vary in both cognitive skill intensity and routineness. Nonroutine occupations require a more diverse set of tasks (for example, consider the tasks required of management consultants vs. computer programmers). In the model, the variance of task productivity draws acts as an elasticity, increasing the gains from task trade and thus the wage returns to social skills.

I am aware of only two other papers that specifically model 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.[9] 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.[10] In contrast, there are no communication tasks in my model, nor are there formal teams.[11] This is consistent with

single skill index, and comparative advantage for higher-skilled workers in relatively more complex tasks. While their model accommodates technological change in a variety of forms, they explain job polarization as a technological change that replaces the tasks performed by medium-skilled workers. In contrast, the model here posits the existence of two types of skill that are distributed arbitarily across workers.

[8]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 2014, Lise and Postel-Vinay 2014). This type of model 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.

[9]Relatedly, Borghans et al. (2008) develop a model of "interpersonal styles" where worker productivity depends on the effectiveness of interpersonal interactions, which are determined by the worker's levels of caring and directness.

[10]In McCann et al. (2014), workers can invest in education (which increases their cognitive skill but not their communication skill), and individuals with high communication skill can become teachers in the school or managers within a firm as adults. When workers who specialize in communication (vertical specialization) become managers of a team, the communication skills of the other workers on the team are irrelevant.

[11]Models with communication or "people" tasks face the challenge of specifying what exactly is being produced. For example, if I spend all day in a meeting, am I devoting all of my daily effort to a communication task? In this model, which treats communication as a friction, groups who have longer meetings conditional on total output have lower average social skill. Additionally, the model does not actually include a role for

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 that is robust to a variety of controls, including widely used measures of cognitive and non-cognitive skill, years of education, and occupation and industry fixed effects.

Similar to Krueger and Schkade (2008), I find that workers with higher social skills sort into social skill-intensive occupations and into nonroutine occupations.[12] I also find that the returns to social skills and skill complementarity are higher in these occupations even after controlling for a variety of occupation and industry characteristics as well as worker fixed effects.[13]

I relate the growing importance of social skills to advances in information and communication technology (ICT) that have shifted the organization of work toward flexible and self-managed team structures, job rotation and worker multitasking (Bresnahan 1999, Lindbeck and Snower 2000, Caroli and Van Reenen 2001, Bresnahan et al. 2002, Dessein and Santos 2006, Bartel et al. 2007, Lazear and Shaw 2007, Bloom and Van Reenen 2011). In the model, higher-skilled workers "crowd out" lower-skilled workers relatively more in routine occupations. Considering computer capital as a factor of production, an increase in computing power (i.e. the cognitive skill of machines) lowers the relative return to routine occupations, which shifts workers into nonroutine occupations that require flexibility and human interaction. This is consistent with case study evidence from the literature on ICT and organizational changes within the firm (Caroli and Van Reenen 2001, Autor et al. 2002, Bresnahan et al. 2002, Bartel et al. 2007).

Finally, I show that the economy-wide shift toward social skill-intensive occupations has occurred disproportionately among women rather than men. This is consistent with a large

cohesive teams that produce independently - rather, workers trade more or less with each other.

[12]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.

[13]One possible explanation for the positive labor market return to social skills is that workers with high social skills are able to extract greater rents when negotiating for wage increases. This would also be consistent with the large establishment-level wage premia found in Card, Heining and Kline (2013) and Card, Cardoso and Kline (2013). However, rent extraction would not explain the finding of relatively larger returns to social skills in nonroutine occupations.

literature showing sex differences in social perceptiveness and the ability to work with others (Hall 1978, Connellan et al. 2000, Woolley et al. 2010, Kirkland et al. 2013).

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).[14] In 2015, employers surveyed by the National Association of Colleges and Employers (NACE) listed "ability to work in a team" as the most desirable attribute of new college graduates, ahead of problem-solving and analytical/quantitative skills (NACE 2015).

Tests of emotional 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.[15]

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).[16] This paper builds on the seminal observation of Heckman (1995) that earnings are likely influenced by multiple dimensions of skill, since measured cognitive ability (i.e. g) explains only a small fraction of the variation in adult wages. Subsequent work, summarized in Heckman and Kautz (2012), finds that "noncognitive" or "soft" skills explain

[14]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.

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

[16]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. Borghans et al. (2014) document a growing labor market return to jobs that require more "people tasks" and document self-selection of sociable workers into these jobs.

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 for three key facts about the growing importance of social skills in the labor market. Section 3 presents the model, first with a simple two-worker and two-task case to build intuition, and then with many workers, a continuum of tasks and a characterization of equilibrium production and wages. Section 4 describes the data. Section 5 presents the empirical models and results. Section 6 discuss two main implications of the findings - the importance of capital-labor substitution and skill complementarity, and the growing female advantage in labor market outcomes. Section 7 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 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 the task content of work. 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?"[17] Second, I closely follow Autor et al. (2003) and define

[17] This definition of routineness differs from the task measures used by Autor et al. (2003), who use the 1977

nonroutine analytical task intensity as the average of three O*NET variables that capture an occupation's mathematical reasoning requirements.[18] Third, I define an occupation's *social skill* intensity as the average of four O*NET skill measures: 1) Coordination; 2) Negotiation; 3) Persuasion; 4) Social Perceptiveness.[19] 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.

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 human interaction in *production*, and are relatively high-paying and cognitive skill-intensive. This distinction is largely missing from prior work on "people" jobs, which typically treats human interaction as a single type of task (Borghans et al. 2014, McCann et al. 2014, Lise and Postel-Vinay 2014).

Figure 3 demonstrates the growing importance of social skills by replicating Figure I of Autor et al. (2003) for the 1980-2012 period using the four key O*NET task measures described above.[20] 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 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

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.

[18] 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.

[19] 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.

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

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, the importance of social skills 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.

Because the task measures in Figure 3 are additive, they may mask changes over time in the *bundles* of tasks demanded by employers. Figure 4 plots smoothed changes in employment shares by occupation between 1980 and 2012 against each occupation's percentile in the 1980 wage distribution. 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. This compares employment growth across occupations that require high math skills, high social skills, both or neither.

The results in Figure 4 are striking. Since 1980, occupations with high math *and* high social skill requirements have grown robustly throughout the wage distribution. Jobs with high social skill and low math requirements have also grown, although they are mostly concentrated in the bottom two-thirds of the wage distribution. The worst performance in terms of employment growth comes from jobs with high math but low social skill requirements. Employment shares declined for all but the very highest-paying jobs in this category.[21] The results are also robust to choosing cutoffs other than the 50th percentile for each type of task.

Figure 5 presents changes in inflation-adjusted median log hourly wages for occupations according to their math and social skill task intensities. With only a few exceptions, real wage growth since 1980 has been greatest in occupations that require workers to have both math skills and social skills. Wage growth for jobs with high math and low social skill requirements has been positive but relatively modest. Finally, real wages have declined for nearly all jobs that are below the median in both math skills and social skills. Taken

[21]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, air traffic controllers, lawyers, actors/directors/producers, editors and reporters, and physical therapists.

together, the evidence in Figures 4 and 5 strongly suggests that the demand for social skills has grown in occupations throughout the wage distribution, particularly for jobs that also have high cognitive skill requirements.

Appendix Figures A3 and A4 hone in on recent trends in the labor market by presenting analogous results with 2000 as the base year. The results are qualitatively very similar. As noted elsewhere, job growth was strongest at the bottom of the wage distribution. However, among occupations paying above median wages, the only net job growth between 2000 and 2012 occurred in high social skill occupations, and only occupations that required high levels of both types of skill experienced consistent real wage growth over the same period.

Figure 6 provides further evidence of growing skill complementarity by presenting the trend in nonroutine analytical (math) task inputs from Figure 3, with occupations split into three terciles of social skill task intensity. The groups are constructed to be of roughly equal size in 1980, and as in Figure 3 all changes are relative to the 1980 distribution of task inputs.[22]

Figure 6 shows clearly that the "great reversal" in the demand for cognitive skills documented by Beaudry et al. (2013) is concentrated in occupations with relatively low social skill intensity. Nonroutine analytical task inputs for occupations in the lowest tercile of social skill intensity declined by nearly 10 centiles between 1980 and 2012, with about half of the decline occurring since 2000. For occupations with moderate social skill requirements, there was an initial period of growth between 1980 and 1990, followed by a decline of about 7 centiles between 1990 and 2012. In contrast, nonroutine analytical task inputs for jobs with the highest social skill requirements grew by about 3 centiles from 1980 to 2000 and then declined by only 2 centiles between 2000 and 2012. Overall, Figures 4 through 6 provide strong evidence for the growing complementarity between math skills and social skills (Weinberger 2014).

Finally, I demonstrate the close linkage between the O*NET definition of "routine" work and a job's reliance on human interaction by estimating the correlation between the routine task measure from the O*NET and social skill task intensity, controlling for a variety of other occupation-level characteristics. The results are in Table 1. Column 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.[23] The conditional

[22]Because the three lines in Figure 6 are measured net of compositional changes in the sizes of each industry-education-sex cell, they will not necessarily add up to the single line for nonroutine analytical tasks in Figure 3.

[23]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.

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 1 is that an occupation's routine task intensity is a very strong predictor of whether that occupation also has low social skill requirements.

In the next section, I develop a model of team production that can explain the following three empirical patterns described above - 1) social skills are valued in jobs throughout the entire wage distribution; 2) social skill and cognitive skill are complements; 3) the importance of social skills is strongly linked to a job's routineness.

3 Model of Team Production

I begin with a simple example to build intuition for the formal model. Assume that the production of research papers consists of only two tasks - data analysis and writing. Assume further that these two tasks are perfect complements, with the Leontief production function:

$$Y = \min\,(D, W) \tag{1}$$

A representative firm in a perfectly competitive labor market employs two workers, Jones and Smith, in the production of research papers. Jones and Smith both produce according to (1), either alone or as a team, and are paid their marginal product in either case. If they trade tasks, the firm does not care who is the "buyer" and who is the "seller" - only about total output (i.e. Jones and Smith are perfect substitutes). They have the following productivity schedules, expressed in number of tasks completed per unit of labor:

	Data Analysis	Writing
Jones	6	3
Smith	3	6

Each worker allocates one unit of labor across the two tasks to maximize the production of research papers. In the absence of task trade (i.e. autarky), workers balance factor proportions and generate the same total output of each task. For Jones, this implies allocating one third of his effort to data analysis and two thirds to writing, generating two total research papers:

$$Y_J = min\left[(0.333 * 6), (0.667 * 3)\right] = 2$$

Smith allocates two thirds of her time to data analysis and one third to writing, also generating two total research papers:

$$Y_S = min[(0.667 * 3), (0.333 * 6)] = 2$$

In total, Jones and Smith each produce two research papers, for a total of four when working alone. However, the firm (and thus workers, since they are paid their marginal product) can do better by "trading tasks", which for the moment is costless. Smith has a comparative advantage in writing, and Jones has a comparative advantage in data analysis. The optimal solution involves complete specialization by Jones in data analysis and Smith in writing (producing 6 units each):

$$Y_J = (e_J^D D_j, e_J^W W_J) = [(1 * 6), (0 * 3)] = (6, 0)$$

$$Y_S = (e_S^D D_S, e_S^W W_S) = [(0 * 3), (1 * 6)] = (0, 6)$$

Having produced a total of 6 units of each task, Jones and Smith can engage in a variety of trades that improve their total productivity relative to the case without task trade. Specifically, any trade where Jones obtains more than 2 units of writing and Smith obtains more than 2 units of data analysis makes them both better off, because their marginal products both increase. This analysis so far closely mirrors Ricardo (1891), with workers as countries and tasks as goods.[24]

Now I assume that trading tasks requires coordination, with *social skill* as a worker-specific reduction in the coordination cost. 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 levels of social skill pay a lower coordination cost to engage in task trade with all other workers. For simplicity, I assume that social skill applies equally to all types of tasks.

Turning first to the simple 2-task, 2-worker case, let $S^* = S_J * S_M$. Since the coordination cost is symmetric (i.e. the cost of trading from Jones to Smith is the same as from Smith to Jones) by assumption, and there are only two workers, it does not matter in this case how social skills are distributed (i.e. $S_J = 0.75$ and $S_M = 0.25$ generate the same results as $S_J = 0.25$ and $S_M = 0.75$). Total productivity is increasing in the social skills of both workers, and there is a threshold level of social skills below which Jones and Smith do not

[24] This example also abstracts away from cost (wage) differences across workers (countries). An alternative approach would be to specify that each worker must be made better off by task trade, rather than only being concerned with final output. This complicates the analysis but does not lead to substantively different insights.

engage in team production. This threshold level is equal to the S^* at which no combination of trades can raise each worker's productivity above its level in autarky (i.e. where $Y_J = 2$ and $Y_S = 2$). The threshold S^* is equal to 0.5 in this case. The symmetric nature of each worker's comparative advantage and the result that they should completely specialize makes this example particularly simple, but as shown by Eaton and Kortum (2012), the solution can be cumbersome to compute even in the two-factor, two-task case.[25]

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.[26] 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. Moreover, note that a worker with low social skills will self-produce more and adjust less to changes in the relative task productivities of her coworkers. 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.

In the next section I develop a formal model that generalizes the analysis above to incorporate a continuum of tasks and an arbitrary number of workers. However, one can see two implications that arise even in this simple example. First, the return to social skills will be increasing in a worker's overall average productivity (i.e. absolute advantage) - for example, if the productivity schedules of each worker doubled, the gains from trade would increase from two extra papers produced to four.[27] Second, the return to social skills

[25]With $S^* = 0.5$, Jones trades 4 units of data analysis to Smith (which becomes $0.5 * 4 = 2$ units) and vice versa for Smith trading writing to Jones. This allocation is exactly equivalent to total production in autarky. Other combinations are possible for this particular S^* as well. For example, Jones could produce 4 units of data analysis and 1 unit of writing (and vice versa for Smith), and they could reach total production in autarky by trading 2 units (becoming 1 unit) of the task in which each specializes.

[26]In principle, one could model idiosyncratic coordination costs between two individuals as an S_{ni} term. One could also consider other functional forms, such as a coordination cost that is the minimum or the maximum of the social skills of the two workers. The model could easily accommodate realistic cases such as group-specific coordination costs based on ethnic or cultural differences as in Charles and Kline (2006), Hjort (2014) and Marx et al. (2015). Finally, while the model treats "task trade" as bilateral, one could incorporate multilateral trade between many team members. In that case the multiplicative functional form for S described above would generate a kind of O-ring production function for tasks, where a single worker with low social skills could greatly disrupt the operation of a team (Kremer 1993).

[27]If Jones' productivity schedule was (12,6) and Smith's was (6,12), they would each produce 4 in autarky, for a total of 8 research papers. With task trade (assuming that $S_i * S_n = 1$ for simplicity, although this need not be true), the optimal allocation is (12,0) for Jones and (0,12) for Smith. This would produce a

will be greater when the across-worker correlation between task productivities is lower (i.e. comparative advantage).[28] I develop these implications more formally below.

3.1 Environment

Consider a measure of firms, each producing a unique final good Y according to a simple perfect substitutes production function:

$$Y = \sum_{i=1}^{I} L_i y_i \tag{2}$$

with L_i denoting the total quantity supplied of factor i. For ease of exposition I assume from here forward that workers are the only factor of production, although later I discuss the implications of the model for capital-labor substitution. Each worker produces output y_i by combining a continuum of tasks t defined over the unit interval. A worker's production function over tasks takes the following Cobb-Douglas form:

$$y_i = \exp\left[\int_0^1 \ln x_i(t)dt\right] \tag{3}$$

Equation (3) captures the idea that tasks must be performed jointly to produce output. I assume a Cobb-Douglas technology for ease of exposition only - any production function with imperfect substitution across tasks generates qualitatively similar results to those below.[29] I assume for simplicity that workers supply a single unit of labor inelastically across tasks, so $L_i = \sum_{t=0}^{1} l_{it} = 1$ and with constant returns to scale. I also assume that each worker can "buy" tasks from other workers by supplying a single unit of effort, so $E_i = \sum_{t=0}^{1} e_{it} = 1$. These assumptions are normalizations that allow me to focus on the wage returns to skills, but they could be easily relaxed.

The firm directs workers to trade with each other in order to maximize total output Y,

total of 12 research papers. Thus the gains from trade double when the productivity of all workers doubles.

[28] It is straightforward to show that the threshold S^* increases - or alternatively, that the gains from trade are lower - with a mean-preserving shift in task productivities that makes the two workers more similar. For example, if Smith's productivity schedule changed from $(3,6)$ to $(4,4)$, she could still produce 2 research papers in autarky. However, the efficient allocation with costless task trade would become $\left(4\frac{2}{3}, \frac{2}{3}\right)$for Jones and $(0,4)$ for Smith, making the total gains from trade $\frac{2}{3}$ of a research paper rather than 2 in the original case. A shift in Smith's productivity schedule from $(3,6)$to $(6,3)$ would eliminate any gains from task trade.

[29] In Becker et al. (1992) and Grossman et al. (2008), tasks are perfect complements in production, meaning each must be performed at the same fixed intensity (i.e. "once") to produce a unit of output. If I instead employ a general constant elasticity of substitution (CES) specification for the production function (i.e. $Y_i = \left[\int_0^1 Q\left(t_i\right)^{\sigma-1/\sigma} dt_i\right]^{\sigma/\sigma-1}$), the only change to the main results is in the constant term γ, which will then depend on σ.

subject to the two adding-up constraints for workers shown above. Workers are paid wages according to their total marginal product, which depends on the worker's own skills, the firm's production technology, and the skills of the other workers in the firm.

Worker i's productivity in task t, denoted by z_{it}, is drawn from a Frechet (or type II extreme value) probability distribution, with cumulative distribution function:

$$F_{it}(z) = Pr(z_{it} \leq z) = \exp\left(-A_i^{\rho} z^{-\theta}\right) \tag{4}$$

Each worker receives an exogenous draw of cognitive skill A_i and social skill S_i, with $A_i > 1$ and $S_{i,n} \in (0,1)$ and $S_{i,i} = 1$ defined as above. Equation (4) maps skills onto tasks probabilistically. While higher cognitive skill A_i makes workers more productive on average, two workers of identical cognitive skill will vary in their productivity for any particular task.

Suppose that each worker experiments with different ways to perform a task until she settles on her own best approach. If the range of possible task productivities has a Pareto distribution, and workers select the maximum value over a large number of draws, the limiting distribution of the maximum will converge to the Frechet (Kortum 1997). Another important reason for choosing the Frechet distribution is analytical convenience, because the exponential form allows for a straightforward characterization of equilibrium task values and worker wages (Eaton and Kortum 2002).

Each firm receives an exogenous draw of two technology parameters, ρ and θ, with $0 < \rho < 1$ and $\theta > 1$. In my empirical work I treat ρ and θ as characteristics of occupations. In the model, I assume that each firm is characterized by a single value of ρ and θ, which is equivalent to assuming that each firm hires workers in only a single occupation. This assumption could be relaxed to incorporate firms with different occupational mixes, which would complicate the model but not yield any substantively different insights.

The technology parameters translate worker skills into task output. As ρ approaches one, cognitive skill becomes relatively more important in determining productivity in *all* tasks. Thus occupations with higher ρ have higher relative returns to cognitive skill.

Occupations with higher θ have a lower variance of productivity draws across workers, making cognitive skill A_i a better predictor of productivity for any task t. As $\theta \to \infty$, the variance shrinks to zero and equation (4) reduces to a model where higher-ability workers are more productive than their less able colleagues in *all* tasks. At lower values of θ, task productivity draws are more dispersed, so even low ability workers may be the most efficient producers of some tasks.

A key assumption of the model is that θ represents the routine task intensity of an occupation. Autor et al. (2003) define a task as "routine" if it can be accomplished by following explicit programmed rules. Relatedly, Bresnahan (1999) argues that computers change the workplace by "organizing, routinizing and regularizing tasks that people- and paper-based systems did more intuitively but more haphazardly". The idea behind both of these statements is that there is a well-established, correct way to perform some tasks. For example, tasks such as complex mathematical calculations require high levels of cognitive skill but are also routine according to this definition.

Thus one interpretation of θ is that it measures the share of tasks in each occupation for which there is a single best approach. As θ increases, the variance of task productivity draws shrinks because a higher share of tasks are "routine". In the model and in the empirical work I assume that the task content of occupations is fixed. However, technological innovation can change which tasks are considered "routine" over time, and in general equilibrium the distribution of ρ and θ in the economy is likely to respond endogenously to changes in human and computer skill (e.g. Acemoglu 1998).

Both firms and workers have full knowledge of A_i, S_i, ρ and θ at the time of hire. However, I assume that the individual z_{it}s are firm-specific (i.e. workers who switch firms receive a new draw) and only observed *after* a worker is hired.[30] Thus as θ increases, a worker's cognitive skill (which the firm observes) becomes a better predictor of productivity in any particular task.

One proxy for the routineness of an occupation is the extent to which job performance can be predicted by "hard" skills or observed measures of applicant quality. Consider two occupations that are both above the 90th percentile in terms of cognitive skill intensity based on O*NET but on opposite ends of the "routineness" spectrum - management analysts and computer scientists. Firms hiring both types of occupations will place a high weight on attributes that proxy for cognitive skill such as GPA and college quality. However, the productivity of management analyst job applicants will depend much more on their strengths and weaknesses relative to their co-workers, because the job requires a greater diversity of tasks (i.e. analyzing data, making presentations, meeting with clients).

3.2 Team Production and Trading Tasks

Workers allocate their labor over tasks to produce output according to (3) and (4). They can produce alone or "trade tasks" with other workers. I assume that worker labor and effort is perfectly observed, as are the individual z_{it}s post-hire. Since workers are perfect substitutes in the firm's production function, the firm only cares about total output and not

[30] Since workers perform a continuum of tasks and there is a finite integer number of workers, this assumption is not strictly necessary. Firms could not hire workers to perform "only" their most productive tasks even if they could perfectly observe all the z_{it}s.

the direction of trade (i.e. whether worker i trades to worker j or vice versa). The firm knows each worker's production over tasks as well as any trades that are made between workers. Taken together, this set of assumptions means that team production will not be hindered by agency issues such as free-riding. Moreover, a worker is not maximizing her own production function - rather, she is maximizing her total contribution to the production functions of all other workers in the firm, including her own.

Incorporating social skills, the normalized "price" of one unit of task t produced by worker i and traded to worker n is:

$$P_{tni} = \frac{1}{z_{it} S_n S_i} \tag{5}$$

Equation (5) shows that the cost per unit of effort of "buying" tasks from other workers is decreasing in worker i's task productivity z_{it} and the social skills of both workers. Substituting P_{tni} into (4) yields an expression for the probability that worker i can trade task t to worker n at a price that is less than or equal to p:

$$G_{tni}(p) = Pr\left(P_{tni} \leq p\right) = 1 - \exp\left[-A_i^{\rho} (S_n S_i)^{\theta} p^{\theta}\right] \tag{6}$$

$G_{tni}(p)$ gives the distribution over tasks t of all prices that worker i could offer to worker n. Under perfect competition, firms direct workers to buy tasks from the worker who provides the lowest price per unit of effort:

$$P_{tn} = min\left\{P_{tni};\, i = 1, ..., N\right\} \tag{7}$$

where N is the total number of workers. This includes the possibility of workers buying from themselves. The lowest price available to worker n will be less than p unless the price of each worker's tasks is greater than p. Thus the distribution $G_{tn}(p) = Pr\left[P_{tn} \leq p\right]$ for the lowest price task trades (i.e. those trades that are actually made) can be obtained by computing the complement of the probability that every worker i offers a price that is greater than p:

$$G_{tn}(p) = Pr(P_{tn} \leq p) = 1 - \prod_{i=1}^{N} \Pr\left(P_{tni} > p\right) \tag{8}$$

Because of the exponential form of the task productivity distribution, substituting in (6) yields the following simple expression for $G_{tn}(p)$:

$$G_{tn}(p) = 1 - \prod_{i=1}^{N} \exp\left[-A_i^{\rho} (S_n S_i)^{\theta} p^{\theta}\right] = 1 - \exp\left(-\phi_n p^{\theta}\right) \tag{9}$$

where:

$$\phi_n = \sum_{i=1}^{N} A_i^{\rho} \left(S_n S_i\right)^{\theta} \tag{10}$$

See the Theory Appendix for a proof. Since ϕ_n is a function of skills only, it takes on the same value for all tasks and thus I drop the t subscript from here forward for convenience. ϕ_n indexes the price (in units of effort) of tasks that worker n can buy from other workers in equilibrium. Worker n's "purchasing power" is increasing in her own social skills and the cognitive skills and social skills of her fellow workers. In the extreme case where worker n has no social skills, $S_n S_i = 0$ for all i and n $(i \neq n)$, and ϕ_n reduces to just A_n^{ρ} (because $S_i S_i = 1$). The intuition is simply that a worker with very low social skills does not work well in a team, and thus finds it most productive to trade only with herself.

With costless task trade (i.e. "zero gravity", $S_n S_i = 1$ for all i and n), ϕ_n takes on the same value for all n workers. In that case, the "law of one price" holds and a single worker is the lowest-price supplier, leading to complete specialization of workers in tasks. However, with variation in social skills, the price of a task traded to or from worker i will vary for each n. The real-life analog is overlap of task performance among workers in a team or a firm. For example, a member of a research team with low social skills might conduct "too much" of her own data analysis rather than allowing her more productive coauthor to specialize.

Because ϕ_n depends only on worker skills, all tasks that are actually traded to worker n in equilibrium have the same price (i.e. they are drawn from the same distribution $G_{tn}(p)$). Thus skills affect the quantity of tasks traded but not the price. As A_i and S_i increase, worker i trades a larger range of tasks to worker n, until the exact point at which worker n is indifferent between trading with worker i and someone else. This accords with intuition from real workplaces, where highly productive workers are asked to perform a broader range of tasks.

Next I derive an expression for the share of tasks traded by worker i to worker n. Since there are a continuum of tasks, this is just equal to the probability that worker i is the lowest-price provider of task t to worker n. Again suppressing the t subscript for clarity, let $\pi_{ni} = Pr\left[P_{ni} \leq min\left\{P_{nk}; k \neq i\right\}\right]$. For any $P_{ni} = p$, the probability that worker i provides the lowest price task trade is just equal to the probability that $P_{nk} \geq p$ for all $k \neq i$:[31]

$$\pi_{ni} = \frac{A_i^{\rho} \left(S_n S_i\right)^{\theta}}{\phi_n} \tag{11}$$

Moreover, since each worker's total labor in selling tasks and total effort in buying tasks sum to one, the share of tasks that worker i trades to worker n is just $\pi_{ni} = \frac{e_{ni}}{E_n} = e_{ni}$.

[31]Equation (11) follows from $\pi_{ni} = Pr\left[P_{ni} \leq min\left\{P_{nk}; k \neq i\right\}\right] = \int_0^{\infty} \prod_{k \neq i} \left[1 - G_{nk}(p)\right] dG_{ni}(p) = \pi_{ni} \int_0^{\infty} dG_n(p) = \pi_{ni}$. See the Theory Appendix for a proof.

Given the expression for ϕ_n above, e_{ni} (and thus π_{ni}) can be thought of as worker i's relative contribution to worker n's total production.

3.3 Labor Market Equilibrium

Because of the Cobb-Douglas production function in (2), the exact price index for the tasks purchased by worker n is just the geometric mean of the price distribution:

$$\bar{P}_n = \gamma \phi_n^{-\frac{1}{\theta}} \tag{12}$$

with γ as a constant.[32] Higher values of $\bar{P}_n$ correspond to lower purchasing power.

Equilibrium with perfect competition requires that workers are paid the marginal product of their labor, which is equal to the sum for worker i of task trades to all workers (including herself) normalized by the price paid (in units of effort) for those trades. Because skills affect only the extensive margin of task trade, the price of every task purchased by worker n is the same, and is equal to the price index $\bar{P}_n$ from equation (12) above:

$$w_i = \sum_{n=1}^{N} \frac{\pi_{ni}}{\bar{P}_n} \tag{13}$$

With enough data, the model could be used to generate many useful predictions about the nature of task trade and the extent of teamwork within a firm given workers' skills and the technology parameters ρ and θ. However, even without direct measures of teamwork, I can still obtain predictions for equilibrium wages. To see this, substitute (11) and (12) into (13):

$$w_i = \gamma^{-1} A_i^{\rho} S_i^{\theta} \sum_{n=1}^{N} S_n^{\theta} \phi_n^{\frac{1-\theta}{\theta}} \tag{14}$$

Equation (14) shows that wages depend on a worker's own skills, the technology parameters ρ and θ, and the skills of the other workers in the firm. Note that worker i's wages are clearly increasing in the social skills of her fellow co-workers, and that teamwork increases productivity.[33] This is consistent with findings that team production and group incentive pay structures boost productivity (Hamilton et al. 2003, Boning et al. 2007, Burgess et al. 2010, Bandiera et al. 2013). Teamwork has been shown to facilitate problem solving and creativity, and has become increasingly important in the production of scientific knowledge

[32] $\gamma = \exp\left(\frac{-\epsilon}{\theta}\right)$, with $\epsilon = 0.577...$ as the Euler constant. See the Theory Appendix for a proof.

[33] $w_i = \gamma^{-1} N A_i^{\rho} \left(\sum_{n=1}^{N} A_n^{\rho}\right)^{\frac{1-\theta}{\theta}}$ is the expression for wages when $S_i = 1$ for all workers. In autarky, wages collapse to $w_i = \gamma^{-1} A_i^{\frac{\rho}{\theta}}$. Thus wages are minimized in the case of no task trade (i.e. $S_n S_i = 0$ for all i and n, $i \neq n$) and maximized when task trade is costless (i.e. $S_n S_i = 1$ for all i and n).

(Wuchty et al. 2007, Maciejovsky et al. 2013, Ramm et al. 2013).

By allowing a worker's productivity to depend on the productivity of her fellow workers, the model naturally builds in 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).

The price parameter ϕ_n differs across workers within a firm for only two reasons: 1) the worker's own social skill S_n, and 2) the fact that self-trade $S_{i,i}$ is normalized to one. As the number of workers in a firm grows large, the relative contribution of self-trade diminishes, leaving S_n as the only reason for variation across workers in a firm in ϕ_n. Noting that ϕ_k can be rewritten as $\phi_n = S_n^\theta \sum_{k=1}^K A_k^\rho S_k^\theta$, we have:

$$w_i = \gamma^{-1} A_i^\rho S_i^\theta \sum_{n=1}^N S_n \left[\sum_{k=1}^K A_k^\rho S_k^\theta \right]^{\frac{1-\theta}{\theta}} \tag{15}$$

Let $\overline{AS} = \frac{\sum_{k=1}^K A_k^\rho S_k^\theta}{K}$ be the average skill level of all other workers in the firm, with worker i's contribution to the average converging to zero as K becomes large, and likewise for $\bar{S}$. Then equation (15) becomes:

$$w_i = \gamma^{-1} A_i^\rho S_i^\theta N^{\frac{1}{\theta}} \bar{S} \left(\overline{AS} \right)^{\frac{1-\theta}{\theta}} \tag{16}$$

Equation (16) shows that there will be positive assortative matching (PAM) in the labor market, both on worker skills and on firm attributes. Given a worker's own skills, her wages will be higher in firms and/or occupations with higher values of ρ and lower values of θ . Likewise, since wages are equal to marginal products, firms with higher ρ and lower θ will be willing to pay more for workers of a given skill level. This leads to PAM in the labor market, with the degree of sorting depending on the distributions of worker skills and firm technology parameters.

Even with additional assumptions about the distribution of A, S, ρ and θ and the correlations between them, solving for the equilibrium allocation of workers to firms is a complicated assignment problem that goes beyond the scope of this paper (see e.g. Abowd et al. 2009, Costinot and Vogel 2010, 2014). As a result, the parameters from the wage equation will not have a structural interpretation. However, I can sign the direction of sorting - equation (16) predicts a positive correlation between a worker's cognitive skill and the cognitive task intensity of her occupation and a negative correlation between social skills and routine task intensity.

Note that equation (16) provides one possible explanation for the existence of large establishment-level wage premiums in models with worker fixed effects and detailed occupation and industry controls (Card, Heining and Kline 2013). A worker with high social skills makes other workers more productive, generating a positive externality that increases the wages of other workers in the firm.

Dividing (16) by itself for worker i compared to worker n yields a simple expression for relative wages within a firm holding the skills of all other workers constant:

$$\frac{w_i}{w_n} = \frac{A_i^{\rho} S_i^{\theta}}{A_n^{\rho} S_n^{\theta}} \tag{17}$$

Equation (17) yields three predictions about the returns to skill across workers:

1. *Wages are increasing in cognitive skill and social skill, conditional on ρ and θ.* This implication is straightforward. In a wage equation that conditions on a variety of worker characteristics and proxies for ρ and θ with covariates such as occupation and industry fixed effects, the coefficients on both cognitive skill and social skill should be positive and statistically significant.

2. *Cognitive skill and social skill are complements.* 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. Intuitively, the return to an increase in social skills is higher when workers have higher cognitive skill, because they are the lowest price provider of a larger share of tasks. I test this prediction by interacting measures of cognitive skill and social skill together in a wage equation, as in Weinberger (2014).

3. *The returns to social (cognitive) skill are increasing in occupations/firms with lower routine (higher cognitive) task intensity.* I test this prediction by interacting measures of cognitive and social skill with the cognitive and routine task intensities of a worker's occupation, controlling for detailed covariates plus occupation and industry fixed effects. I can also estimate models that control for worker fixed effects. This accounts for sorting of workers to occupations and identifies the relative returns to skill from within-worker job transitions.

The model generates two other predictions about the wages of a worker with fixed, pre-market skill who transitions across occupations or firms. To see this, simplify equation (16) by taking logs:

$$ln(w_i) = -ln\gamma + \rho lnA_i + \theta lnS_i + \frac{1}{\theta}lnN + ln\bar{S} + \left(\frac{1-\theta}{\theta}\right) ln\left(\overline{AS}\right) \quad (18)$$

The first prediction is that wages are increasing in firm/team size, with relatively greater returns to scale when work is less routine. The positive empirical relationship between firm size and wages is well-documented and has been attributed to a variety of factors (e.g. Oi and Idson 1999). In this model, the size-wage gradient arises from the positive productivity spillover that workers have on each other through task trade.[34] I test this prediction by estimating a model with worker fixed effects and asking whether the firm size-wage gradient is larger when workers are employed in nonroutine occupations.

The second prediction is that wages are decreasing in the average skill level of other workers, with larger declines when work is more routine. Since $\theta > 1$, the last term in the wage equation is always negative and ranges between zero and negative one as work becomes more routine (i.e. $\theta \to \infty$). This term captures the idea that routine work magnifies "crowd-out" of lower-skilled workers. Intuitively, as θ increases, higher-skilled workers substitute more completely for lower-skilled workers.[35] In contrast, as $\theta \to 1$ there is no wage loss from adding more productive factors, because the set of tasks is sufficiently diverse that worker i is still the most efficient producer of many of them.

I test this prediction by asking whether a worker's wage declines *more* in routine occupations as a rival factor - computer capital - becomes more "skilled". I measure the "skill" of computer capital using data on the intensity of computer use by industry, following Autor et al. (1998) and Autor et al. (2003). One can conceive of advances in computing power over the last fifty years as increasing the cognitive skill of machines. Prior research has argued that computerization enlarges the set of tasks that machines can perform by supplanting workers in tasks of increasing cognitive sophistication (Bresnahan 1999, Bresnahan et al. 2002, Autor et al. 2003). The social skill of computers has also increased over time through advances in computerization and information technology (Levy and Murnane 2012). Bartel et al. (2007) document improvements in information technology (IT) in the valve manufacturing industry such as fusion control, which makes the programming of machines "more conversational and simpler to complete and execute".

This prediction provides a mechanism for understanding the pattern of employment

[34] Becker and Murphy (1992) specify a model where the coordination cost of team production increases as a function of N (team size). Adding this assumption would make the overall firm size-wage gradient disappear (in fact, it would predict higher wages in smaller firms all else equal). However, the result that the firm size-wage gradient is relatively larger in nonroutine occupations would still hold.

[35] For simplicity consider the wage equation under "zero gravity", i.e. $S_n S_i = 1$ for all i and n. In that case, as $\theta \to \infty$ log wages reduce to $ln(w_i) = -ln\gamma + \rho lnA_i - ln\left(\sum_{n=1}^{N} \frac{A_i^{\rho}}{N}\right)$.

growth in routine occupations across the skill distribution shown in Figure 1. As computer "skill" increases, workers of a given skill level are crowded out relatively more in routine occupations. I test this prediction by interacting computer use intensity by industry and year with the routine task intensity of a worker's occupation.

4 NLSY Data

I test the predictions of the model using data from 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 natural log of hourly wages, excluding respondents who are enrolled in school. The results are robust to alternative outcomes and sample restrictions such as using the log of 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).[36]

Several psychometrically valid and field-tested measures of social skills exist, but none are used by the NLSY. 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[37]

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.

[36] I adjust AFQT scores for age at test by subtracting the age-specific mean from each respondent's score, then I normalize the age-adjusted scores to have a mean of zero and a standard deviation of one.

[37] 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 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 0.32 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 most specifications. I also control for two pre-market measures of "non-cognitive" skills - the Rotter Locus of Control and the Rosenberg Self-Esteem Scale - which are also used by Heckman et al. (2006). To the extent that my measure of social skills is an imperfect or even poor proxy for the underlying construct, the results will 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, which I match to CPS data on computer usage at work from the CPS following Autor et al. (1998) and Autor et al. (2003). I also control for industry fixed effects and occupation-by-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. Appendix Table A1 presents selected results for heterogeneity in the returns to skills by race, gender and education. 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. Overall, the NLSY79 sample is more disadvantaged and more representative of the U.S. population.

5 Empirical Models and Results

5.1 Occupational Sorting on Skills

I test the first prediction of the model by regressing measures of the task content of occupations on worker skills and a variety of other covariates:

$$T_{ijt} = \alpha + \beta_1 COG_i + \beta_2 SS_i + \beta_3 COG_i * SS_i + \gamma X_{ijt} + \delta_j + \zeta_t + \epsilon_{ijt} \tag{19}$$

where T indexes the task content of a worker's occupation. The baseline model includes cognitive skills (AFQT), social skills (the composite measure described above), the interaction between cognitive skills and social skills, race-by-gender indicators, age and year fixed effects (indexed by t), fixed effects for years of completed schooling, and industry-region-urbanicity fixed effects (indexed by j). Each observation is a person-year, and I cluster standard errors at the individual level. The model predicts that workers with higher cognitive skills will sort into cognitive occupations, and that workers with higher social skills will sort into nonroutine occupations.

The first two columns of Table 2 present results from an estimate of equation (19) where the outcome is the nonroutine analytical (math) task measure from O*NET. Column 1 presents results from the basic model. Since the O*NET task measure is on a 0 to 10 point scale, a one standard deviation increase in cognitive skill increases the nonroutine analytic task content of a worker's occupation by about 4.3 percentiles, and the impact is highly statistically significant. Social skill also predicts the nonroutine analytic task content of a worker's occupation, although the coefficient is only about one-fifth the size of the coefficient on cognitive skill. Finally, note that the interaction between cognitive skills and social skills is negative in Column 1, suggesting that workers with high levels of both kinds of skill are somewhat *less* likely to sort into math-intensive occupations.

Column 2 adds controls for three other O*NET task measures related to social interaction. This reduces the coefficient on cognitive skills to about half its size in Column 1, and reduces the coefficient on social skills to zero. Columns 3 and 4 repeat the same pattern except with the routine task intensity of an occupation as the outcome. With no task controls, the coefficient on cognitive skill is indistinguishable from zero and the coefficient on social skill is negative and statistically significant. Adding controls for cognitive task content in Column 4 switches the sign on the AFQT coefficient to positive, yet the coefficient on social skills remains negative statistically significant. In both models, the coefficient on the interaction between cognitive skills and social skills is negative and statistically significant. The outcome in Columns 5 and 6 is the social skill intensity of an occupation, and the pattern of results is very similar (but opposite in sign) to Columns 3 and 4.

Overall, the first prediction of the model is strongly supported by the results in Table 2. Workers with higher cognitive skills sort into occupations that are more cognitive skill-intensive, and workers with higher social skills sort into occupations with higher non-routine and social skill task intensity. Moreover, there is strong evidence for sorting on skill complementarity, particularly for routine occupations.

5.2 Labor Market Returns to Skills

The model predicts that there will be a positive return to cognitive skill and social skill in the labor market, holding ρ and θ constant. It also predicts complementarity between cognitive skill and social skill. I test these predictions by regressing log hourly wages on both measures of skill plus their interaction:

$$ln(wage_{ijt}) = \alpha + \beta_1 COG_i + \beta_2 SS_i + \beta_3 COG_i * SS_i + \gamma X_{ijt} + \delta_j + \zeta_t + \epsilon_{ijt} \tag{20}$$

The results are in Table 3. As in Table 2, the regression includes controls for demographic covariates, each observation is a person-year and standard errors are clustered at the individual level. Columns 1 and 2 present estimates of a sparse model that only controls for demographic covariates. Column 1 shows that the return to social skills is positive and statistically signiifcant. A one standard deviation increase in social skills increases log hourly earnings by 9.3 percent. Column 2 adds the AFQT, the interaction between AFQT and social skills, and the two measures of non-cognitive skill. This shrinks the coefficient on social skills down to about 4 percent, although it is still highly statistically significant.

Column 2 shows that the two non-cognitive skill measures are strongly correlated with wages. However, the coefficient on social skills increases to only 4.6 percent when they are excluded, which suggests that the social skill measure includes independent information about productivity. The interaction between cognitive skills and social skills is positive and statistically significant at the 10 percent level.

Column 3 adds controls for years of completed education and drops 13 percent of the sample in public sector jobs such as teachers and government employees, since their wages are likely to be determined by rigid pay scales. This reduces the coefficient on social skills further to about 3.1 percent and reduces the impact of a one standard deviation increase in AFQT from 16.2 percent to 10 percent, although both remain statistically significant. Column 4 adds controls for ρ and θ using the full set of occupational task intensities from O*NET, dropping the coefficient on AFQT further to 6.8 percent but leaving the coefficient on social skill nearly unchanged.

Column 5 includes occupation by industry by region by urbanicity fixed effects in an attempt to completely control for ρ and θ. The coefficients on AFQT and social skill fall to 5.8 percent and 2.1 percent respectively, but both are still statistically significant at the less than one percent level. Interestingly the coefficient on the interaction between cognitive skills and social skills, which hovered around statistical significance in Columns 2 through 4, is largest in Column 5 (0.9 percent, statistically significant at the 5 percent level). The R-squared of the regression moves from 0.38 in Column 1 to 0.71 in Column 5. Table 3 strongly confirms the model's predictions about the returns to skill and skill complementarity.

5.3 Heterogeneous Returns to Skill by Occupation Task Intensity

Columns 6 and 7 of Table 3 add interactions between skills and task intensities by occupation. Column 6 includes interactions between cognitive skill and nonroutine analytic (math) task intensity and between social skill and routine task intensity. Column 7 repeats the exercise except with the direct measure of an occupation's social skill task intensity instead of routine. The model predicts that the returns to cognitive skill will be increasing in the cognitive task intensity of a worker's occupation, and that the returns to social skill will be decreasing in routine (or increasing in social skill) task intensity. I also include the cross-interactions as a check, as well as triple interactions between both measures of skill and occupation task content.

Column 6 provides strong support for the predictions of the model. I find that the return to cognitive skills is relatively higher in math intensive occupations - the coefficient on the interaction is positive and statistically significant at the less than 1 percent level. The magnitude implies that the return to cognitive skill for a worker with an AFQT score that is one standard deviation above the average increases by about 5.5 percent when moving from an occupation in the 1st to the 100th percentile of math task intensity. The coefficient on the interaction between social skills and routine task intensity is negative, similar in size, and statistically significant at the less than one percent level. I also find some evidence of relatively lower returns to cognitive skill in routine occupations.[38]

Column 7 replaces routine task intensity with social skill task intensity. A significant share of the increasing return to cognitive skills is accounted for by the social skill task measure. The coefficient on the interaction between AFQT and social skill task intensity is

[38] The cross-interactions (i.e. between social skill and cognitive task intensity, and between AFQT and routine task intensity) are sometimes statistically significant. One possible reason is that skills in the NLSY (particularly social skills) are mismeasured. Another possibility is that sorting across occupations, combined with the fact that AFQT and social skills are correlated about 0.3 for individuals, leads to positive cross-interactions.

larger than the interaction with math task intensity, and the latter is no longer statistically significant. This is broadly consistent with the results in Figures 4 through 6, which show weak demand for cognitive tasks that are not also accompanied by social skill tasks.

Table 4 estimates models with worker fixed effects, plus interactions between skills and occupation task intensities:

$$ln(wage_{ijt}) = \alpha + \beta_1 COG_i * T_{ijt} + \beta_2 SS_i * T_{ijt} + \beta_3 COG_i * SS_i * T_{ijt} + \delta X_{ijt} + \zeta_t + \eta_i + \epsilon_{ijt} \quad (21)$$

This restricts the variation to within-worker job transitions, and so only the interactions with skills and other time-invariant covariates are identified. I also control for the full complement of O*NET task measures and age, year, census division, and urbanicity fixed effects. Column 1 estimates equation (21) with interactions between the math and routine task intensity of a worker's occupation and worker skills. Column 2 repeats the same exercise, except with social skill instead of routine task intensity.

The results in Columns 1 and 2 are broadly similar to the results in Columns 6 and 7 of Table 3, even though the variation is identified from worker job transitions. I find a positive and statistically significant interaction between cognitive skill and the math task intensity of an occupation. I also find a negative and statistically significant interaction between routine task intensity and cognitive skill. The interactions between the social skill intensity of worker's occupation and the worker's cognitive and social skill are large, positive and statistically significant. A worker who switches to an occupation that is 10 percentage points higher in the distribution of social skill intensity earns a wage increase of about 1.6 percent when they have average cognitive skill (the main effect on social skill intensity in Column 2), but 2.3 percent when their cognitive skill is one standard deviation above the average. By comparison, the coefficient on the interaction between social skills and social skill task intensity is about half as large, but also statistically significant at the less than one percent level. Finally, the interactions between math task intensity and worker skills become small and statistically insignificant after conditioning on the social skill task intensity of an occupation.

Columns 3 and 4 repeat the same exercise as Columns 1 and 2, except with added controls for the natural log of the number of employers in the worker's primary job in each year plus an indicator variable that is equal to one if the worker's employer has multiple establishments. Data on firm size are available in the NLSY for all years except the 1981-1985 period, so these years are excluded from the regression. Controlling for firm size has little impact on the results. While I do not report the results here, the estimates in Table 4 are robust to controlling for industry fixed effects, to using alternative outcome measures such as log total earnings, and to adding interactions with other O*NET task measures.

One possible interpretation of the positive coefficients on social skills is that they reflect the promotion of employees to management positions. To test for this possibility, Columns 5 and 6 present results like Columns 3 and 4 except that the sample excludes any occupation with the words "manage" or "manager" in the title. This eliminates about 15 percent of the sample, and importantly it does not reflect wage gains for workers from occupational switches that sound like promotions such as "sales representative" to "sales manager". Columns 5 and 6 show that eliminating managers from the sample has almost no impact on the main results. In fact, the coefficients on skill complementarity are somewhat larger when managers are excluded. Overall, the results in Columns 5 and 6 suggest that the return to social skill is not driven by the promotion of socially skilled workers into management positions.

However, social skills may still be important for managers. Lazear et al. (2012) show that managers have a large impact on worker productivity and retention. In Garicano and Rossi-Hansberg (2004), Garicano and Rossi-Hansberg (2006) and Antras et al. (2006), managers have greater knowledge than workers, and production is organized so that highly skilled managers can optimally leverage their knowledge. Lazear (2012) presents a model of leadership skill where successful leaders have high ability, seek out higher-variance settings (where the value of a correct decision is greatest), and are "generalists" with a broad range of skills.[39]

While the model here has no hierarchy, one could readily accommodate management in a variety of ways. I assumed that task productivities are unknown when a worker is hired but perfectly observed thereafter. One approach would be to treat managers as receiving noisy signals of factor productivity in each task, with the accuracy of the signal increasing in the manager's skill. The manager's problem is then to allocate factors across projects or divisions of the firm with different values of ρ and θ, maximizing total output given workers' skills. This is consistent with Adhvaryu et al. (2014), who find that "relatable" managers smooth productivity shocks by more efficiently reallocating low-performing workers.

A related approach would add managerial skill as another coordination cost that affects all task trades under the manager's purview. An unskilled manager would impose a high coordination cost on task trade between workers, leading to more self-production and lowering the gains from trade. This accords with the intuition that effective managers encourage more collaboration between the workers that they supervise, and that effective managers are optimally assigned a larger span of control.

[39]Lazear (2004) presents a similar model of the importance of balanced skills to entrepreneurship.

5.4 Firm Size and Nonroutine Task Intensity

I test the model's prediction about the relationship between firm size and routine task intensity by estimating equation (21) above, with added controls for firm size plus interactions between firm size and the cognitive and routine task intensity of a worker's occupation. As above, I also control for an indicator variable that is equal to one if the worker's employer has multiple establishments. The results are in Table 5. Columns 1 and 2 of Table 5 report results where firm size is interacted with routine and social skill task intensity respectively.

The main effects on firm size in Columns 1 and 2 show that workers earn higher wages overall when they transition to larger firms, which is consistent with prior work on the firm size-wage gradient. In Column 1 the coefficient on the interaction between firm size and routine task intensity is negative and statistically significant. The magnitude of the coefficient suggests that the wage return to firm size shrinks by more than 50 percent (from 0.045 to 0.020) as the routine task intensity of a worker's occupation shifts from 0 to 100 percent. This is consistent with Mueller et al. (2015), who find that within-firm wage differentials by size can be explained by larger firms being more likely to automate routine tasks. The results in Column 2 substitute social skill for routine task intensity, yielding very similar (but opposite-signed) results. Interestingly, Columns 1 and 2 show that the firm size-wage gradient is significantly *decreasing* in an occupation's cognitive task intensity. One possible explanation is that larger firms are also more likely to automate mathematically intensive tasks.

5.5 Computer Usage and Nonroutine Task Intensity

Over the last few decades, computers have become capable of performing workplace tasks of rapidly increasing complexity (e.g. Brynjolfsson and McAfee 2012). The model predicts that increases in the "skill" of rival factors such as computer capital will lead to relatively larger wage declines for workers in routine occupations. I proxy for increases in the skill of computer capital with the intensity of computer use at work by industry. This question is asked of CPS respondents in selected years, and following Autor et al. (1998) and Autor et al. (2003) I collapse the questions about the frequency of computer use at work to the industry level. The first year of data that is available is 1984, and the CPS stopped asking this question in 2003. I first assume that the share of workers who used a computer in 1984 is a constant measure of the intensity of computer usage by industry. I also construct a time-varying measure using all available years between 1984 and 2003 and interpolating data for missing years.

The results are in Table 6. Columns 1 and 2 estimate equation (21), adding interactions for firm size and industry computer intensity in 1984. Columns 3 and 4 substitute the time-varying measure of computer usage, which restricts the sample to the years between 1984 and 2003. In both cases I find that workers experience larger relative wage declines in computer-intensive industries when they are employed in routine occupations. The estimates in Column 3 suggest that a 10 percentage point increase in industry computer usage raises wages by around 1.5 percent (the main effect on industry computer use intensity) for the least routine occupations, but *lowers* wages by 1.5 percent for the most routine occupations. Similarly, the results in Column 4 imply that a 10 percentage point increase in industry computer usage leads to impacts on wages that range from -1.2 to 4.3 percent as occupations range from least to most social skill-intensive.

In Columns 1 and 3, I also find statistically significant relative wage gains in computer-intensive industries for workers in cognitive occupations, which is consistent with many other studies (e.g. Krueger 1993, Autor et al. 1998). Notably, however, this association disappears completely in Columns 2 and 4 once interactions between social skill and computer use are included in the model. Overall, I find strong support for the prediction that more intensive use of computer capital widens wage differentials between routine and nonroutine work.

6 Implications of the Growing Importance of Social Skills

6.1 Capital-Labor Substitution and Skill Complementarity

The results in Tables 4 through 6 show that the relative return to both cognitive skills and social skills is higher in social skill-intensive occupations. Strikingly, after adjusting for the social skill intensity of an occupation, there is no evidence of a greater return to skills in math-intensive occupations. The results in Table 6 also show no impact of increasing computer usage on wages in math-intensive occupations after controlling for social skill task intensity. At first glance this may seem inconsistent with the literature on the labor market effects of computerization and information and communication technology (ICT), which generally finds that they complement highly skilled work (e.g. Caroli and Van Reenen 2001, Bresnahan et al. 2002, Autor et al. 2003, Bartel et al. 2007, Akerman et al. 2015).

The literature has mostly focused on complementarity between technological change and cognitive skill. However, the results here and a closer look at the case study evidence both suggest that computerization and ICT may actually increase the returns to *skill complementarity*. A key theme of studies of ICT and organizational change is the reallocation of workers into flexible, team-based settings that facilitate problem-solving. While past work has mostly focused on the implications for rising returns to cognitive skill (and education), one can also interpret this evidence as increasing the returns to social skill by making work less routine (i.e. lower θ).

As an example, consider the impact of digital check imaging (modeled here as an increase in the cognitive skill of machines) on the operation of a bank, described in detail by Autor et al. (2002). The tasks of sorting, reading and proofing check deposits were somewhat cognitive skill-intense - "proof machine operators" had to be able to quickly perform mathematical calculations and find and correct errors - yet also quite routine. Digital check imaging allowed banks to replace the routine tasks performed by proof machine operators at lower cost, leading to falling employment and wages for these workers (Autor et al. 2002).

However, the remaining workplace tasks became less routine and thus less amenable to computerization. Banks bundled exceptions processing tasks so that workers were assigned to customer accounts rather than to exception types. Autor et al. (2002) discuss how this change led to an increase in skill demands - recruiting was reorganized to focus on problem-solving and the ability to "see the whole picture", and candidates were "interviewed by supervisors from several groups and could only be hired if multiple supervisors vetted the hire".

Caroli and Van Reenen (2001) argue that increases in worker skill complement ICT by decentralizing decision-making within the firm - the idea is that skilled workers are better at analyzing and synthesizing information and are also 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 (computer numerically controlled machines, or CNCs) are more likely to simultaneously 1) require worker skill upgrading through technical training programs; 2) reorganize workers into problem-solving teams; and 3) introduce regular shop floor meetings.

The case study evidence is consistent with computerization leading to increasing demand for *complementarity* between cognitive skills and social skills. I investigate this hypothesis empirically by estimating a version of equation (21) with occupation and industry fixed effects, plus additional interactions between task intensity, worker skill, and year. This specification asks whether the returns to skill are increasing over time within-worker *and* within-occupation and industry. In other words, has the return to skills changed for workers holding the same jobs, as the structure of the workplace changes? The evidence discussed above would predict a relatively greater return to *skill complementarity* over time, as workplaces increasingly adopt ICT and reorganize work.

Figure 7 presents coefficients and 90 percent confidence intervals for the interaction between cognitive skill, social skill, the social skill task intensity of the worker's occupation (the solid line), and year. I group NLSY survey waves into four-year or six-year intervals to aid with precision, with the first four years of the survey (1979 to 1982) as the base period. The regression is fully saturated with all the other interactions (skill by year, task by year, etc.), although those results are not shown. Thus the reported coefficients represent changes over time in the relative return to skill complementarity within-worker, within-occupation and within-industry. Following the results in Columns 5 and 6 of Table 4, I exclude managers from the regression.

The results in Figure 7 are consistent with a growing return to skill complementarity. The coefficients increase gradually, from near zero in the 1980s to large, positive and statistically significant by the 2000s. The magnitudes are economically significant - for example, they imply that an individual worker with cognitive skill and social skill one standard deviation above the average would earn about 5 percent more in the same occupation and industry in 2010 compared to the 1980s. However, one limitation of this approach is that the structure of the NLSY sample does not allow separate identification of age and cohort effects. Although I exclude managers and control for age and year fixed effects plus interactions between year and other variables, I cannot confidently rule out the hypothesis that returns to skill complementarity increase with age and experience rather than year.

6.2 Social Skills and Gender

Since 1980, U.S. gender gaps in achievement, educational attainment, employment and wages have narrowed substantially and in some cases reversed (Welch 2000, Goldin et al. 2006, Autor and Wasserman 2013). Several authors have shown that narrowing gender employment and wage gaps can be explained by technological change that favors women - colloquially, that women have a comparative advantage in "brains" relative to "brawn" (Welch 2000, Bacolod and Blum 2010, Black and Spitz-Oener 2010, Beaudry and Lewis 2014).

While past work has usually grouped "cognitive" tasks together, it is possible that the relationship between computerization and narrowing gender gaps is driven primarily by a female advantage in social skills. Females consistently score higher on tests of emotional and social intelligence (Hall 1978, Woolley et al. 2010, Kirkland et al. 2013). Sex differences in sociability and social perceptiveness have been shown to have biological origins, with differences appearing in infancy and higher levels of fetal testosterone associated with lower scores on tests of social intelligence (Connellan et al. 2000, Baron-Cohen et al. 2005, Chapman et al. 2006). Woolley et al. (2010) show that teams with a higher share of female participants perform better on group tasks, even after conditioning on group-average cognitive skills. Large gender gaps in "non-cognitive" skills and problem behaviors appear early in life and are strongly correlated with later educational outcomes (Jacob 2002, DiPrete and Jennings 2012, Bertrand and Pan 2013).

Figures 8 and 9 show the importance of sex differences in explaining the changing task content of work by reproducing Figure 3 (the extension of Figure 1 from Autor et al. (2003) that uses O*NET task measures) separately by gender.[40] Figure 8 presents trends in the task content of work between 1980 and 2012 for males, and Figure 9 presents analogous results for females. Since 1980, the task content of work for males has barely changed. In contrast, Figure 9 shows a dramatic decline in routine task intensity (from 57 to 35 centiles) for females. Not surprisingly, this is matched by an increase of nearly-equal size (approximately 19 centiles) in social skill task inputs. While there has also been an increase in nonroutine analytic task inputs for females, it has been only about half as large as the increase in social skills.

The patterns in Figures 8 and 9 are driven by two factors - 1) changes in the task composition of the labor force that favor female-dominated occupations; 2) changes in the gender composition of social skill and nonroutine-intensive occupations. In Figure 10, I restrict attention to the latter channel by plotting the within-occupation change in female employment share between 1980 and 2012 against the occupation's social skill task intensity. Each dot is an occupation, and the dashed line represents the results of a linear regression with weights equal to the occupation's 1980 labor supply. The patten is clear - occupations with higher social skill requirements employ relatively more women in 2012 than they did in 1980. While not shown, this pattern holds inversely for occupations that are relatively routine task-intensive.

In results not reported here, I find that the labor market returns to social skills are very similar by gender. Additionally, if I reproduce Figure 10 with the change between 1980 and 2012 in male-female log relative wages, I find that there is no relationship between social skill and nonroutine task intensity and the closing of gender wage gaps. While this result appears puzzling at first, it could reflect differential selection into social-skill intensive occupations over time. As shown in Figure 9, women (who have a comparative advantage in social skills) have increasingly sorted into social skill-intensive occupations. All else equal, this should lower the average productivity of female workers in that occupation, bringing gender wage differences back down to their original level. This mechanism, where changes in skill

[40]One key difference between the results here and Autor et al. (2003) and Autor and Price (2013) is that the DOT task values were linked to the 1971 CPS microdata, which allowed the authors to compute separate task values by gender for each occupation. This analysis assigns the same task values for an occupation by gender, and is thus only comprised of gender differences across Census occupation codes.

prices (and possibly discrimination as well) are captured primarily by the extensive margin of occupational sorting, is consistent with the results in Mulligan and Rubinstein (2008) and Hsieh et al. (2013).

7 Conclusion

In a much discussed paper, Frey and Osborne (2013) estimate that 47 percent of total U.S. employment is at high risk of automation over the next one to two decades, suggesting that even highly skilled workers may eventually lose the "Race Against the Machine" (Brynjolfsson and McAfee 2012). In this paper, I show that high-paying, difficult-to-automate jobs increasingly require *social skill*s. Nearly all job growth since 1980 has been in occupations that are relatively social skill-intensive. Jobs that require high levels of analytical and mathematical reasoning but low levels of social interaction have fared especially poorly.

Why are social skills so important in the modern labor market? The reason is that computers are still very poor at simulating human interaction. Reading the minds of others and reacting is an unconscious process, and skill in social settings has evolved in humans over thousands of years. Human interaction in the workplace involves team 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. The growing importance of social skills can potentially explain a number of other trends in educational outcomes and the labor market, such as the narrowing - and in some cases reversal - of gender gaps in completed education and earnings.

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. However, the benefits of teamwork can only be realized through costly coordination among workers. I model social skills as a reduction in *worker-specific* coordination costs. Workers with high social skills can "trade tasks" at a lower cost, enabling them to work with others more efficiently.

The model generates testable predictions about sorting and the relative returns to skills across occupations. 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 determinants of wages. I also find that cognitive skill and social skill are complements in the wage equation, and that skill complementarity has grown over time. Finally, I find that workers with higher social skills are more likely to work in social skill-intensive and less routine occupations, and they earn a relatively higher wage return in these occupations. I identify the key results of the model on the relative returns to skills across occupations using worker fixed effects, i.e. transitions of the same worker across different types of jobs.

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

Abowd, J. M., Kramarz, F., Pérez-Duarte, S. and Schmutte, I.: 2009, A formal test of assortative matching in the labor market, *Technical report*, National Bureau of Economic Research.

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.

Acemoglu, D., Dorn, D., Hanson, G. H., Price, B. et al.: 2014, Import competition and the great us employment sag of the 2000s, *Technical report*, National Bureau of Economic Research.

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

Adhvaryu, A., Kala, N. and Nyshadham, A.: 2014, Management and shocks to worker productivity: Evidence from air pollution exposure in an indian garment factory.

Akerman, A., Gaarder, I. and Mogstad, M.: 2015, The skill complementarity of broadband internet, *Technical report*, National Bureau of Economic Research.

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*, National Bureau of Economic Research.

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

Autor, D. H., 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. H., Katz, L. F. and Krueger, A. B.: 1998, Computing inequality: Have computers changed the labor market?*, *The Quarterly journal of economics* **113**(4), 1169–1213.

Autor, D. H., 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., *Quarterly Journal of Economics* **118**(4).

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

Autor, D. and Wasserman, M.: 2013, Wayward sons: The emerging gender gap in labor markets and education, *Third Way Report* **20013**.

Bacolod, M., Blum, B. S. and Strange, W. C.: 2009, Urban interactions: Soft skills versus specialization, *Journal of Economic Geography* **9**(2), 227–262.

Bacolod, M. P. and Blum, B. S.: 2010, Two sides of the same coin us residual inequality and the gender gap, *Journal of Human Resources* **45**(1), 197–242.

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.

Bandiera, O., Barankay, I. and Rasul, I.: 2013, Team incentives: evidence from a firm level experiment, *Journal of the European Economic Association* **11**(5), 1079–1114.

Baron-Cohen, S.: 2000, Theory of mind and autism: A fifteen year review.

Baron-Cohen, S., Knickmeyer, R. C. and Belmonte, M. K.: 2005, Sex differences in the brain: implications for explaining autism, *Science* **310**(5749), 819–823.

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, *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.: 2013, The great reversal in the demand for skill and cognitive tasks, *Technical report*, National Bureau of Economic Research.

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. and Lewis, E.: 2014, Do male-female wage differentials reflect differences in the return to skill? cross-city evidence from 1980-2000, *American Economic Journal: Applied Economics* **6**(2), 178–94.

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.

Bertrand, M. and Pan, J.: 2013, The trouble with boys: Social influences and the gender gap in disruptive behavior, *American Economic Journal: Applied Economics* **5**(1), 32–64.

Black, S. E. and Spitz-Oener, A.: 2010, Explaining women's success: technological change and the skill content of women's work, *The Review of Economics and Statistics* **92**(1), 187–194.

Bloom, N. and Van Reenen, J.: 2011, Human resource management and productivity, *Handbook of labor economics* **4**, 1697–1767.

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

Boning, B., Ichniowski, C. and Shaw, K.: 2007, Opportunity counts: Teams and the effectiveness of production incentives, *Journal of Labor Economics* **25**(4), 613–650.

Borghans, L., Ter Weel, B. and Weinberg, B. A.: 2008, Interpersonal styles and labor market outcomes, *Journal of Human Resources* **43**(4), 815–858.

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, *American Economic Review* **82**(3), 371–92.

Bresnahan, T.: 1999, Computerisation and wage dispersion: An analytical reinterpretation, *Economic Journal* **109**(456), F390–415.

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

Brynjolfsson, E. and McAfee, A.: 2012, *Race against the machine: How the digital revolution is accelerating innovation, driving productivity, and irreversibly transforming employment and the economy*, Brynjolfsson and McAfee.

Burgess, S., Propper, C., Ratto, M., Scholder, K., von Hinke, S. and Tominey, E.: 2010, Smarter task assignment or greater effort: The impact of incentives on team performance*, *The Economic Journal* **120**(547), 968–989.

Camerer, C., Loewenstein, G. and Prelec, D.: 2005, Neuroeconomics: How neuroscience can inform economics, *Journal of economic Literature* pp. 9–64.

Card, D., Cardoso, A. R. and Kline, P.: 2013, Bargaining and the gender wage gap: A direct assessment.

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, *Quarterly journal of economics* pp. 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.*, ERIC.

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.

Chapman, E., Baron-Cohen, S., Auyeung, B., Knickmeyer, R., Taylor, K. and Hackett, G.: 2006, Fetal testosterone and empathy: evidence from the empathy quotient (eq) and the reading the mind in the eyes test, *Social Neuroscience,* **1**(2), 135–148.

Charles, K. K. and Kline, P.: 2006, Relational costs and the production of social capital: Evidence from carpooling*, *The Economic Journal* **116**(511), 581–604.

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.

Connellan, J., Baron-Cohen, S., Wheelwright, S., Batki, A. and Ahluwalia, J.: 2000, Sex differences in human neonatal social perception, *Infant Behavior and Development* **23**(1), 113–118.

Costinot, A. and Vogel, J.: 2010, Matching and inequality in the world economy, *Journal of Political Economy* **118**(4).

Costinot, A. and Vogel, J.: 2014, Beyond ricardo: Assignment models in international trade, *Technical report*, National Bureau of Economic Research.

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* pp. 111–134.

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

DiPrete, T. A. and Jennings, J. L.: 2012, Social and behavioral skills and the gender gap in early educational achievement, *Social Science Research* **41**(1), 1–15.

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* pp. 823–839.

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

Eaton, J. and Kortum, S.: 2012, Putting ricardo to work, *The Journal of Economic Perspectives* pp. 65–89.

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

Frey, C. B. and Osborne, M.: 2013, The future of employment, *How Susceptible Are Jobs to Computerisation* .

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, *American Economic Review* pp. 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), F437–F458.

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

Goldin, C., Katz, L. F. and Kuziemko, I.: 2006, The homecoming of american college women: The reversal of the college gender gap, *The Journal of Economic Perspectives* **20**(4), 133–156.

Goleman, D.: 2006, *Emotional intelligence*, Bantam.

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.

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

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

Hall, J. A.: 1978, Gender effects in decoding nonverbal cues., *Psychological bulletin* **85**(4), 845.

Hamilton, B. H., Nickerson, J. A. and Owan, H.: 2003, Team incentives and worker heterogeneity: An empirical analysis of the impact of teams on productivity and participation, *Journal of political Economy* **111**(3), 465–497.

Heckman, J. J.: 1995, Lessons from the bell curve, *Journal of Political Economy* pp. 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* pp. 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, *Review of Economics and Statistics* **83**(1), 1–12.

Hjort, J.: 2014, Ethnic divisions and production in firms, *The Quarterly Journal of Economics* **129**(4), 1899–1946.

Hsieh, C.-T., Hurst, E., Jones, C. I. and Klenow, P. J.: 2013, The allocation of talent and us economic growth, *Technical report*, National Bureau of Economic Research.

Jacob, B. A.: 2002, Where the boys aren't: Non-cognitive skills, returns to school and the gender gap in higher education, *Economics of Education review* **21**(6), 589–598.

Jaimovich, N. and Siu, H. E.: 2012, The trend is the cycle: Job polarization and jobless recoveries, *Technical report*, National Bureau of Economic Research.

Jerald, C. D.: 2009, Defining a 21st century education, *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* (0), e1–e8.

Juhn, C., Murphy, K. M. and Pierce, B.: 1993, Wage inequality and the rise in returns to skill, *Journal of political Economy* pp. 410–442.

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

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

Kirkland, R. A., Peterson, E., Baker, C. A., Miller, S. and Pulos, S.: 2013, Meta-analysis reveals adult female superiority in" reading the mind in the eyes test, *North American Journal of Psychology* **15**(1), 121–146.

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.

Kortum, S. S.: 1997, Research, patenting, and technological change, *Econometrica* **65**(6), 1389.

Kremer, M.: 1993, The o-ring theory of economic development, *The Quarterly Journal of Economics* pp. 551–575.

Krueger, A. B.: 1993, How computers have changed the wage structure: Evidence from microdata, 1984-1989, *The Quarterly Journal of Economics* **108**(1), 33–60.

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**(05), 911–920.

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

Lazear, E. P.: 2004, Balanced skills and entrepreneurship, *American Economic Review* pp. 208–211.

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

Lazear, E. P.: 2012, Leadership: A personnel economics approach, *Labour Economics* **19**(1), 92–101.

Lazear, E. P. and Shaw, K. L.: 2007, Personnel economics: The economist's view of human resources, *Journal of Economic Perspectives* **21**(4), 91–114.

Lazear, E. P., Shaw, K. L. and Stanton, C. T.: 2012, The value of bosses, *Technical report*, National Bureau of Economic Research.

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.: 2014, Sorting multidimensional types: Theory and application.

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* pp. 101–128.

Lise, J. and Postel-Vinay, F.: 2014, Multidimensional skills, sorting, and human capital accumulation, *Technical report*, Mimeo.

Lu, Q.: 2015, The end of polarization? technological change and employment in the us labor market.

Maciejovsky, B., Sutter, M., Budescu, D. V. and Bernau, P.: 2013, Teams make you smarter: How exposure to teams improves individual decisions in probability and reasoning tasks, *Management Science* **59**(6), 1255–1270.

Marx, B., Pons, V. and Suri, T.: 2015, Diversity and team performance in a kenyan organization.

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, *Annu. Rev. Psychol.* **59**, 507–536.

McCann, R. J., Shi, X., Siow, A. and Wolthoff, R.: 2014, Becker meets ricardo: Multisector matching with communication and cognitive skills.

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.

Mueller, H. M., Ouimet, P. P. and Simintzi, E.: 2015, Wage inequality and firm growth, *Technical report*, National Bureau of Economic Research.

Mulligan, C. B. and Rubinstein, Y.: 2008, Selection, investment, and women's relative wages over time, *The Quarterly Journal of Economics* pp. 1061–1110.

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), 251–66.

NACE: 2015, 2015 job outlook, *Bethlehem, Pennsylvania, November* .

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.

Oi, W. Y. and Idson, T. L.: 1999, Firm size and wages, *Handbook of labor economics* **3**, 2165–2214.

Premack, D. and Woodruff, G.: 1978, Does the chimpanzee have a theory of mind?, *Behavioral and brain sciences* **1**(04), 515–526.

Ramm, J., Tjotta, S. and Torsvik, G.: 2013, Incentives and creativity in groups.

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

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.

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* pp. 665–691.

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

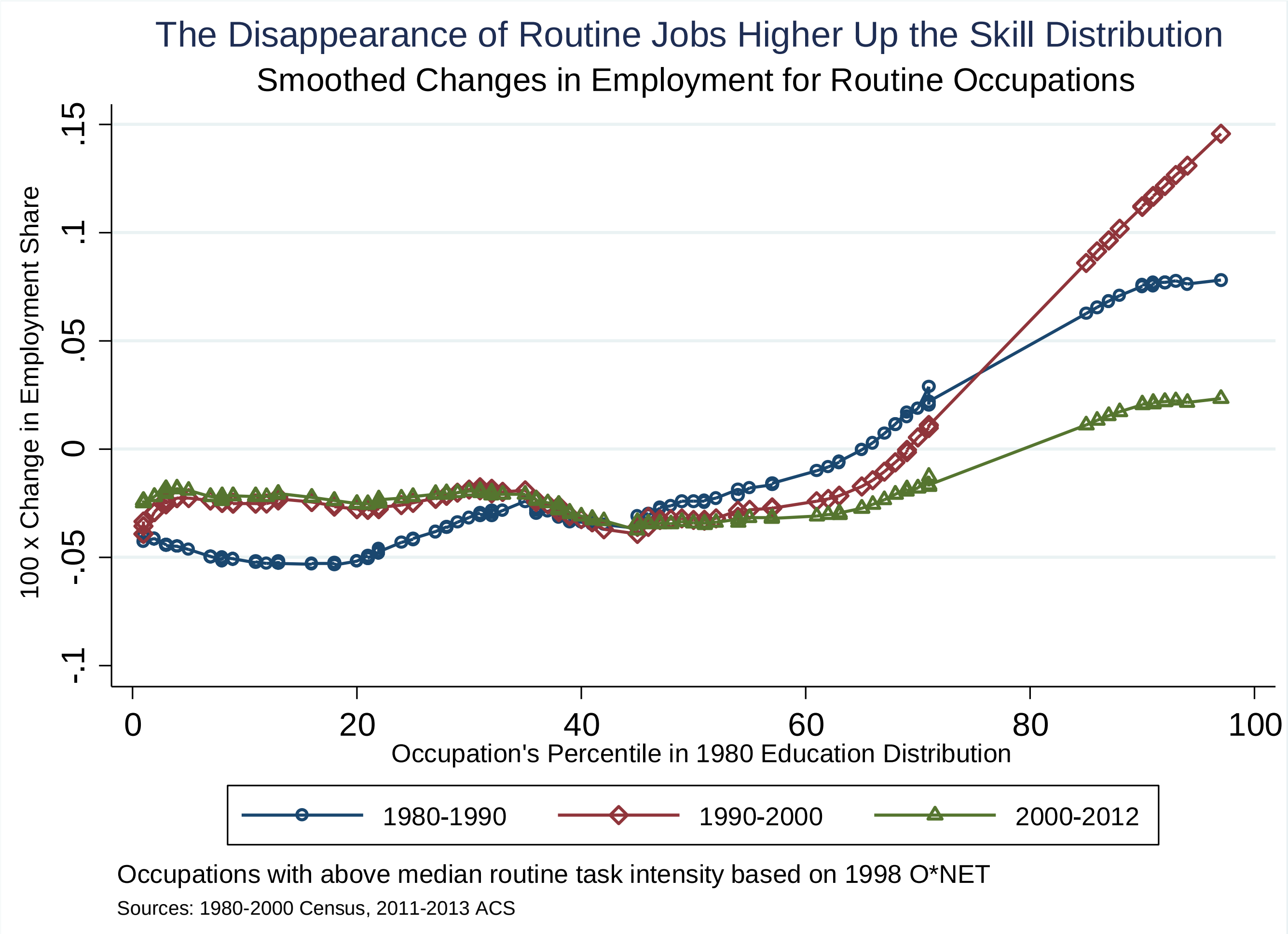
Welch, F.: 2000, Growth in women's relative wages and in inequality among men: One phenomenon or two?, *American Economic Review* pp. 444–449.

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.

Wuchty, S., Jones, B. F. and Uzzi, B.: 2007, The increasing dominance of teams in production of knowledge, *Science* **316**(5827), 1036–1039.

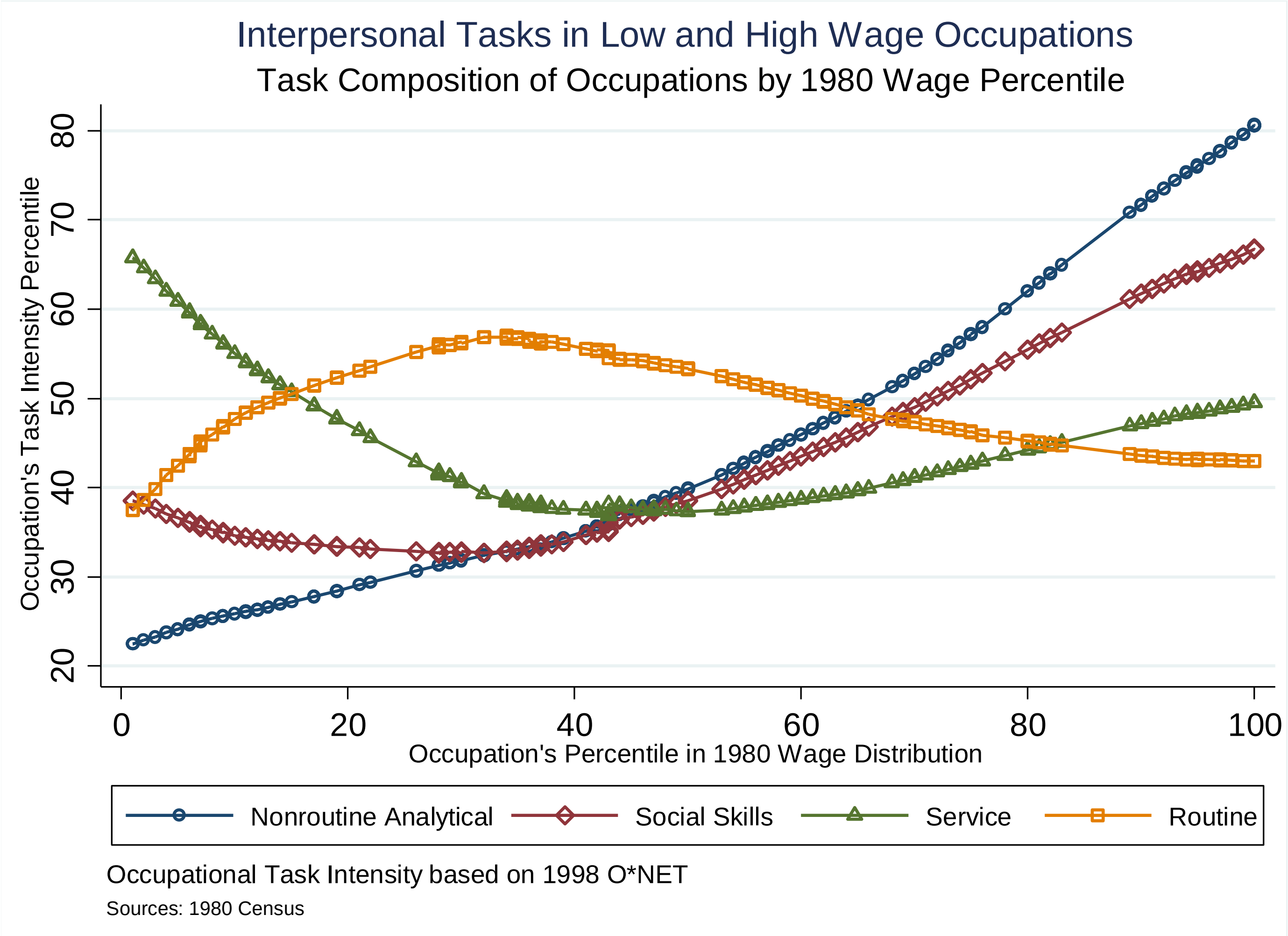
Yamaguchi, S.: 2012, Tasks and heterogeneous human capital, *Journal of Labor Economics* **30**(1), 1–53.

Figure 1



Each line plots 100 times the change in employment shares for the indicated period and is smoothed using a locally weighted regression with bandwidth 0.5. Wage percentiles are measured as the employment-weighted percentile rank of an occupation's mean years of completed education in the Census IPUMS 1980 5 percent extract. The sample is restricted to a consistent set of occupations that ranked at the 50th percentile or above in routine task intensity in 1980 based on the 1998 O*NET. Mean education in each occupation is 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 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

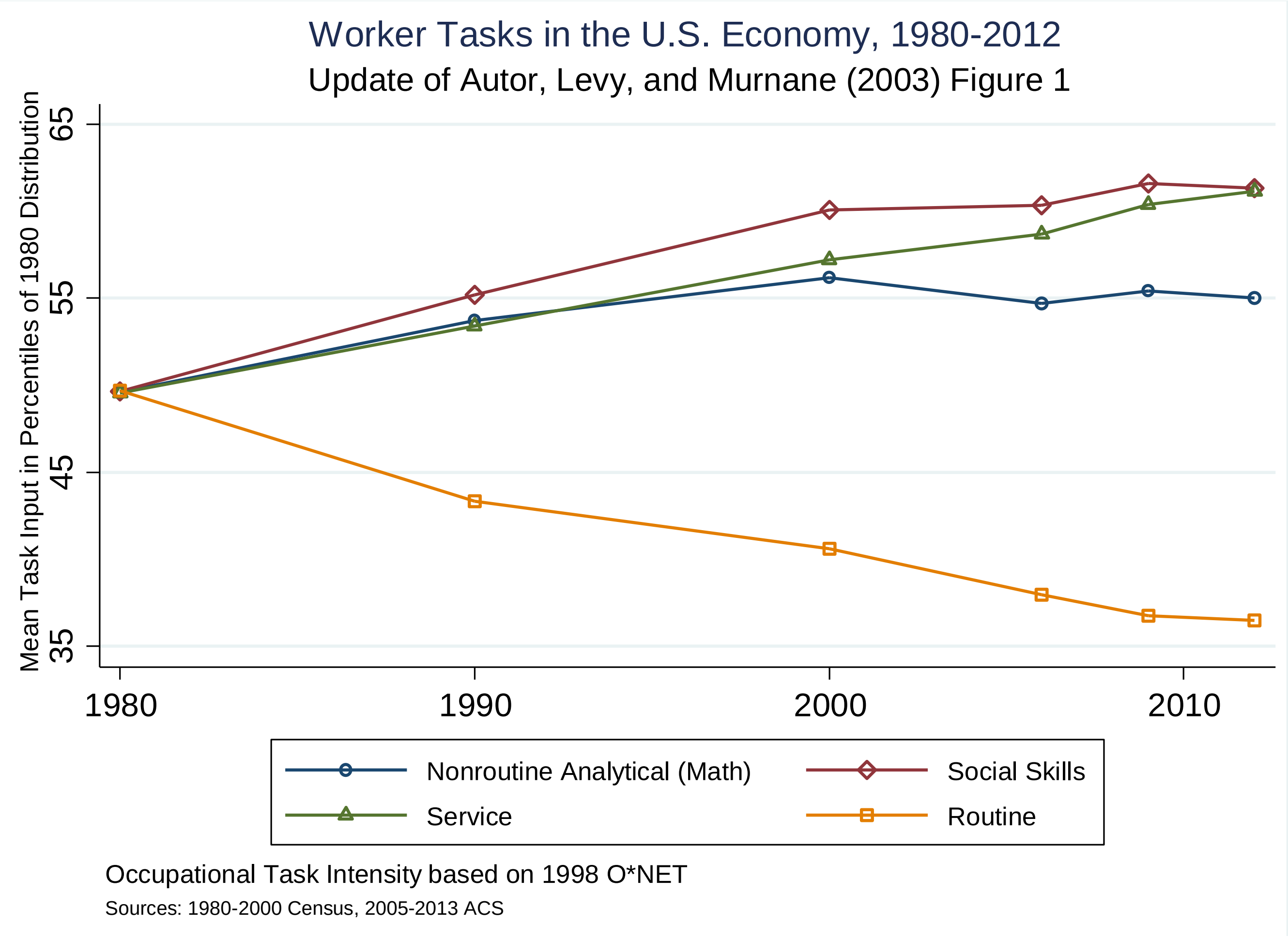
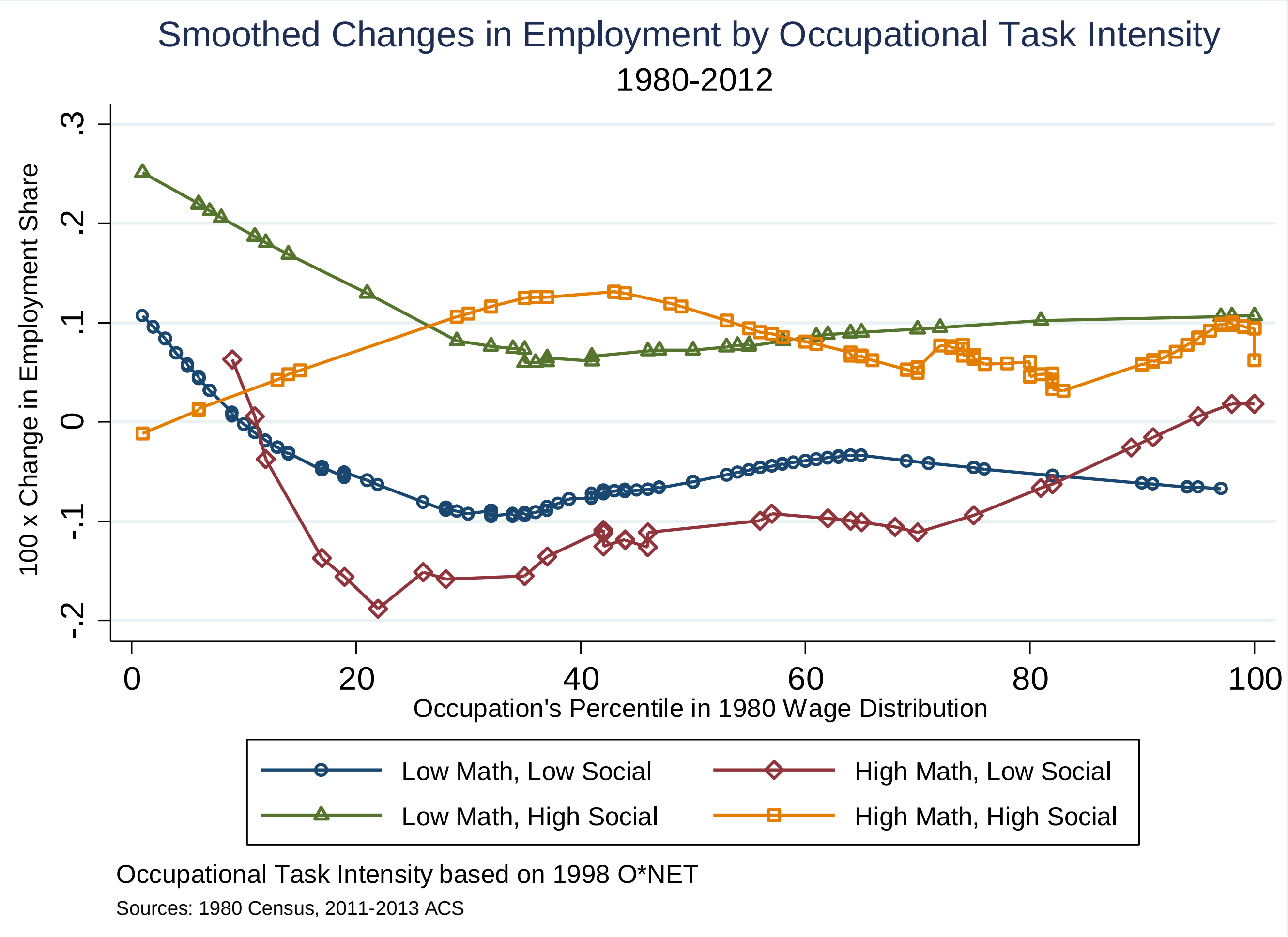


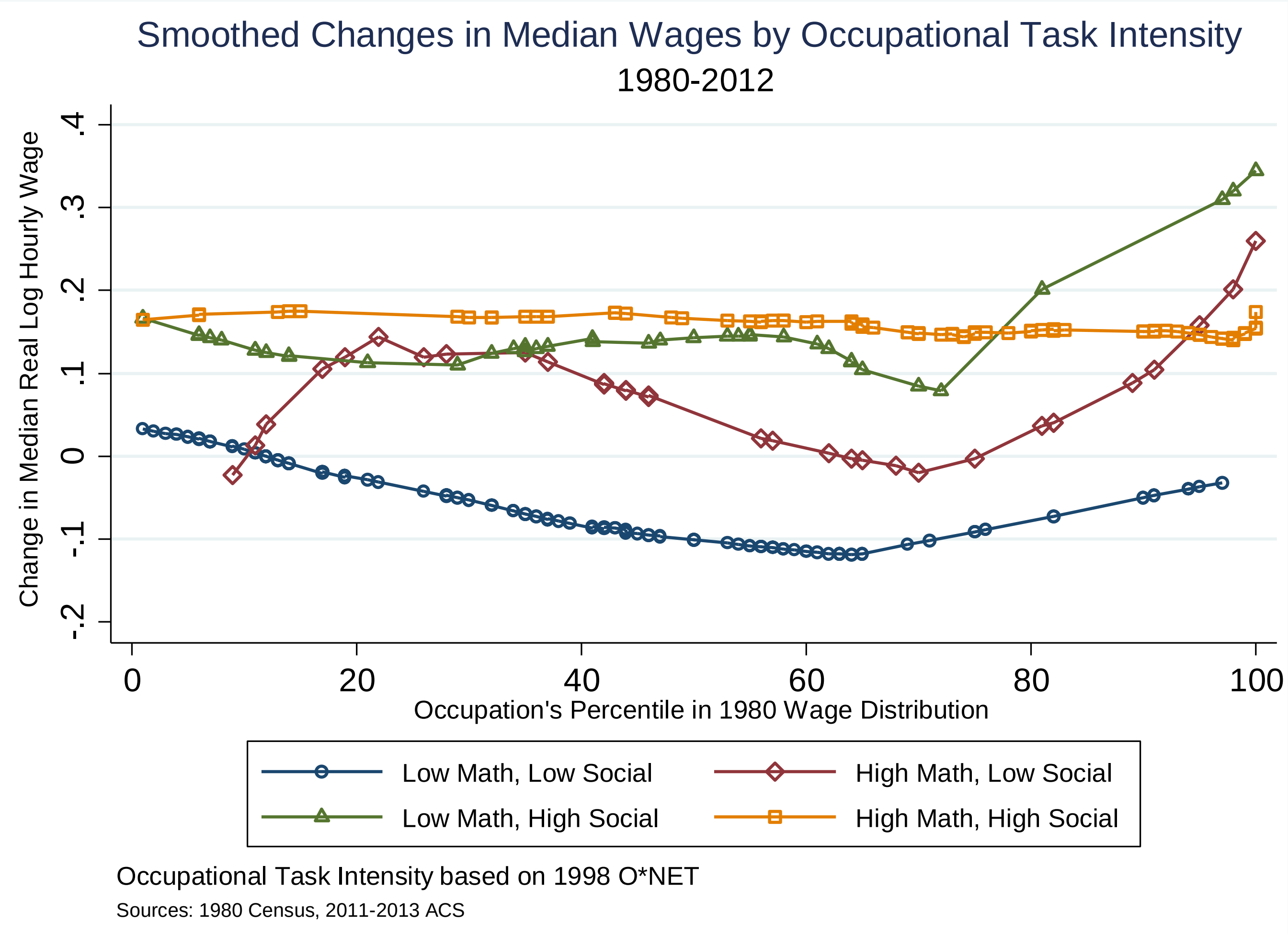
Figure 3 is constructed to parallel Figure I of Autor, Levy and Murnane (2003). O*NET 1998 task measures by occupation are paired with data from the IPUMS 1980-2000 Censuses and the 2005-2013 American Community Survey samples. Consistent occupation codes for 1980-2012 are from Autor and Dorn (2013) and 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 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 5



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 6

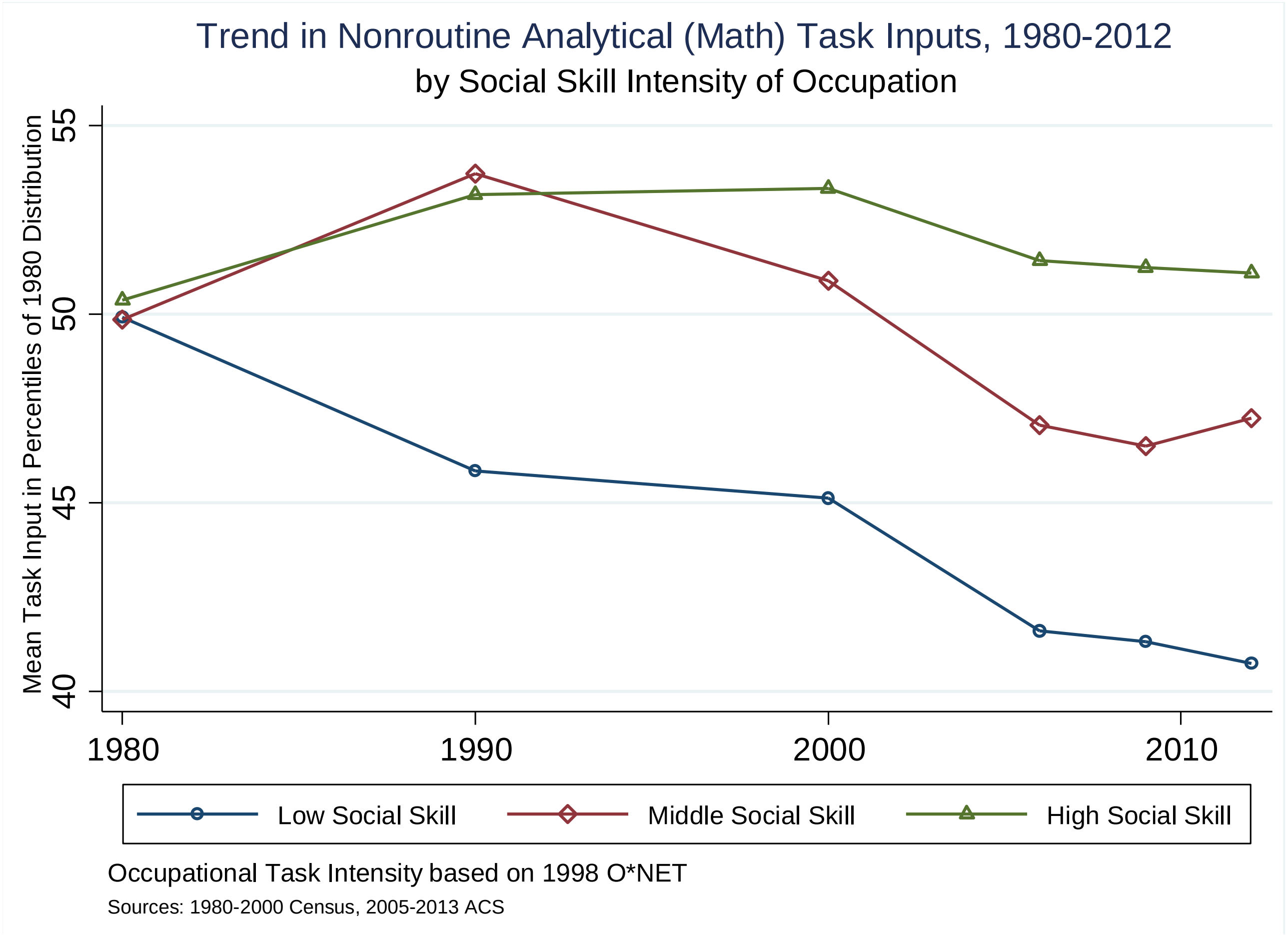


Figure 6 is constructed following the method of Figure I of Autor, Levy and Murnane (2003). O*NET 1998 nonroutine analytical task measures by occupation are paired with data from the IPUMS 1980-2000 Censuses and the 2005-2013 American Community Survey samples. Consistent occupation codes for 1980-2012 are updated 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. Occupations are divided into three groups of roughly equal size (centiles 0-37, 38-75, 76-100) by their social skill task intensity. See the text and Appendix for details on the construction of O*NET task measures.

Figure 7

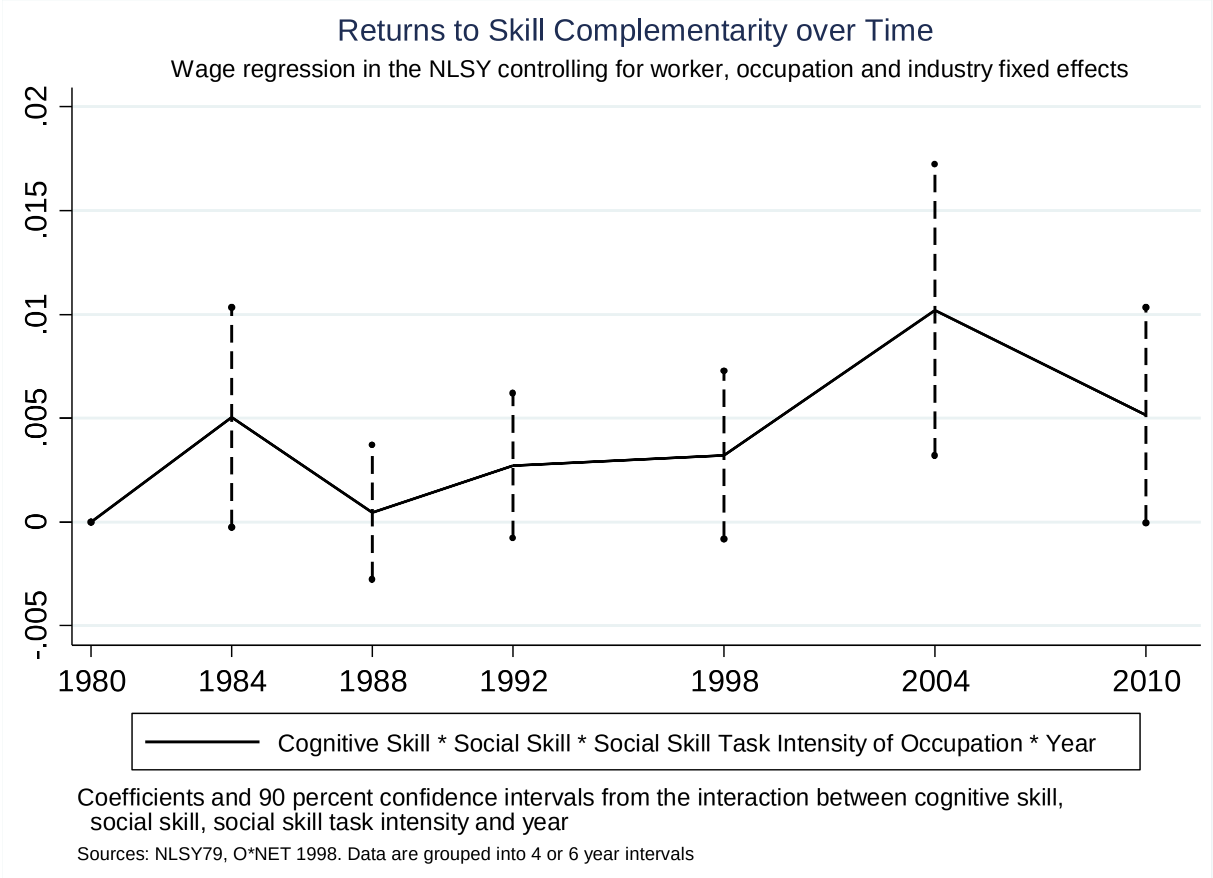


Figure 7 presents coefficients and 90 percent confidence intervals from a version of equation (21) in the paper, with log hourly wages as the outcome and person-year as the unit of observation. Cognitive skills are measured by each NLSY79 respondent's score on the Armed Forces Qualifying Test (AFQT), and are normed by age and standardized to have a mean of zero and a standard deviation of one. 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. The reported coefficients are interactions between cognitive skill, social skill and the social skill task intensity of a worker's occupation. The model is fully saturated with other interactions and main effects, although those coefficients are not reported. Person-years employed in managerial occupations and in public sector jobs are excluded from the sample. All models include fixed effects for individual workers, occupation, industry, age, year and census division by urbanicity and controls for firm size. Standard errors are clustered at the individual level.

Figure 8

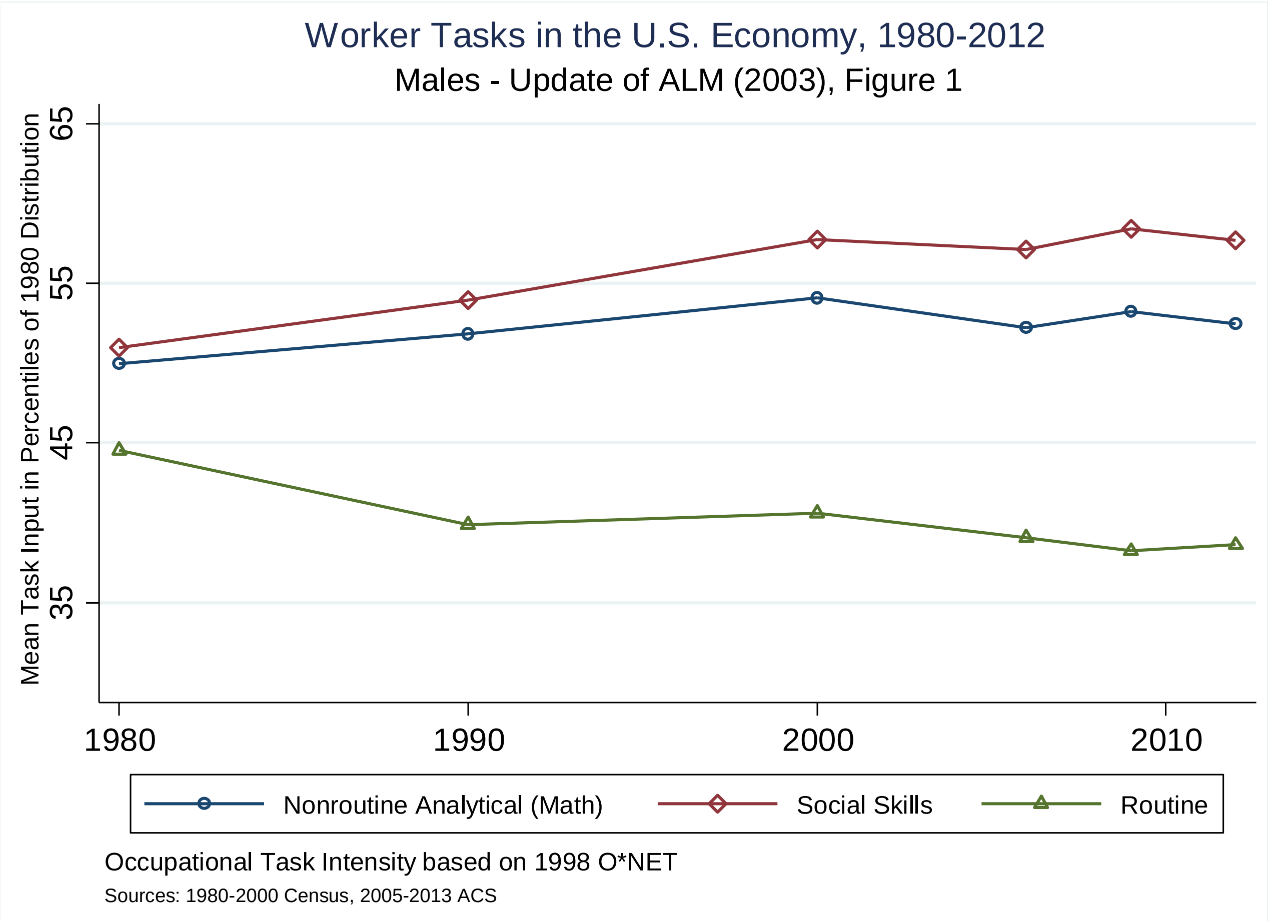


Figure 8 is constructed to parallel Figure I of Autor, Levy and Murnane (2003), with the sample restricted to males. O*NET 1998 task measures by occupation are paired with data from the IPUMS 1980-2000 Censuses and the 2005-2013 American Community Survey samples. Consistent occupation codes for 1980-2012 are updated 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 9

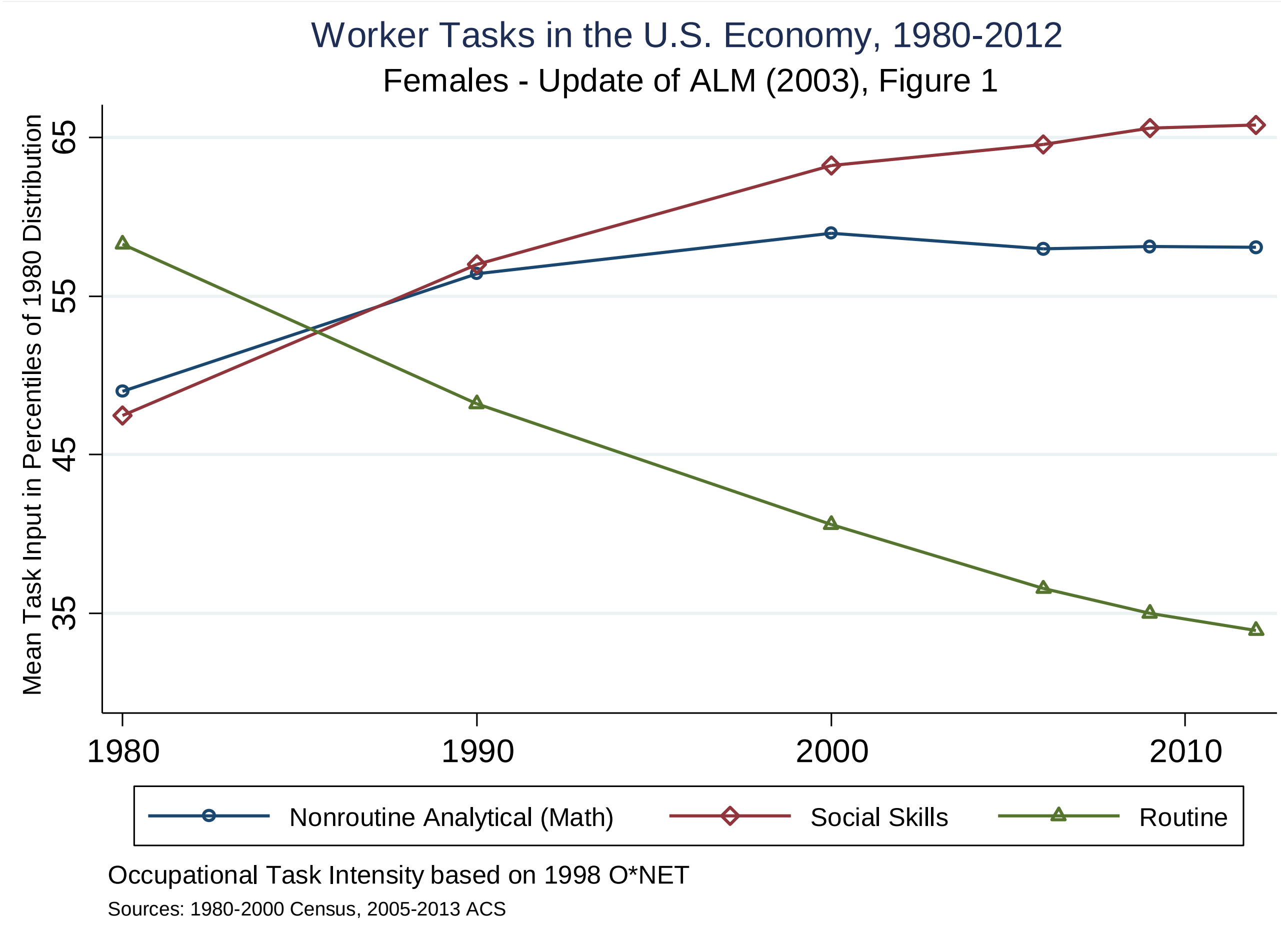


Figure 9 is constructed to parallel Figure I of Autor, Levy and Murnane (2003), with the sample restricted to females. O*NET 1998 task measures by occupation are paired with data from the IPUMS 1980-2000 Censuses and the 2005-2013 American Community Survey samples. Consistent occupation codes for 1980-2012 are from Autor and Dorn (2013) and Autor and Price (2013). Data are aggregated to industry-education 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 10

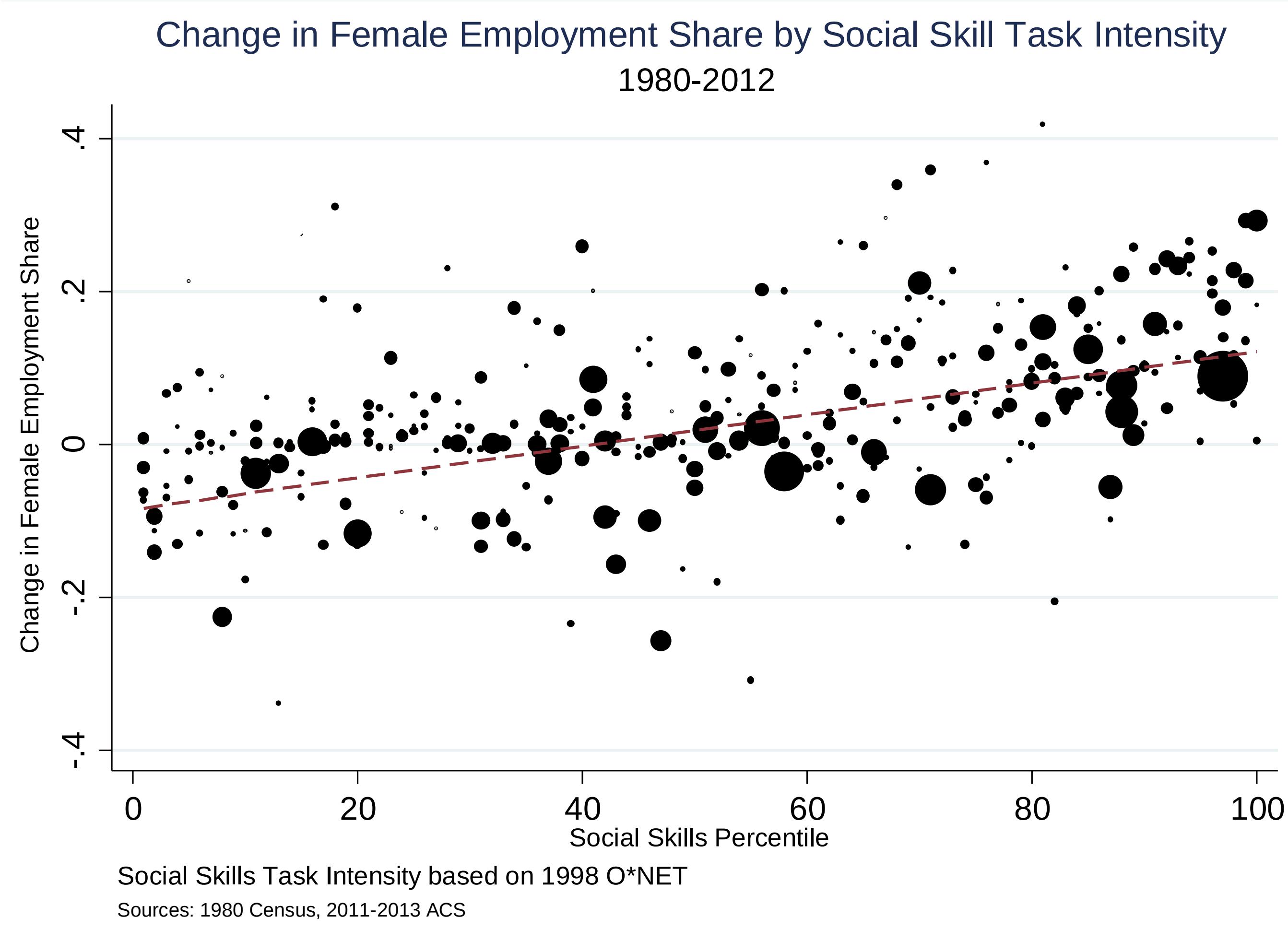


Figure 10 plots the within-occupation change in female employment share between 1980 and 2012 against the percentile of each occupation's social skill task intensity from the 1998 O*NET. Dots are weighted by the occupation's labor supply in 1980, based on the IPUMS 1980 Census 5 percent extract. The dashed line is a fitted regression line that is weighted by 1980 labor supply. A small number of dots greater than 0.5 in absolute value are excluded from the graph for convenience. 2012 occupation shares are computed using the 2011-2013 ACS IPUMS extracts. Consistent occupation codes for 1980-2012 are updated from Autor and Dorn (2013) and Autor and Price (2013).

Table 1 - 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 Census and the 1998 O*NET. Observations are at the occupation level. Additional O*NET task measures are Nonroutine Analytical (Math), the Service task composite, Number Facility, Inductive/Deductive Reasoning, Use/Analyze Information, Require Social Interaction, Coordinate and Interact. All O*NET variables are transformed into percentiles weighted by the 1980 employment distribution, then divided by ten. See text and Appendix for details on all O*NET task measures. Both models also control for log hourly wages and are weighted by total labor supply in each cell in 1980. Standard errors are clustered at the occupation level. *** $p<0.01$, ** $p<0.05$, * $p<0.10$

Table 2 - Sorting into Occupations by Cognitive and Social Skills

*Outcomes are O*NET Task Measures*	Analytical (Math)		Routine		Social Skills	
	(1)	(2)	(3)	(4)	(5)	(6)
Cognitive Skills (AQT, standardized)	0.428***	0.225***	-0.011	0.097***	0.267***	-0.031***
	[0.019]	[0.014]	[0.020]	[0.017]	[0.017]	[0.011]
Social Skills (standardized)	0.094***	-0.007	-0.150***	-0.095***	0.162***	0.065***
	[0.014]	[0.011]	[0.015]	[0.013]	[0.013]	[0.008]
Cognitive * Social	-0.037***	-0.040***	-0.040***	-0.030**	0.003	0.015*
	[0.014]	[0.011]	[0.014]	[0.013]	[0.012]	[0.008]
Controls for O*NET Interactive Tasks		X				
Controls for O*NET Cognitive Tasks				X		X
Observations	174,382	174,382	174,382	174,382	174,382	174,382
R-squared	0.359	0.615	0.258	0.426	0.354	0.729

Notes: Each column reports results from an estimate of equation (19) 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 normed by age and standardized to have a mean of zero and a standard deviation of one. 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. The regression also controls for race-by-gender indicator variables, fixed effects for years of completed education, age and year fixed effects, and industry-by-census division-by urbanicity fixed effects. Standard errors are in brackets and clustered at the individual level. *** p<0.01, ** p<0.05, * p<0.10

Table 3 - Labor Market Returns to Cognitive Skills and Social Skills

Outcome is Log Hourly Wage	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Cognitive Skills (AQT, standardized)		0.1621***	0.1002***	0.0679***	0.0580***	0.0526***	0.0231**
		[0.0050]	[0.0058]	[0.0052]	[0.0055]	[0.0114]	[0.0090]
Social Skills (standardized)	0.0932***	0.0396***	0.0310***	0.0298***	0.0206***	0.0353***	0.0028
	[0.0044]	[0.0042]	[0.0044]	[0.0039]	[0.0041]	[0.0101]	[0.0081]
Cognitive * Social		0.0073*	0.0067	0.0077*	0.0089**	0.0119	-0.0020
		[0.0043]	[0.0045]	[0.0041]	[0.0042]	[0.0100]	[0.0084]
Rotter Locus of Control		0.0209***	0.0210***	0.0181***	0.0144***	0.0143***	0.0143***
		[0.0041]	[0.0041]	[0.0037]	[0.0038]	[0.0038]	[0.0038]
Rosenberg Self-Esteem Scale		0.0475***	0.0414***	0.0348***	0.0259***	0.0263***	0.0265***
		[0.0043]	[0.0044]	[0.0039]	[0.0040]	[0.0040]	[0.0040]
Cognitive * Math Task Intensity						0.0055***	0.0028
						[0.0016]	[0.0020]
Social * Math Task Intensity						0.0011	-0.0016
						[0.0014]	[0.0017]
Cognitive * Social * Math						0.0004	-0.0003
						[0.0014]	[0.0017]
Cognitive * Routine Task Intensity						-0.0038***	
						[0.0015]	
Social * Routine Task Intensity						-0.0044***	
						[0.0012]	
Cognitive * Social * Routine						-0.0021	
						[0.0013]	
Cognitive * Social Skill Task Intensity							0.0052**
							[0.0021]
Social * Social Skill Task Intensity							0.0050***
							[0.0018]
Cognitive * Social * Social Skill							0.0014
							[0.0019]
Years of completed education			X	X	X	X	X
Exclude government jobs			X	X	X	X	X
O*NET task measures				X			
Occ-Ind-Region-Urban Fixed Effects					X	X	X
Observations	143,163	143,163	125,013	125,013	125,013	125,013	125,013
R-squared	0.3786	0.4188	0.4503	0.4927	0.7087	0.7091	0.7090

Notes: Each column reports results from an estimate of equation (20) in the paper, with log 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 normed by age and standardized to have a mean of zero and a standard deviation of one. 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. The Rotter and Rosenberg scores are widely used measures of "non-cognitive" skills. The models in Columns 3-7 drop person-years employed in public sector jobs, which comprise about 13 percent of the employed sample. The regression also controls for race-by-gender indicator variables, and age, year, census region, and urbanicity fixed effects - plus additional controls as indicated. Column 4 includes controls for the following O*NET occupation task measures - Nonroutine analytical (Math), Social Skills, Routine, Service, Require Social Interaction, Number Facility, Inductive/Deductive Reasoning, Analyze/Use Information - see the text and Appendix for details. Standard errors are in brackets and clustered at the individual level. *** p<0.01, ** p<0.05, * p<0.10

Table 4 - Returns to Skills by Occupation Task Intensity - Worker Fixed Effects Models

Outcome is Log Hourly Wage	(1)	(2)	(3)	(4)	(5)	(6)
Math Task Intensity	0.0153***	0.0153***	0.0146***	0.0147***	0.0155***	0.0151***
	[0.0031]	[0.0031]	[0.0031]	[0.0031]	[0.0033]	[0.0033]
Cognitive * Math	0.0026**	-0.0011	0.0023**	-0.0011	0.0027**	0.0003
	[0.0011]	[0.0013]	[0.0011]	[0.0013]	[0.0012]	[0.0014]
Social Skills * Math	0.0007	-0.0010	0.0007	-0.0010	0.0008	-0.0010
	[0.0011]	[0.0013]	[0.0011]	[0.0013]	[0.0013]	[0.0014]
Cognitive * Social * Math	0.0026**	0.0022*	0.0024**	0.0020	0.0032**	0.0021
	[0.0011]	[0.0013]	[0.0011]	[0.0013]	[0.0013]	[0.0014]
Routine Task Intensity	0.0115***	0.0106***	0.0095***	0.0087***	0.0099***	0.0092***
	[0.0011]	[0.0011]	[0.0011]	[0.0011]	[0.0013]	[0.0012]
Cognitive * Routine	-0.0021**		-0.0018*		-0.0008	
	[0.0010]		[0.0009]		[0.0011]	
Social Skills * Routine	-0.0012		-0.0011		-0.0014	
	[0.0010]		[0.0010]		[0.0011]	
Cognitive * Social * Routine	-0.0010		-0.0011		-0.0020*	
	[0.0009]		[0.0009]		[0.0011]	
Social Skill Task Intensity	0.0174***	0.0159***	0.0171***	0.0157***	0.0122***	0.0111***
	[0.0022]	[0.0022]	[0.0022]	[0.0022]	[0.0026]	[0.0026]
Cognitive * Social Skill		0.0070***		0.0065***		0.0062***
		[0.0013]		[0.0013]		[0.0016]
Social Skills * Social Skill		0.0034***		0.0032**		0.0046***
		[0.0013]		[0.0013]		[0.0016]
Cognitive * Social * Social Skill		0.0012		0.0013		0.0028*
		[0.0013]		[0.0013]		[0.0015]
O*NET Task Measures	X	X	X	X	X	X
Worker Fixed Effects	X	X	X	X	X	X
Controls for firm size			X	X	X	X
Exclude management occupations					X	X
Observations	96,104	96,104	96,104	96,104	81,442	81,442
R-squared	0.4056	0.4060	0.4117	0.4121	0.4017	0.4021
Number of individuals	10,421	10,421	10,421	10,421	10,294	10,294

Notes: Each column reports results from an estimate of equation (21) in the paper, with log 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 normed by age and standardized to have a mean of zero and a standard deviation of one. 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. The interactions between cognitive/social skills and nonroutine analytical/routine/social skill task intensity measure whether the returns to skills vary with the task content of the worker's occupation. All models drop person-years employed in public sector jobs, which comprises about 13 percent of the employed sample. All models control for worker fixed effects - plus age, year and census division by urbanicity fixed effects and the following O*NET occupation task measures - Nonroutine analytical (math), Social Skills, Routine, Service, Require Social Interaction, Number Facility, Inductive/Deductive Reasoning, Analyze/Use Information - see text and Appendix for details. Columns 3 and 4 add controls for the natural log of firm size and an indicator variable for whether the worker's firm has multiple establishments. Columns 5 and 6 drop any occupation with the words "manage", "manager" or "supervisor" in the title, as well as CEOs. Standard errors are in brackets and clustered at the individual level. *** p<0.01, ** p<0.05, * p<0.10

Table 5 - Firm Size and the Returns to Nonroutine Task Intensity

Outcome is Log Hourly Wage	(1)	(2)
Cognitive * Math Task Intensity	0.0025**	-0.0006
	[0.0011]	[0.0013]
Social Skill * Math Task Intensity	0.0007	-0.0008
	[0.0011]	[0.0013]
Cognitive * Social * Math	0.0024**	0.0019
	[0.0011]	[0.0013]
Cognitive * Routine Task Intensity	-0.0012	
	[0.0009]	
Social Skill * Task Routine Intensity	-0.0009	
	[0.0009]	
Cognitive * Social * Routine	-0.0011	
	[0.0009]	
Cognitive * Social Skill Task Intensity		0.0060***
		[0.0013]
Social Skills * Social Skill Task Intensity		0.0029**
		[0.0013]
Cognitive * Social * Social Skill		0.0014
		[0.0013]
Ln (Firm Size)	0.0445***	0.0230***
	[0.0027]	[0.0021]
Firm Size * Math Task Intensity	-0.0024***	-0.0044***
	[0.0004]	[0.0005]
Firm Size * Routine Task Intensity	-0.0025***	
	[0.0003]	
Firm Size * Social Skill Task Intensity		0.0039***
		[0.0005]
Observations	96,104	96,104
Number of individuals	10,421	10,421

Notes: Each column reports results from an estimate of equation (21) in the paper, with log 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 normed by age and standardized to have a mean of zero and a standard deviation of one. 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. The interactions between cognitive/social skills and nonroutine analytical/routine/social skill task intensity measure whether the returns to skills vary with the task content of the worker's occupation. All models drop person-years employed in public sector jobs, which comprises about 13 percent of the employed sample. All regressions control for worker fixed effects - plus age, year and census division by urbanicity fixed effects and the following O*NET occupation task measures - Nonroutine analytical (math), Social Skills, Routine, Service, Require Social Interaction, Number Facility, Inductive/Deductive Reasoning, Analyze/Use Information - see text and Appendix for details. Standard errors are in brackets and clustered at the individual level. *** p<0.01, ** p<0.05, * p<0.10

Table 6 - Firm Size, Computer Usage and the Returns to Nonroutine Task Intensity

Outcome is Log Hourly Wage	(1)	(2)	(3)	(4)
AFQT * Math Task Intensity	0.0021*	-0.0007	0.0015	-0.0004
	[0.0011]	[0.0013]	[0.0012]	[0.0014]
Social Skill * Math Task Intensity	0.0001	-0.0011	-0.0004	-0.0005
	[0.0011]	[0.0013]	[0.0011]	[0.0014]
AFQT * Social * Math	0.0023**	0.0021	0.0002	0.0001
	[0.0011]	[0.0013]	[0.0012]	[0.0014]
AFQT * Routine Task Intensity	-0.0008		-0.0006	
	[0.0010]		[0.0010]	
Social Skill * Task Routine Intensity	-0.0008		-0.0004	
	[0.0010]		[0.0011]	
AFQT * Social * Routine	-0.0009		-0.0009	
	[0.0009]		[0.0010]	
AFQT * Social Skill Task Intensity		0.0052***		0.0038***
		[0.0013]		[0.0014]
Social Skills * Social Skill Task Intensity		0.0025*		0.0005
		[0.0013]		[0.0014]
AFQT * Social * Social Skill		0.0007		0.0004
		[0.0013]		[0.0013]
Industry Computer Use Intensity	0.2297***	-0.0504*	0.1527***	-0.1172***
	[0.0390]	[0.0302]	[0.0320]	[0.0256]
Computer Use * Math Task Intensity	0.0152***	-0.0115*	0.0231***	-0.0063
	[0.0049]	[0.0060]	[0.0041]	[0.0050]
Computer Use * Routine Intensity	-0.0337***		-0.0301***	
	[0.0047]		[0.0037]	
Computer Use * Social Skill Intensity		0.0492***		0.0547***
		[0.0061]		[0.0051]
Computer Usage in 1984 (fixed)	X	X		
Computer Usage (time-varying, 84-03)			X	X
Observations	94,525	94,525	72,231	72,231
R-squared	0.4113	0.4117	0.2647	0.2658
Number of individuals	10,416	10,416	10,028	10,028

Notes: Each column reports results from an estimate of equation (21) in the paper, with log 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 normed by age and standardized to have a mean of zero and a standard deviation of one. 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. The interactions between cognitive/social skills and nonroutine analytical/routine/social skill task intensity measure whether the returns to skills vary with the task content of the worker's occupation. Computer usage is the share of workers who report using a computer at work by industry and year from the 1984-2003 Current Population Survey Computer Use Supplements. Columns 1 and 2 interact the indicated O*NET task intensities of a worker's occupation with industry computer usage in 1984. Columns 3 and 4 interact time-varying industry computer usage with occupation task intensities from 1984-2003, and computer usage is interpolated for missing CPS years - see text for details. All models drop person-years employed in public sector jobs, which comprises about 13 percent of the employed sample. All models control for firm size and worker fixed effects - plus age, year and census division by urbanicity fixed effects and the following O*NET occupation task measures - Nonroutine analytical (math), Social Skills, Routine, Service, Require Social Interaction, Number Facility, Inductive/Deductive Reasoning, Analyze/Use Information - see text and Appendix for details. Standard errors are in brackets and clustered at the individual level. *** p<0.01, ** p<0.05, * p<0.10