The Growing Importance of Social Skills in the Labor Market

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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.

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

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 skills*. 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:

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

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:

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

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.

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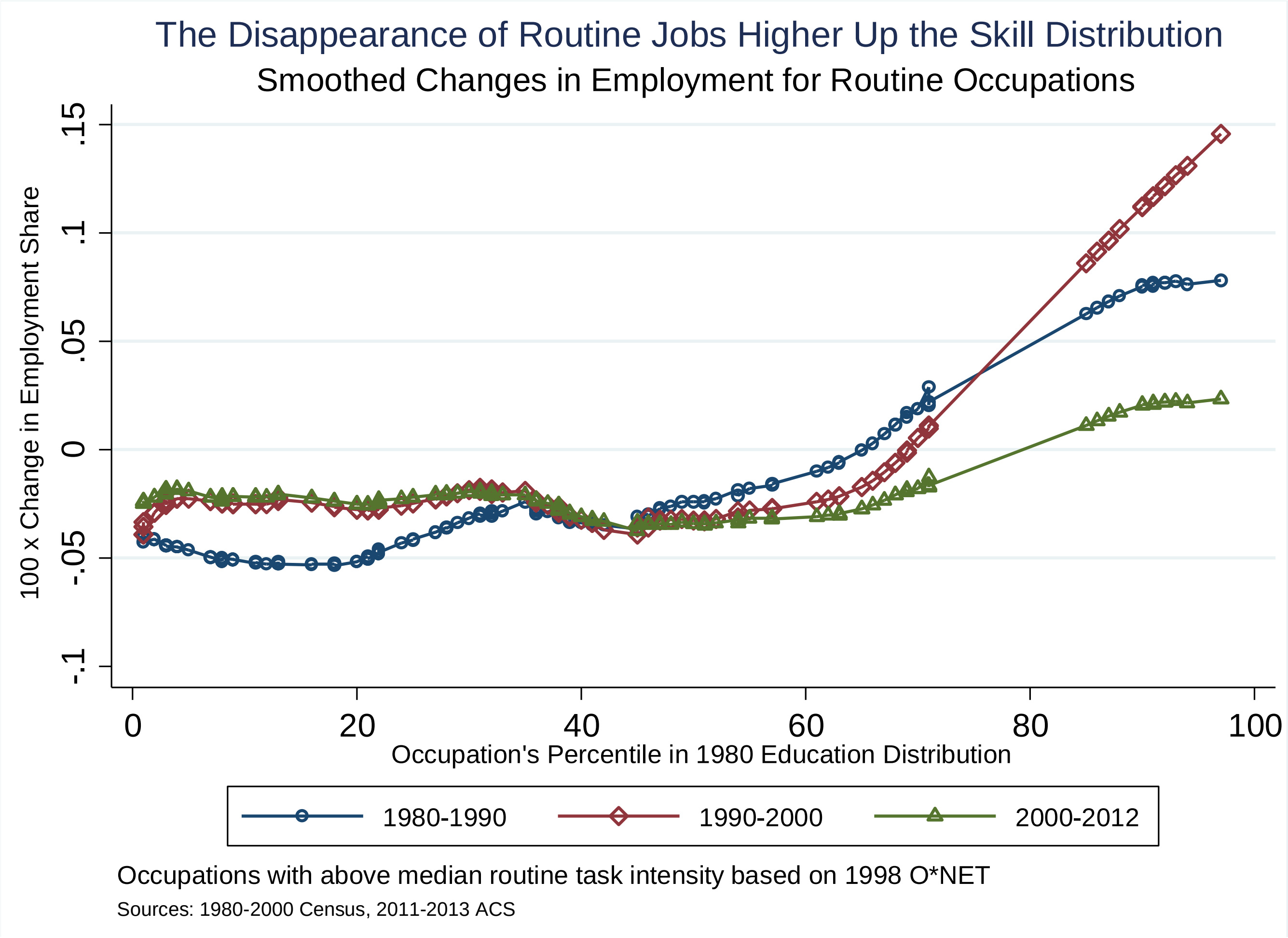
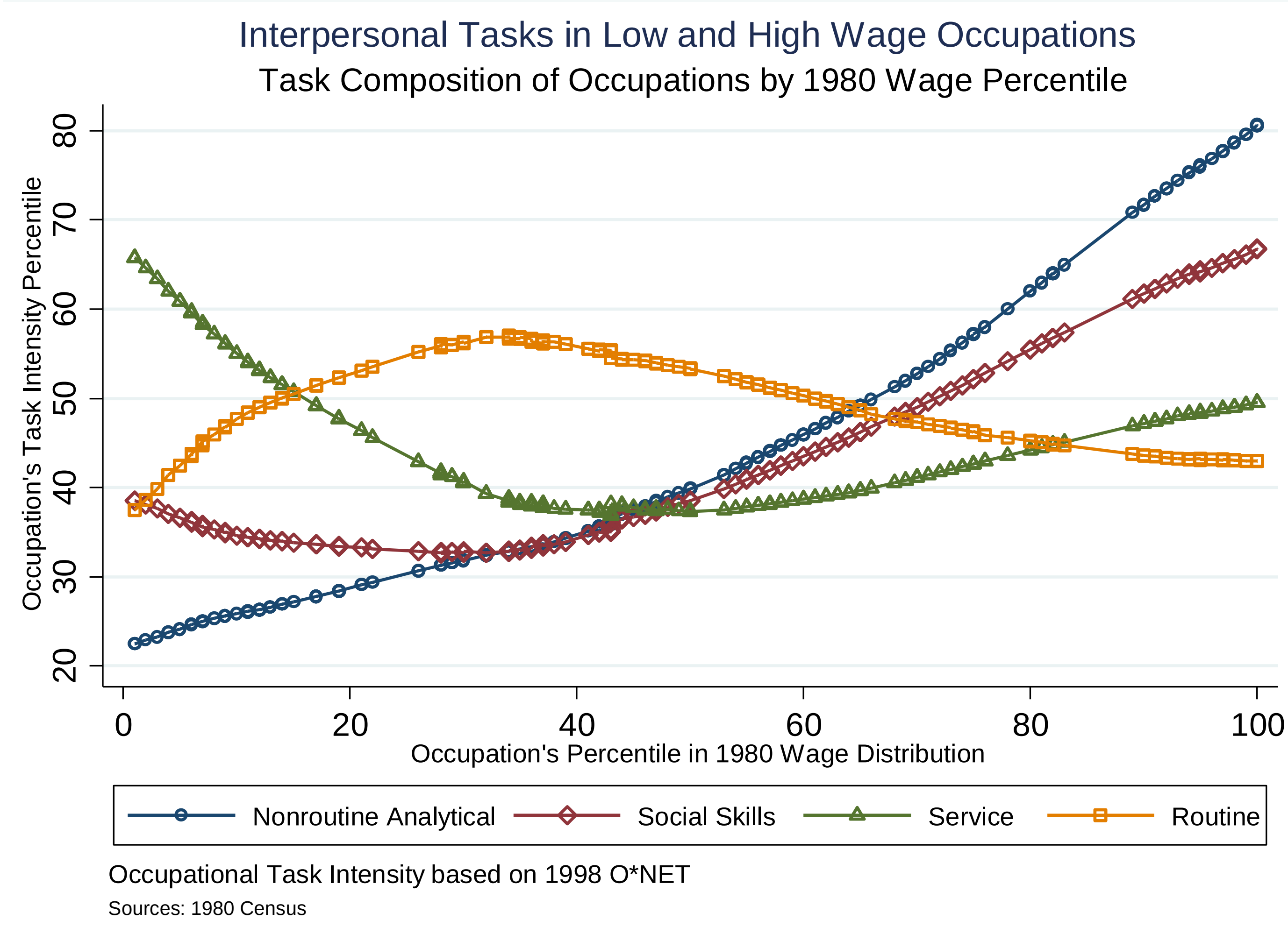
Figure 1



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

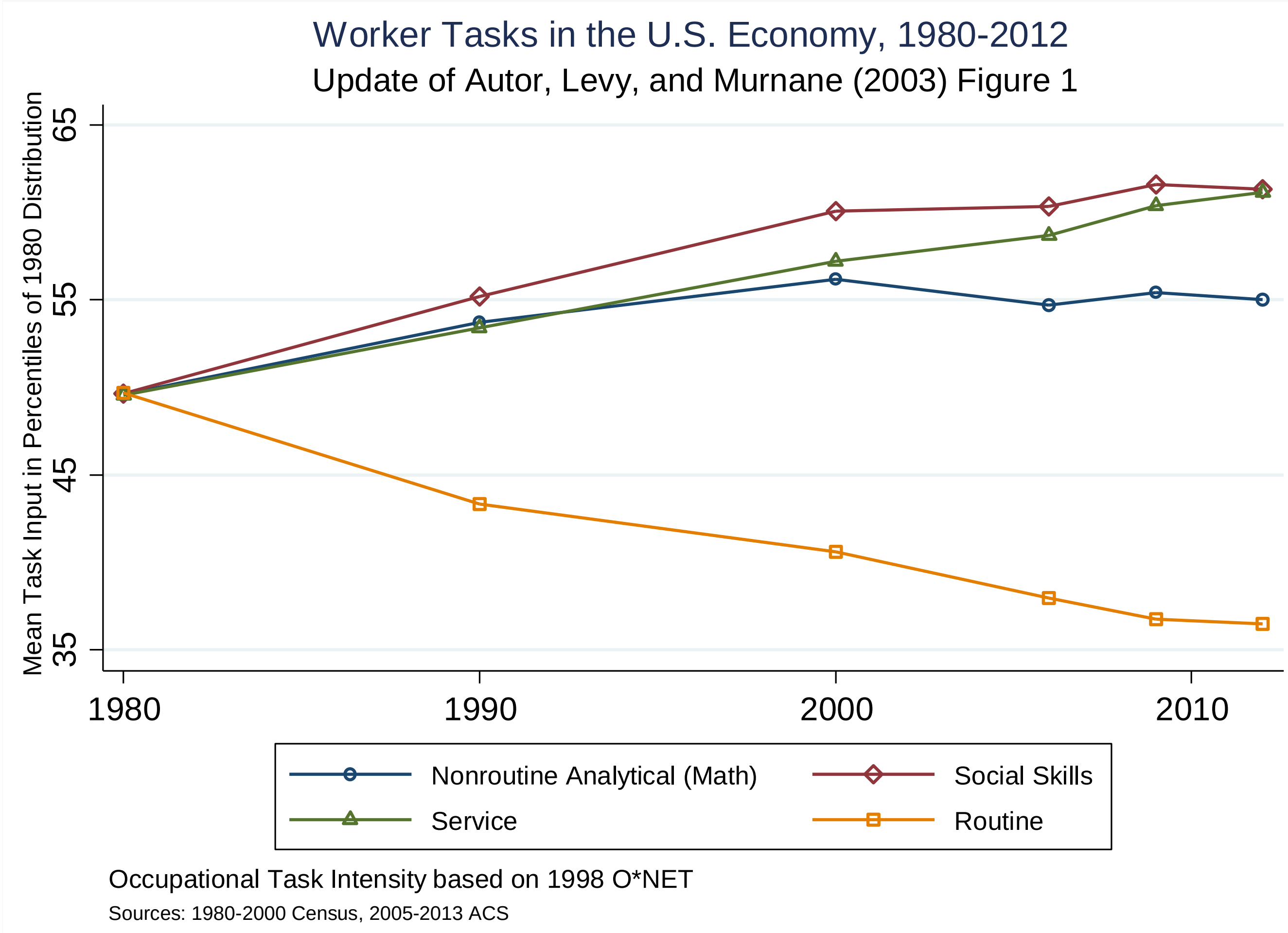
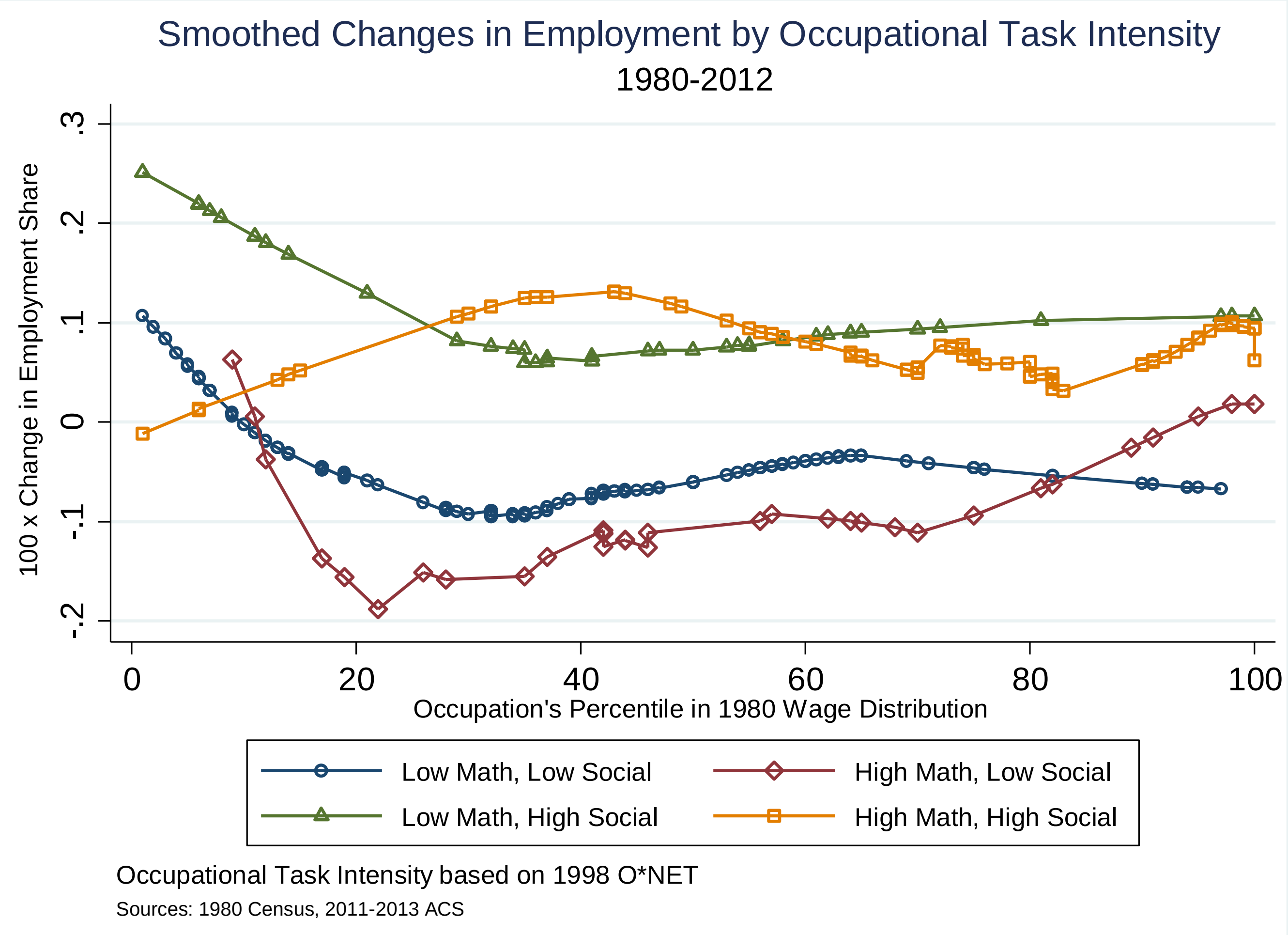


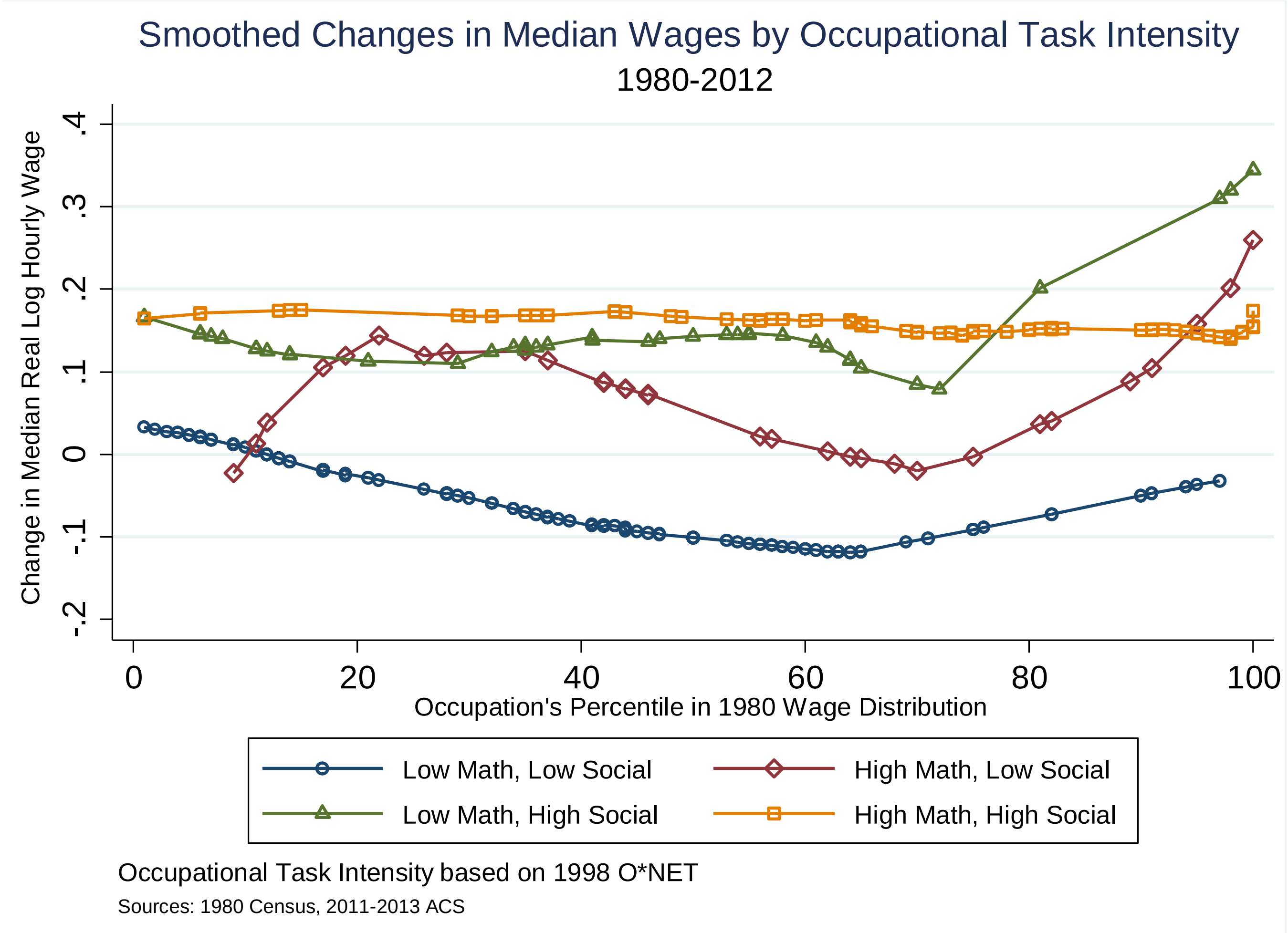
Figure 3 is constructed to parallel Figure I of Autor, Levy and Murnane (2003). O*NET 1998 task measures by occupation are paired with data from the IPUMS 1980-2000 Censuses and the 2005-2013 American Community Survey samples. Consistent occupation codes for 1980-2012 are from Autor and Dorn (2013) and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

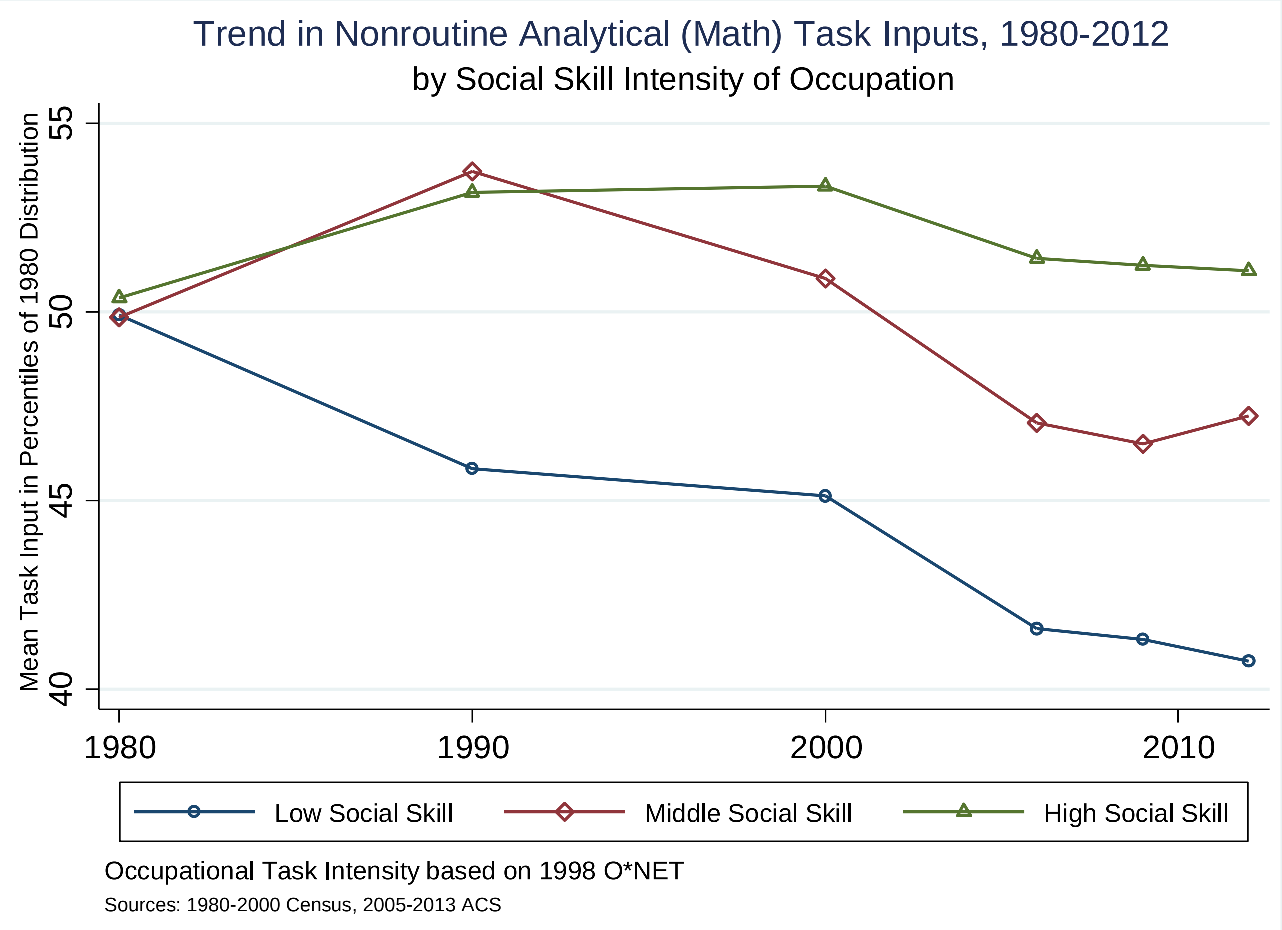


Figure 6 is constructed following the method of Figure I of Autor, Levy and Murnane (2003). O*NET 1998 nonroutine analytical task measures by occupation are paired with data from the IPUMS 1980-2000 Censuses and the 2005-2013 American Community Survey samples. Consistent occupation codes for 1980-2012 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

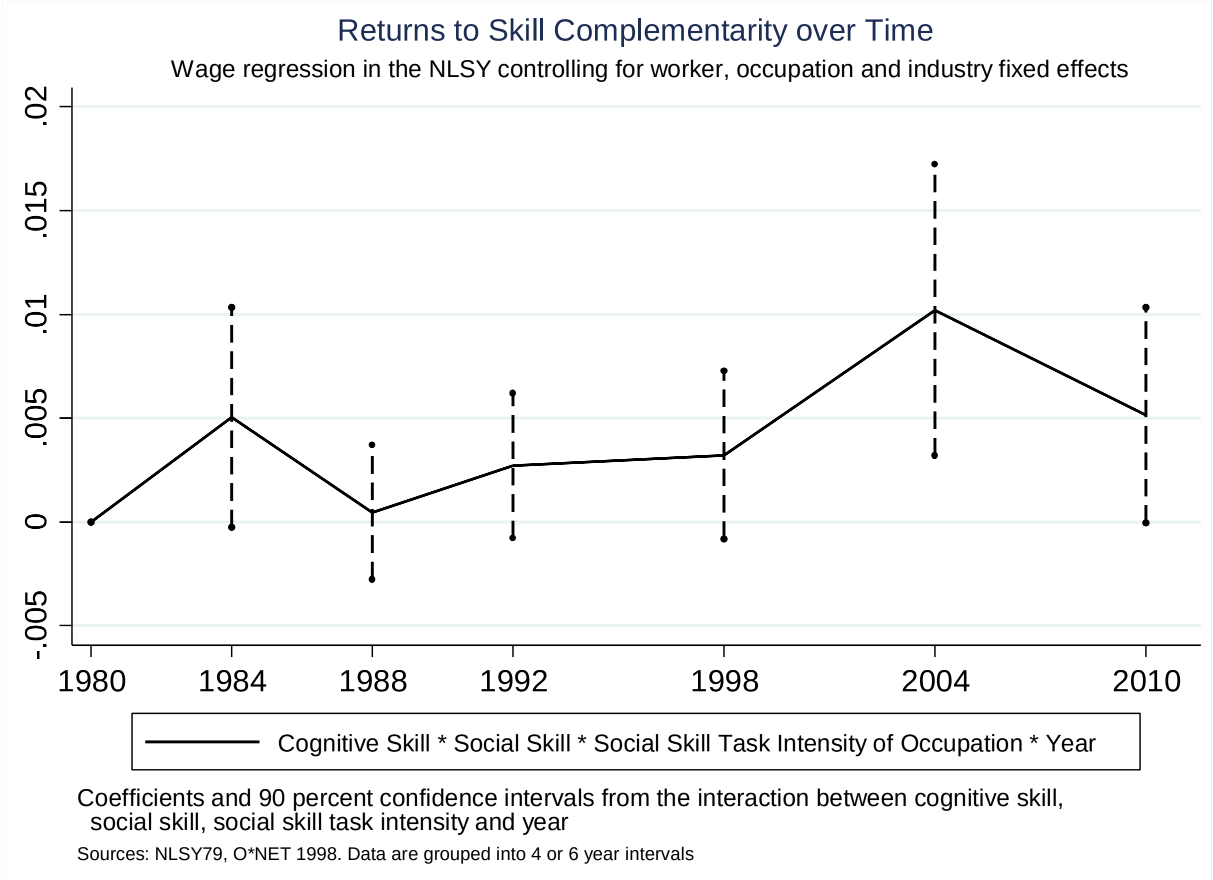


Figure 7 presents coefficients and 90 percent confidence intervals from a version of equation (21) in the paper, with log hourly wages as the outcome and person-year as the unit of observation. Cognitive skills are measured by each NLSY79 respondent's score on the Armed Forces Qualifying Test (AFQT), 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

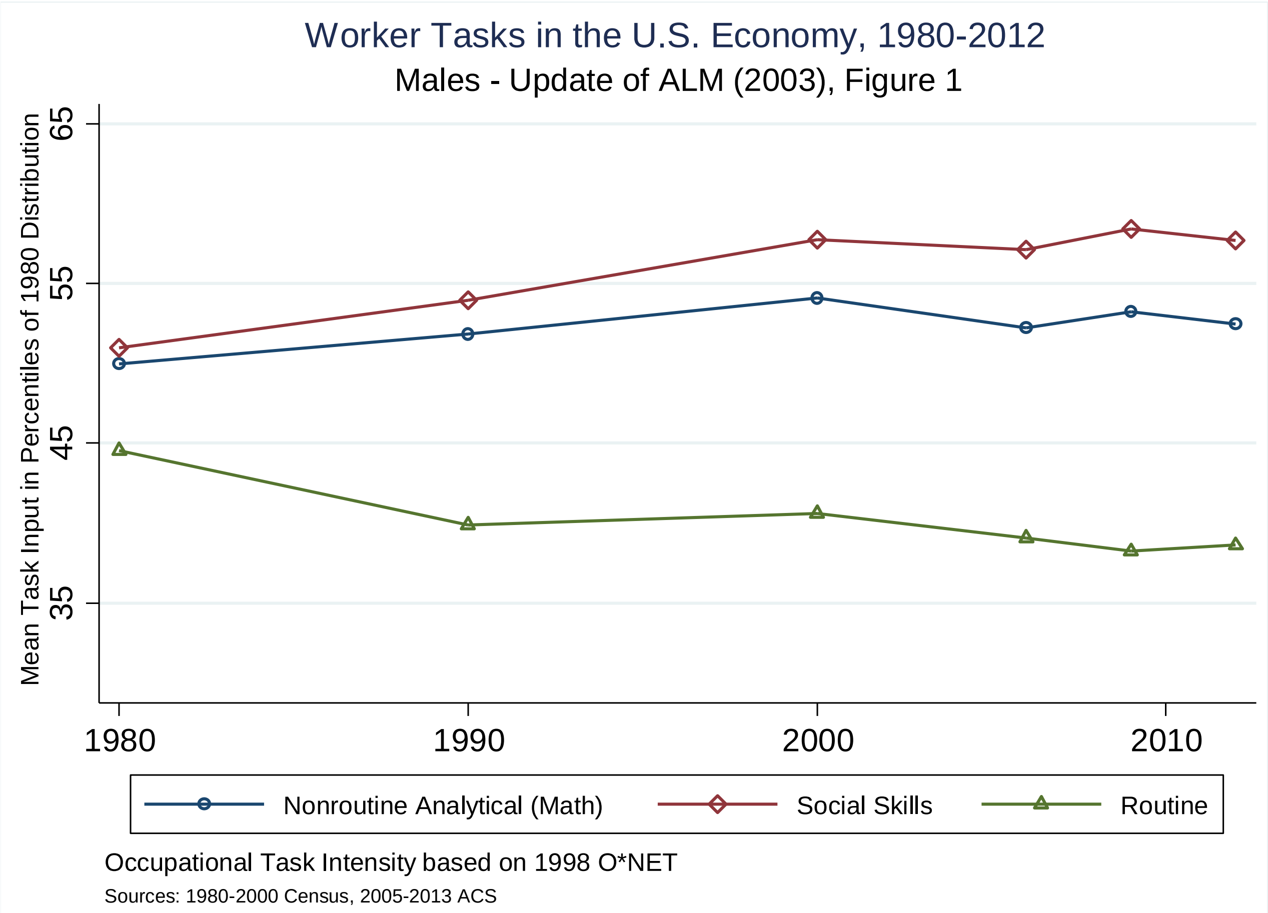


Figure 8 is constructed to parallel Figure I of Autor, Levy and Murnane (2003), with the sample restricted to males. O*NET 1998 task measures by occupation are paired with data from the IPUMS 1980-2000 Censuses and the 2005-2013 American Community Survey samples. Consistent occupation codes for 1980-2012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

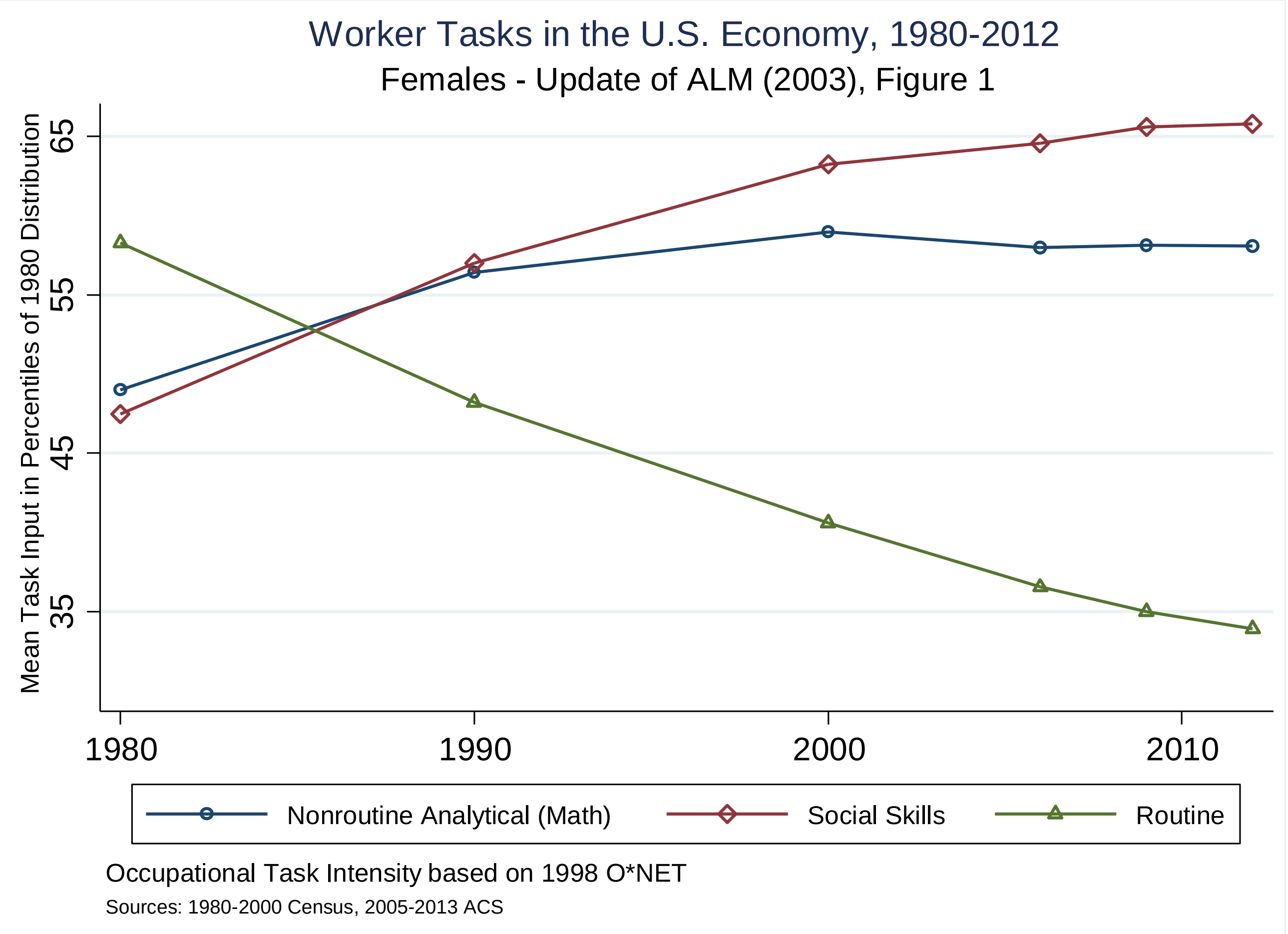


Figure 9 is constructed to parallel Figure I of Autor, Levy and Murnane (2003), with the sample restricted to females. O*NET 1998 task measures by occupation are paired with data from the IPUMS 1980-2000 Censuses and the 2005-2013 American Community Survey samples. Consistent occupation codes for 1980-2012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

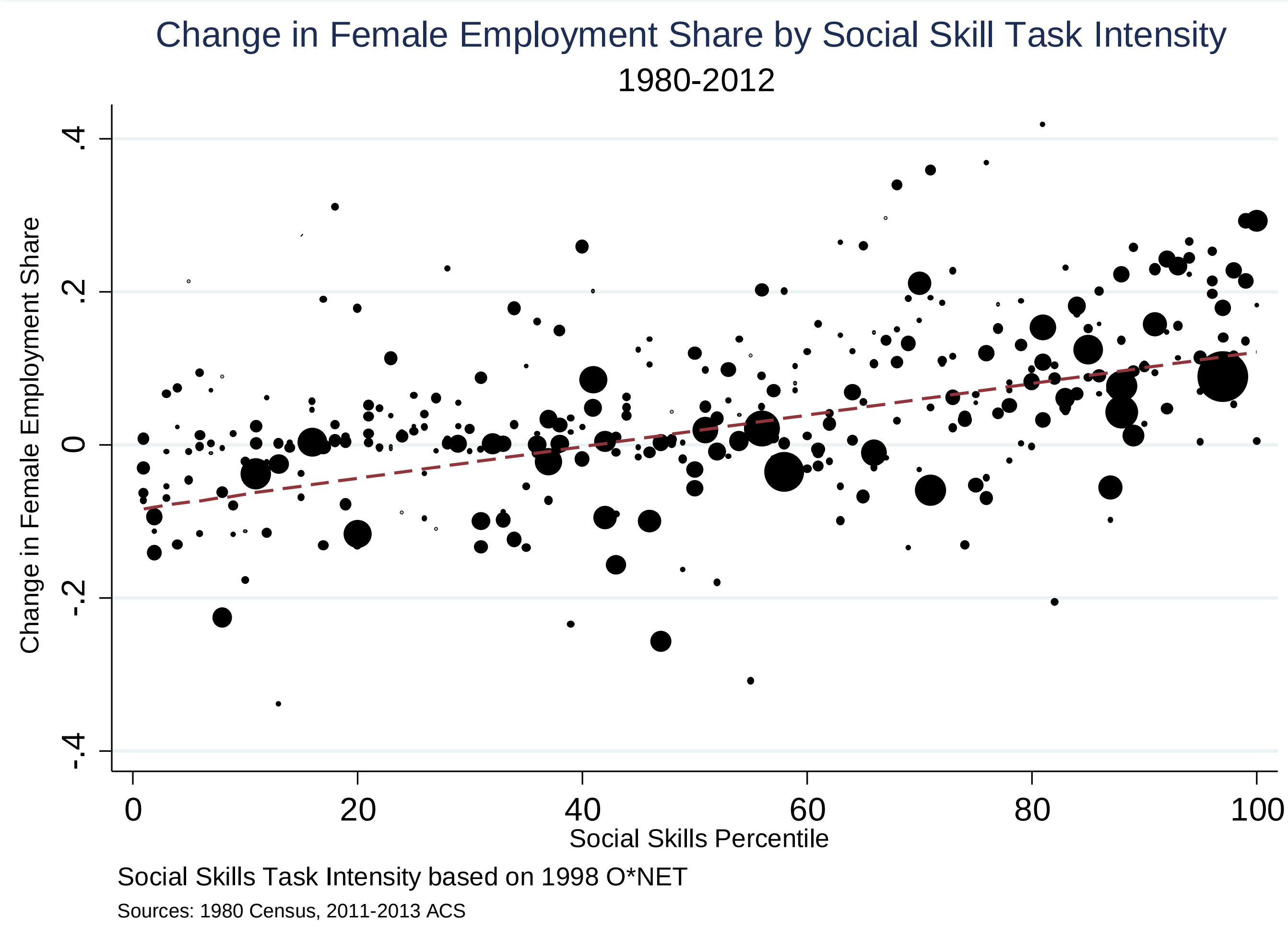


Figure 10 plots the within-occupation change in female employment share between 1980 and 2012 against the percentile of each occupation's social skill task intensity from the 1998 O*NET. Dots are weighted by the occupation's labor supply in 1980, based on the IPUMS 1980 Census 5 percent extract. The 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

Data Appendix

August 2015

1 O*NET Task Measures

I use data from the initial 1998 release of the Occupational Information Network (O*NET) to measure the task content of occupations in the U.S. economy. The data are available from the Database Releases Archive at the O*NET Resource Center. As noted above, the O*NET survey asks many different questions about the abilities, skills, knowledge and work activities required in an occupation, as well as the work context of a job. I create 10 composite variables that describe the tasks performed in an occupation, as follows:

1. *Social skills*: The social skills measure consists of the average of four variables, 1) *social perceptiveness* (defined as "being aware of others' reactions and understanding why they react the way they do"), 2) *coordination* ("adjusting actions in relation to others' actions), 3) *persuasion* ("persuading others to approach things differently"), and 4) *negotiation* ("bringing others togethers and trying to reconcile differences"). All four variables are categorized by the O*NET content model as cross-functional skills.

2. *Nonroutine analytical*: The nonroutine analytical measure averages three variables that assess the mathematical competence required of workers in an occupation, namely 1) *mathematical reasoning ability* ("the ability to understand and organize a problem and then to select a mathematical method or formula to solve the problem"), 2) *mathematics knowledge* ("knowledge of numbers, their operations, and interrelationships including arithmetic, algebra, geometry, calculus, statistics, and their applications"), and 3) *mathematics skill* ("using mathematics to solve problems").

3. *Routine*: The routine measure averages two variables that describe the work context of occupations, specifically, 1) *degree of automation* (defined as "the level of automation of this job") and 2) *importance of repeating same tasks* (which answers the question, "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?").

4. *Service*: The service measure is composed of the average of 1) *assisting and caring for others* (defined as "providing assistance or personal care to others") and 2) *service orientation* ("actively looking for ways to help people"). The first variable is defined as a work activity, while the second is classified as a cross-functional skill.

5. *Deductive and inductive reasoning*: This measure is the average of three ability variables, 1) *written comprehension* ("the ability to read and understand information and ideas presented in writing"), 2) *dedutive reasoning* ("the ability to apply general rules to specific problems to come up with logical answers"), and 3) *inductive reasoning* ("the ability to combine separate pieces of information, or specific answers to problems, to form general rules or conclusions").

6. *Number facility*: This measure consists of a single ability variable, *number facility*, which assesses "the ability to add, subtract, multiply, or divide quickly and correctly."

7. *Information use*: The information use measure averages four work activity variables, 1) *getting information needed to do the job* (defined as "observing, receiving, and otherwise obtaining information from all relevant sources"), 2) *identifying objects, actions and events* ("identifying information received by making estimates or categorizations, recognizing differences or similarities, or sensing changes in circumstances or events"), 3) *processing information* ("compiling, coding, categorizing, calculating, tabulating, auditing, verifying, or processing information or data"), and 4) *analyzing data or information* ("identifying underlying principles, reasons, or facts by breaking down information or data into separate parts").

8. *Require social interaction*: This measure is composed of a single work context variable, *job-required social interaction*, which answers the question, "How much does this job require the worker to be in contact (face-to-face, by telephone, or otherwise) with others in order to perform it?"

9. *Coordinate*: The coordinate measure averages two work activity variables, 1) *coordinating work and activities of others* (defined as "coordinating members of a work group to accomplish tasks") and 2) *developing and building teams* ("encouraging and building mutual trust, respect, and cooperation among team members").

10. *Interact*: The interact measure consists of the average of four work activity variables, 1) *interpreting the meaning of information to others* (defined as "translating or explaining what information means and how it can be understood or used to support responses or feedback to others"), 2) *communicating with other workers* ("providing information to supervisors, fellow workers, and subordinates"), 3) *communicating with persons outside the organization* ("representing the organization to customers, the public, government, and other external sources") and 4) *establishing and maintaining relationships* ("developing constructive and cooperative working relationships with others").

Nearly all of the variables from which the 10 composites are created are measured on an ordinal "level" scale that ranges from 1 (low) to 7 (high). The exception is the *importance of repeating same tasks* variable, which uses an "importance" scale that ranges from 1 ("minimally important") to 5 ("extremely important"). All the component variables are rescaled to fall between 0 and 10 before being averaged to create the composites.

The composites are linked to the 1990 Census Occupation Classification (COC) codes using a crosswalk from the 1998 O*NET codes provided in the O*NET data release. Next, the O*NET measures are linked to the *occ1990dd* codes using a crosswalk described in Section 2 below. Over 99 percent of the O*NET codes contained in the 1998 data release are successfully matched to the 1990 COC codes, and all 1990 COC codes with valid O*NET data are matched to the *occ1990dd* crosswalk. In the figures based on Census and ACS data, the O*NET variables are transformed into percentiles weighted by the 1980 labor supply distribution. For the NLSY79 regressions, the O*NET variables are transformed into percentiles and then divided by 10, so that a one-unit increase in the task measures can be interpreted as a 10-percentage point increase in task intensity according to the 1980 distribution of employment across occupations.

The first four O*NET composites (*social skills*, *nonroutine analytical*, *routine* and *service*) are my preferred measures of occupational task content. *Deductive and inductive reasoning*, *number facility* and *information use* constitute supplemental measures of cognitive tasks that I include as controls in the regression analysis. Similarly, I include *require social interaction* as an additional measure of interactive tasks. Finally, *interact* and *coordinate* are alternative definitions of social skills. Figure A1 replicates Figure 2 - which plots average task intensity against percentile in the 1980 wage distribution - for *interact*, *coordinate* and the preferred *social skills* measure. The relationship between task intensity and wages is very similar for the three composite variables, suggesting that the *social skills* measure is robust to alternative definitions.

Figure A2 replicates Figure 3 with both the O*NET measures and comparable variables from the 1977 Dictionary of Occupational Titles (DOT) used by Autor et al. (2003). The DOT *nonroutine analytical* analog is *MATH*, the mathematics sub-score on the GED (General Education Development) exam. The *routine* analog consists of the average of two DOT variables, *STS* ("adaptability to situations requiring the precise attainment of set limits, tolerances or standards") and *FINGER* ("finger dexterity"). Finally, the DOT analog for *social skills* is *DCP*, which assesses "adaptability to accepting responsibility for the direction, control or planning of an activity." Figure A2 indicates that the O*NET and DOT measures track each other closely in terms of average task intensity over the period 1980 to 2013.

2 Changes to the *Occ1990dd* Occupation System

I made edits to the Autor and Dorn (2013) *Occ1990dd* Occupation System to:

1. extend the system to cover the 2010 Census/ACS occupation codes;
2. attempt to improve consistency of definitions of occupations over time; and
3. dissagregate codes in *occ1990dd* when possible.

This edited and updated version of the *occ1990dd* occupation system contains 341 occupation codes.

2.1 2010 Occupation Codes

To extend the system to cover the 2010 occupation codes, I examined the mapping between the 2005-2009 ACS OCC codes and the 2010-2013 ACS OCC codes.[1] For each 2010 OCC code with an equivalent 2005 OCC code, I assigned the *occ1990dd* code that was associated with the equivalent 2005 OCC code, as given by Autor and Dorn's crosswalk between *occ1990dd* codes and 2005 OCC codes. For example, the 2005 OCC code 12 (Financial Managers) is mapped to the in the *occ1990dd* code 7. Therefore, I map the 2010 OCC code 120 (Financial Managers) to the *occ1990dd* code 7 as well. For the few new 2010 OCC codes that did not have an obvious equivalent in the set of 2005 OCC codes, I used my best judgment. For example, I mapped the 2010 OCC code 0425 (Emergency Management Directors) to *occ1990dd* code 22 (Managers and administrators, n.e.c.). Using this procedure, I created a crosswalk between the 2010 Census/ACS occupation codes and the existing *occ1990dd* codes provided by Autor and Dorn.

2.2 Improving Consistency of Definitions Over Time

After creating the crosswalk between the 2010 occupation codes and the existing *occ1990dd* codes, I attempted to improve the consistency of definitions of occupations over time. To do so, I examined each *occ1990dd* code and the associated 1980, 1990, 2000, 2005, and now 2010 OCC codes. I checked for consistency in definitions across time, using the 1990-2000 OCC codes crosswalk in Table 2 of Scopp (2003) as

[1] Retrieved from https://usa.ipums.org/usa/volii/c2ssoccup.shtml on July 17, 2015

a reference. When I found an inconsistency, I attempted to resolve it by remapping OCC codes to the appropriate *occ1990dd* code. For example, prior to editing, the *occ1990dd* code 308 (Computer and peripheral equipment operators) was linked to the 1980 and 1990 OCC codes: 304, 308, and 309 and the 2000 OCC code 580 as shown in Panel A of Table 1.

Table 1: Improving Consistency of Definitions (Example)

Panel A: *Occ1990dd* codes 303 and 308, prior to editing

***Occ1990dd* code**	**1980 Census Codes**	**1990 Census Codes**	**2000 Census (5% Sample) Codes**	**2005 ACS Codes**	**2010 ACS Codes**
303-Office supervisors	**303**-Supervisors, general office **305**-Supervisors, financial records processing	**303**-Supervisors, general office **305**-Supervisors, financial records processing	**500**-First-line supervisors/ managers of office and administrative support workers	**500**-First-line supervisors/ managers of office and administrative support workers	**500**0-First-line supervisors/ managers of office and administrative support workers
308-Computer and peripheral equipment operators	**304**-Supervisors, computer equipment operators **308**-Computer operators **309**-Peripheral equipment operators	**304**-Supervisors, computer equipment operators **308**-Computer operators **309**-Peripheral equipment operators	**580**-Computer operators	**580**-Computer operators	**5800**-Computer operators

Panel B: *Occ1990dd* codes 303 and 308, after editing

***Occ1990dd* code**	**1980 Census Codes**	**1990 Census Codes**	**2000 Census (5% Sample) Codes**	**2005 ACS Codes**	**2010 ACS Codes**
303-Office supervisors	**303**-Supervisors, general office **304**-Supervisors, computer equipment operators **305**-Supervisors, financial records processing	**303**- Supervisors, general office **304**-Supervisors, computer equipment operators **305**-Supervisors, financial records processing	**500**-First-line supervisors/ managers of office and administrative support workers	**500**-First-line supervisors/ managers of office and administrative support workers	**500**0-First-line supervisors/ managers of office and administrative support workers
308-Computer and peripheral equipment operators	**308**-Computer operators **309**-Peripheral equipment operators	**308**-Computer operators **309**-Peripheral equipment operators	**580**-Computer operators	**580**-Computer operators	**5800**-Computer operators

According to Scopp's (2003) 1990-2000 crosswalk, the 1990 OCC code 304 (Supervisors, computer equipment operators) gets entirely redistributed into the 2000 OCC code 500 (First-line supervisors/managers of office and administrative support workers), which is linked to *occ1990dd* code 303 (Office supervisors). Therefore, I remap the 1980 and 1990 OCC code 304 to the *occ1990dd* code 303 (Office supervisors) so that supervisors of computer equipment operators are consistently contained over time in the *occ1990dd* code 303. In contrast, the 1990 OCC code 309 (Peripheral equipment operators) largely redistributes into the 2000 OCC code 580 (Computer operators), so the 1980 and 1990 OCC code 309 remains mapped to *occ1990dd* code 308 as shown in Panel B of Table 1.

2.3 Disaggregating Codes

To disaggregate *occ1990dd* codes when possible, I also examined each *occ1990dd* code and the associated 1980, 1990, 2000, 2005, and 2010 OCC codes. Among the codes associated with each *occ1990dd* code, I searched for a set of 1980, 1990, 2000, 2005, and 2010 OCC codes that provided a consistent definition of an occupation that could stand alone as a separate occupation group. For example, prior to editing, the *occ1990dd* code 59 (Engineers and other professionals, n.e.c.) was mapped to OCC codes as shown in Panel A of Table 2. Among this group of codes, the occupation Marine Engineers and Naval Architects can be separated into its own group. Therefore, I created an additional *occ1990dd* code 58 (Marine engineers and naval architects) consisting of 1980 OCC code 58, 1990 OCC code 58, 2000 OCC code 144, 2005 OCC code 144, and 2010 OCC code 1440 as shown in Panel B of Table 2.

In contrast, the occupation Nuclear Engineers cannot stand alone as its own *occ1990dd* code. The occupation Nuclear Engineers has its own OCC code in 1980 (49), 1990 (49), and 2000 (151), but the occupation is joined with the miscellaneous engineers OCC code 153 in 2005 and 2010. This occupation cannot be separated from the other codes associated with *occ1990dd* code 59 (Engineers and other professionals, n.e.c.).

Table 2: Disaggregating Codes (Example)

Panel A: *Occ1990dd* code 59, prior to editing

***Occ1990dd* code**	**1980 Census Codes**	**1990 Census Codes**	**2000 Census (5% Sample) Codes**	**2005 ACS Codes**	**2010 ACS Codes**
59-Engineers and other professionals, n.e.c.	**49**-Nuclear engineers **54**-Agricultural engineers **58**-Marine engineers and naval architects **59**-Engineers, n.e.c	**49**-Nuclear engineers **54**-Agricultural engineers **58**-Marine engineers and naval architects **59**-Engineers, n.e.c	**142**-Environmental engineers **144**-Marine engineers **151**-Nuclear engineers **153**-Miscellaneous engineers, including agricultural and biomedical	**134**-Biomedical and agricultural engineers **142**-Environmental engineers **144**-Marine engineers and Naval architects **153**-Miscellaneous engineers including nuclear engineers	**1340**-Biomedical and agricultural engineers **1420**-Environmental engineers **1440**-Marine engineers and naval architects **1530**-Miscellaneous engineers including nuclear engineers

Panel B: *Occ1990dd* codes 58 and 59, after editing

***Occ1990dd* code**	**1980 Census Codes**	**1990 Census Codes**	**2000 Census (5% Sample) Codes**	**2005 ACS Codes**	**2010 ACS Codes**
59-Engineers and other professionals, n.e.c.	**49**-Nuclear engineers **54**-Agricultural engineers **59**-Engineers, n.e.c	**49**-Nuclear engineers **54**-Agricultural engineers **59**-Engineers, n.e.c	**142**-Environmental engineers **151**-Nuclear engineers **153**-Miscellaneous engineers, including agricultural and biomedical	**134**-Biomedical and agricultural engineers **142**-Environmental engineers **153**-Miscellaneous engineers including nuclear engineers	**1340**-Biomedical and agricultural engineers **1420**-Environmental engineers **1530**-Miscellaneous engineers including nuclear engineers
58-Marine engineers and naval Architects	**58**-Marine engineers and naval architects	**58**-Marine engineers and naval architects	**144**-Marine engineers	**144**-Marine engineers and naval architects	**1440**-Marine engineers and naval architects

The updated and edited *occ1990dd* codes, descriptions and associated OCC codes are displayed in Table 3.

Table 3: Updated and edited *occ1990dd* occupation system, based on earlier work by Autor and Dorn (2013)

Occ1990dd code	Occ1990dd code description	Census 1980 Codes	Census 1990 Codes	Census 2000 (5% Sample) Codes	ACS 2005 Codes	ACS 2010 Codes
4	Chief executives, public administrators, and legislators	3	3	1	1	10
		4	4	3		
7	Financial managers	7	7	12	12	120
8	Human resources and labor relations managers	8	8	13	13	135
						136
						137
9	Purchasing managers	9	9	15	15	150
13	Managers in marketing, advert., PR	13	13	4	4	40
				5	5	50
				6	6	60
14	Managers in education and related fields	14	14	23	23	230
15	Managers of medicine and health occupations	15	15	35	35	350
18	Managers of properties and real estate	16	18	41	41	410
19	Funeral directors	18	19	32	32	4465
22	Managers and administrators, n.e.c.	5	5	2	2	20
		17	16	10	10	100
		19	17	11	11	110
			21	14	14	140
			22	16	16	160
				22	22	220
				30	30	300
				31	31	310
				33	33	330
				34	34	340
				36	36	360
				40	42	420
				42	43	425
				43	60	430
				60	72	600
				72	430	725
				430		4300
23	Accountants and auditors	23	23	80	80	800
				93	93	930
24	Insurance underwriters	24	24	86	86	860
25	Other financial specialists	25	25	82	82	820
				83	83	830
				84	84	840
				85	85	850
				91	91	910
				94	94	940
				95	95	950
26	Management analysts	26	26	71	71	710
27	Personnel, HR, training, and labor rel. specialists	27	27	62	62	630
						640
						650
28	Purchasing agents and buyers of farm products	28	28	51	51	510
29	Buyers, wholesale and retail trade	29	29	52	52	520
33	Purchasing agents and buyers, n.e.c.	33	33	53	53	530
34	Business and promotion agents	34	34	50	50	500
35	Construction inspectors	35	35	666	666	6660
36	Inspectors and compliance officers, outside	36	36	56	56	565
				90	90	900
37	Management support occupations	37	37	73	73	726
						740
43	Architects	43	43	130	130	1300
44	Aerospace engineers	44	44	132	132	1320
45	Metallurgical and materials engineers	45	45	145	145	1450
47	Petroleum, mining, and geological engineers	46	46	152	152	1520
		47	47			

Occ1990dd code	Occ1990dd code description	Census 1980 Codes	Census 1990 Codes	Census 2000 (5% Sample) Codes	ACS 2005 Codes	ACS 2010 Codes
47	Petroleum, mining, and geological engineers	46	46	152	152	1520
		47	47			
48	Chemical engineers	48	48	135	135	1350
53	Civil engineers	53	53	136	136	1360
55	Electrical engineers	55	55	140	140	1400
				141	141	1410
56	Industrial engineers	56	56	143	143	1430
57	Mechanical engineers	57	57	146	146	1460
58	Marine engineers and naval architects	58	58	144	144	1440
59	Engineers and other professionals, n.e.c.	49	49	142	134	1340
		54	54	151	142	1420
		59	59	153	153	1530
64	Computer systems analysts and computer scientists	64	64	100	100	1005
				102	102	1006
				104	104	1007
				106	106	1020
				110	110	1030
				111	111	1050
						1060
						1105
						1106
						1107
65	Operations and systems researchers and analysts	65	65	70	70	700
				122	122	1220
66	Actuaries	66	66	120	120	1200
68	Mathematicians and statisticians	67	67	124	124	1240
		68	68			
69	Physicists and astronomists	69	69	170	170	1700
73	Chemists	73	73	172	172	1720
74	Atmospheric and space scientists	74	74	171	171	1710
75	Geologists	75	75	174	174	1740
76	Physical scientists, n.e.c.	76	76	176	176	1760
77	Agricultural and food scientists	77	77	160	160	1600
78	Biological scientists	78	78	161	161	1610
79	Foresters and conservation scientists	79	79	164	164	1640
83	Medical scientists	83	83	165	165	1650
84	Physicians	84	84	306	306	3060
85	Dentists	85	85	301	301	3010
86	Veterinarians	86	86	325	325	3250
87	Optometrists	87	87	304	304	3040
88	Podiatrists	88	88	312	312	3120
89	Other health and therapy occupations	89	89	300	300	3000
				326	326	3260
95	Registered nurses	95	95	313	313	3255
						3256
						3258
96	Pharmacists	96	96	305	305	3050
97	Dieticians and nutritionists	97	97	303	303	3030
98	Respiratory therapists	98	98	322	322	3220
99	Occupational therapists	99	99	315	315	3150
103	Physical therapists	103	103	316	316	3160
104	Speech therapists	104	104	314	314	3140
				323	323	3230
105	Therapists, n.e.c.	105	105	320	320	3200
				321	321	3210
				324	324	3245
106	Physicians' assistants	106	106	311	311	3110

Occ1990dd code	Occ1990dd code description	Census 1980 Codes	Census 1990 Codes	Census 2000 (5% Sample) Codes	ACS 2005 Codes	ACS 2010 Codes
154	Subject instructors, college	113	113	220	220	2200
		114	114			
		115	115			
		116	116			
		117	117			
		118	118			
		119	119			
		123	123			
		124	124			
		125	125			
		126	126			
		127	127			
		128	128			
		129	129			
		133	133			
		134	134			
		135	135			
		136	136			
		137	137			
		138	138			
		139	139			
		143	143			
		144	144			
		145	145			
		146	146			
		147	147			
		148	148			
		149	149			
		153	153			
		154	154			
155	Kindergarten and earlier school teachers	155	155	230	230	2300
156	Primary school teachers	156	156	231	231	2310
157	Secondary school teachers	157	157	232	232	2320
158	Special education teachers	158	158	233	233	2330
159	Teachers, n.e.c.	159	159	234	234	2340
				255	255	2550
163	Vocational and educational counselors	163	163	200	200	2000
164	Librarians	164	164	243	243	2430
165	Archivists and curators	165	165	240	240	2400
166	Economists, market and survey researchers	166	166	180	180	735
				181	181	1800
167	Psychologists	167	167	182	182	1820
169	Social scientists and sociologists, n.e.c.	168	168	186	186	1860
		169	169			
173	Urban and regional planners	173	173	184	184	1840
174	Social workers	174	174	201	201	2010
175	Religious workers, n.e.c.	177	177	205	205	2050
				206	206	2060
176	Clergy	176	176	204	204	2040
177	Welfare service workers	467	465	202	202	2015
						2016
						2025
178	Lawyers and judges	178	178	210	210	2100
		179	179	211		2105
183	Writersandauthors	183	183	285	285	2850
184	Technical writers	184	184	284	284	2840
185	Designers	185	185	263	263	2630
186	Musicians and composers	186	186	275	275	2750
187	Actors, directors, and producers	187	187	270	270	2700
				271	271	2710
188	Painters, sculptors, craft-artists, and print-makers	188	188	260	260	2600
189	Photographers	189	189	291	291	2910
				292	292	2920
193	Dancers	193	193	274	274	2740
194	Art/entertainment performers and related occs	194	194	276	276	2760
				286	286	2860

Occ1990dd code	Occ1990dd code description	Census 1980 Codes	Census 1990 Codes	Census 2000 (5% Sample) Codes	ACS 2005 Codes	ACS 2010 Codes
195	Editors and reporters	195	195	281	281	2810
				283	283	2830
197	Specialists in marketing, advert., PR	197	197	282	282	2825
198	Announcers	198	198	280	280	2800
199	Athletes, sports instructors, and officials	199	199	272	272	2720
203	Clinical laboratory technologies and technicians	203	203	330	330	3300
204	Dental hygienists	204	204	331	331	3310
205	Health record technologists and technicians	205	205	351	351	3510
206	Radiologic technologists and technicians	206	206	332	332	3320
207	Licensed practical nurses	207	207	350	350	3500
208	Health technologists and technicians, n.e.c.	208	208	340	340	3400
				341	341	3420
				353	353	3535
				354	354	3540
214	Engineering and science technicians	213	213	155	155	1550
		214	214	193	193	1930
		215	215			1940
		216	216			
		225	225			
217	Drafters	217	217	154	154	1540
218	Surveryors, cartographers, mapping scientists/techs	63	63	131	131	1310
		218	218	156	156	1560
		867	867			
223	Biological technicians	223	223	190	190	1900
				191	191	1910
224	Chemical technicians	224	224	192	192	1920
226	Airplane pilots and navigators	226	226	903	903	9030
227	Air traffic controllers	227	227	904	904	9040
228	Broadcast equipment operators	228	228	290	290	2900
229	Computer programmers	229	229	101	101	1010
233	Programmers of numerically controlled machine tools	233	233	790	790	7900
		714	714			
234	Legal assistants and paralegals	234	234	214	214	2145
		314	314	215	215	2160
235	Technicians, n.e.c.	235	235	196	196	1950
						1965
243	Sales supervisors and proprietors	243	243	470	470	4700
				471	471	4710
253	Insurance sales occupations	253	253	481	481	4810
254	Real estate sales occupations	254	254	81	81	810
				492	492	4920
255	Financial service sales occupations	255	255	482	482	4820
256	Advertising and related sales jobs	256	256	480	480	4800
258	Sales engineers	258	258	493	493	4930
269	Parts salesperson	269	269	475	475	4750
270	Sales workers	263	263	476	476	4760
		264	264			
		265	265			
		266	266			
		267	267			
		268	268			
		274	274			
274	Sales occupations and sales representatives	257	257	484	484	4840
		259	259	485	485	4850
				494	494	4940
275	Sales counter clerks	275	275	474	474	4740
276	Cashiers	276	276	472	472	4720
				513	513	5130
277	Door-to-door sales, street sales, and news vendors	277	277	495	495	4950
		278	278			
283	Sales demonstrators, promoters, and models	283	283	490	490	4900
285	Auctioneers and sales support occupations, n.e.c.	284	284	496	496	4965
		285	285			

Occ1990dd code	Occ1990dd code description	Census 1980 Codes	Census 1990 Codes	Census 2000 (5% Sample) Codes	ACS 2005 Codes	ACS 2010 Codes
303	Office supervisors	303	303	500	500	5000
		304	304			
		305	305			
		306	306			
		307	307			
308	Computer and peripheral equipment operators	308	308	580	580	5800
		309	309			
313	Secretaries and administrative assistants	313	313	570	570	5700
315	Typists	315	315	582	582	5820
316	Interviewers, enumerators, and surveyors	316	316	523	523	5230
				531	531	5310
				534	534	5340
317	Hotel clerks	317	317	530	530	5300
318	Transportation ticket and reservation agents	318	318	483	483	4830
				541	541	5410
319	Receptionists and other information clerks	319	319	540	540	5400
		323	323			
326	Correspondence and order clerks	325	325	535	535	5350
		326	326			
		327	327			
328	Human resources clerks, excl payroll and timekeeping	328	328	536	536	5360
329	Library assistants	329	329	244	244	2440
				532	532	5320
335	File clerks	335	335	526	526	5260
336	Records clerks	336	336	520	520	5200
				542	542	5420
337	Bookkeepers and accounting and auditing clerks	337	337	512	512	5120
338	Payroll and timekeeping clerks	338	338	514	514	5140
344	Billing clerks and related financial records processing	339	339	511	511	5110
		343	343			
		344	344			
347	Office machine operators, n.e.c.	345	345	590	590	5900
		347	347			
348	Telephone operators	348	348	501	501	5010
				502	502	5020
349	Other telecom operators	349	353	503	503	5030
		353				
354	Postal clerks, exluding mail carriers	354	354	554	554	5540
				556	556	5560
355	Mail carriers for postal service	355	355	555	555	5550
356	Mail clerks, outside of post office	346	346	585	585	5850
		356	356			
357	Messengers	357	357	551	551	5510
359	Dispatchers	359	359	552	552	5520
364	Shipping and receiving clerks	364	364	550	550	5500
				561	561	5610
365	Stock and inventory clerks	365	365	515	515	5150
		374	374	562	562	5620
366	Meter readers	366	366	553	553	5530
368	Weighers, measurers, and checkers	368	368	563	563	5630
		369				
373	Material recording, sched., prod., plan., expediting cl.	363	363	560	560	5600
		373	373			
375	Insurance adjusters, examiners, and investigators	375	375	54	54	540
				584	584	5840
376	Customer service reps, invest., adjusters, excl. insur.	376	376	524	524	5240
				533	533	5330
377	Eligibility clerks for government prog., social welfare	377	377	525	525	5250
378	Bill and account collectors	378	378	510	510	5100
379	General office clerks	379	379	586	586	5860
383	Bank tellers	383	383	516	516	5160
384	Proofreaders	384	384	591	591	5910

Occ1990dd code	Occ1990dd code description	Census 1980 Codes	Census 1990 Codes	Census 2000 (5% Sample) Codes	ACS 2005 Codes	ACS 2010 Codes
385	Data entry keyers	385	385	581	581	5810
386	Statistical clerks	386	386	592	592	5920
387	Teacher's aides	387	387	254	254	2540
389	Administrative support jobs, n.e.c.	389	389	522	522	5165
				583	593	5220
				593		5940
405	Housekeepers, maids, butlers, and cleaners	405	405	423	423	4230
		407	407			
		449	449			
408	Laundry and dry cleaning workers	748	748	830	830	8300
413	Supervisors, firefighting and fire prevention occupations	413	413	372	372	3720
414	Supervisors, police and detectives	6	6	371	371	3710
		414	414			
415	Supervisors of guards	415	415	373	373	3730
417	Fire fighting, inspection, and prevention occupations	416	416	374	374	3740
		417	417	375	375	3750
418	Police and detectives, public service	418	418	370	370	3700
				382	382	3820
				385	385	3850
423	Sheriffs, bailiffs, correctional institution officers	423	423	380	380	3800
		424	424	384	384	3840
425	Crossing guards	425	425	394	394	3940
426	Guards and police, except public service	426	426	391	391	3910
				392	392	3930
427	Protective service, n.e.c.	427	427	390	390	3900
				395	395	3955
433	Supervisors of food preparation and service	433	433	401	401	4010
434	Bartenders	434	434	404	404	4040
435	Waiters and waitresses	435	435	411	411	4110
436	Cooks	404	404	400	400	4000
		436	436	402	402	4020
		437				
439	Food preparation workers	439	439	403	403	4030
444	Miscellanious food preparation and service workers	438	438	405	405	4050
		443	443	406	406	4060
		444	444	412	412	4120
				413	413	4130
				414	414	4140
				415	415	4150
445	Dental assistants	445	445	364	364	3640
447	Health and nursing aides	446	446	360	360	3600
		447	447	361	361	3610
				362	362	3620
				365	365	3645
				461	461	3646
						3647
						3648
						3649
						3655
						4610
448	Supervisors of cleaning and building service	448	448	420	420	4200
450	Superv. of landscaping, lawn service, groundskeeping	485	485	421	421	4210
451	Gardeners and groundskeepers	474	474	425	425	4250
		486	486			
453	Janitors	453	453	422	422	4220
455	Pest control occupations	455	455	424	424	4240
457	Barbers	457	457	450	450	4500
458	Hairdressers and cosmetologists	458	458	451	451	4510
				452	452	4520
459	Recreation facility attendants	459	459	440	440	4400
				443	443	4430

Occ1990dd code	Occ1990dd code description	Census 1980 Codes	Census 1990 Codes	Census 2000 (5% Sample) Codes	ACS 2005 Codes	ACS 2010 Codes
461	Guides	463	461	454	454	4540
462	Ushers	464	462	442	442	4420
464	Baggage porters, bellhops and concierges	466	464	453	453	4530
466	Recreation and fitness workers	175	175	462	462	4620
467	Motion picture projectionists	773	773	441	441	4410
468	Childcareworkers	406	406	460	460	4600
		468	466	464	464	4640
			467			
			468			
469	Personal service occupations, n.e.c	469	469	363	363	3630
				446	446	4460
				465	465	4650
470	Supervisors of personal service jobs, n.e.c	456	456	432	432	4320
471	Public transportation attendants	465	463	455	455	9050
						9415
472	Animal caretakers, except farm	487	487	435	435	4350
473	Farmers, ranchers, and other agricultural managers	473	473	20	20	205
		475	475	21	21	
		476	476			
479	Farm workers, incl. nursery farming, and marine life cultivation workers	479	479	434	434	4340
		483	483	605	605	6050
		484	484			
488	Graders and sorters of agricultural products	488	488	604	604	6040
489	Inspectors of agricultural products	489	489	601	601	6010
494	Supervisors, forestry and logging workers	477	477	600	600	6005
		494	494			
496	Timber, logging, and forestry workers	495	495	612	612	6120
		496	496	613	613	6130
498	Fishing and hunting workers	497	497	610	610	6100
		498	498			
		499	499			
503	Supervisors of mechanics and repairers	503	503	700	700	7000
505	Automobile mechanics and repairers	505	505	720	720	7200
		506	506			
507	Bus, truck, and stationary engine mechanics	507	507	721	721	7210
508	Aircraft mechanics	508	508	714	714	7140
		515	515			
509	Small engine repairers	509	509	724	724	7240
514	Auto body repairers	514	514	715	715	7150
				716	716	7160
516	Heavy equipement and farm equipment mechanics	516	516	722	722	7220
		517	517			
518	Industrial machinery repairers	518	518	733	733	7330
519	Machinery maintenance occupations	519	519	735	735	7350
523	Repairers of industrial electrical equipment	523	523	710	710	7100
				712	712	7120
525	Repairers of data processing equipment	525	525	701	701	7010
		538	538			
526	Repairers of household appliances and power tools	526	526	732	732	7320
527	Telecom and line installers and repairers	527	527	702	702	7020
		529	529	742	742	7420
533	Repairers of electrical equipment, n.e.c.	533	533	703	703	7030
				704	704	7040
				711	711	7110
534	Heating, air conditioning, and refrigeration mechanics	534	534	731	731	7315
535	Precision instrument and equipment repairers	535	535	743	743	7430
536	Locksmiths and safe repairers	536	536	754	754	7540
539	Repairers of mechanical controls and valves	539	539	730	730	7300
543	Elevator installers and repairers	543	543	670	670	6700
544	Millwrights	544	544	736	736	7360
549	Mechanics and repairers, n.e.c.	547	547	734	734	7340
		549	549	751	751	7510
		864		755	755	7550
				756	756	7560
				762	762	7630

Occ1990dd code	Occ1990dd code description	Census 1980 Codes	Census 1990 Codes	Census 2000 (5% Sample) Codes	ACS 2005 Codes	ACS 2010 Codes
558	Supervisors of construction work	553 554 555 556 557 558 613	553 554 555 556 557 558 613	620	620	6200
563	Masons, tilers, and carpet installers	563 564 565 566	563 564 565 566	622 624	622 624	6220 6240
567	Carpenters	567 569	567 569	623	623	6230
573	Drywall installers	573	573	633	633	6330
575	Electricians	575 576	575 576	635 713	635 713	6355 7130
577	Electric power installers and repairers	577	577	741	741	7410
579	Painters, construction and maintenance	579	579	642	642	6420
583	Paperhangers	583	583	643	643	6430
584	Plasterers	584	584	646	646	6460
585	Plumbers, pipe fitters, and steamfitters	585 587	585 587	644	644	6440
588	Concrete and cement workers	588	588	625	625	6250
589	Glaziers	589	589	636	636	6360
593	Insulation workers	593	593	640 672	640 672	6400 6720
594	Paving, surfacing, and tamping equipment operators	594	594	630	630	6300
595	Roofers	595	595	651	651	6515
597	Structural metal workers	597	597	653 774	650 653 774	6500 6530 7740
598	Drillers of earth	598	598	682	682	6820
599	Misc. construction and related occupations	599	599	671 675 676	671 676	6710 6765
614	Drillers of oil wells	614	614	680	680	6800
615	Explosives workers	615	615	683	683	6830
616	Miners	616	616	684	684	6840
617	Other mining occupations	617	617 868	694	694	6940
628	Production supervisors or foremen	633 863	628	770	770	7700
634	Tool and die makers and die setters	634 635	634 635	813	813	8130
637	Machinists	637 639	637 639	803	803	8030
643	Boilermakers	643	643	621	621	6210
644	Precision grinders and fitters	644	644	821	821	8210
645	Patternmakers and model makers, metal and plastic	645 676	645 676	806	806	8060
647	Jewelers and precious stone and metal workers	647	647	875	875	8750
649	Engravers	649 793	649 793	891	891	8910
653	Sheet metal workers	596 653 654	596 653 654	652	652	6520
657	Cabinetmakers and bench carpeters	657	657	850	850	8500
658	Furniture and wood finishers	658	658	851	851	8510
666	Tailors, dressmakers, and sewers	666 667	666 667	835	835	8350
668	Upholsterers	668	668	845	845	8450
669	Shoe and leather workers and repairers	669	669	833	833	8330
675	Hand molders, shapers, and casters, except jewelers	675 787	675 787	892	892	8920

Occ1990dd code	Occ1990dd code description	Census 1980 Codes	Census 1990 Codes	Census 2000 (5% Sample) Codes	ACS 2005 Codes	ACS 2010 Codes
677	Optical goods workers	677	677	352	352	3520
678	Dental laboratory and medical applicance technicians	678	678	876	876	8760
684	Miscellaneous precision workers, n.e.c.	646	646	816	822	8220
		684	684	822		
		705	705			
		715	715			
		717	717			
686	Butchers and meat cutters	686	686	781	781	7810
687	Bakers	687	687	780	780	7800
688	Batch food makers	688	688	784	784	7840
694	Water and sewage treatment plant operators	694	694	862	862	8620
695	Power plant operators	695	695	860	860	8600
696	Plant and system operators, stationary engineers	696	696	861	861	8610
699	Other plant and system operators	699	699	863	863	8630
703	Lathe and turning machine operatives	703	703	801	801	8010
		704	704			
706	Punching and stamping press operatives	706	706	795	795	7950
707	Rollers, roll hands, and finishers of metal	707	707	794	794	7940
708	Drilling and boring machine operators	708	708	796	796	7960
709	Grinding, abrading, buffing, and polishing workers	655	655	800	800	8000
		709	709			
713	Forge and hammer operators	713	713	793	793	7930
719	Molders and casting machine operators	719	719	810	810	8100
723	Metal platers	723	723	820	820	8200
724	Heat treating equipment operators	724	724	815	815	8150
727	Sawing machine operators and sawyers	727	727	853	853	8530
729	Nail, tacking, shaping and joining mach ops (wood)	726	726	854	854	8540
		728	728			
		729	729			
733	Misc. woodworking machine operators	656	656	855	855	8550
		659	659			
		733	733			
734	Bookbinders and printing machine operators, n.e.c.	679	679	823	823	8255
		734	734	824	824	8256
		737	737	826	826	
736	Typesetters and compositors	735	735	825	825	8250
		736	736			
738	Winding and twisting textile and apparel operatives	738	738	842	842	8420
739	Knitters, loopers, and toppers textile operatives	739	739	841	841	8410
743	Textile cutting and dyeing machine operators	743	743	836	840	8400
				840		
744	Textile sewing machine operators	744	744	832	832	8320
745	Shoemaking machine operators	745	745	834	834	8340
747	Clothing pressing machine operators	403	403	831	831	8310
		747	747			
749	Miscellanious textile machine operators	673	674	846	846	8460
		674	749			
		749				
753	Cementing and gluing machne operators	753	753	885	885	8850
754	Packers, fillers, and wrappers	754	754	880	880	8800
755	Extruding and forming machine operators	755	755	792	792	7920
		758	758	872	872	8720
756	Mixing and blending machine operators	725	725	865	865	8650
		756	756			
		768	768			
757	Separating, filtering, and clarifying machine operators	757	757	864	864	8640
763	Food roasting and baking machine operators	763	763	783	783	7830
764	Washing, cleaning, and pickling machine operators	764	764	886	886	8860

Occ1990dd code	Occ1990dd code description	Census 1980 Codes	Census 1990 Codes	Census 2000 (5% Sample) Codes	ACS 2005 Codes	ACS 2010 Codes
765	Paper folding machine operators	765	765	893	893	8930
766	Furnance, kiln, and oven operators, apart from food	766	766	804	804	8040
				873	873	8730
769	Slicing and cutting machine operators	769	769	871	871	8710
		786	786			
774	Photographic process machine operators	774	774	883	883	8830
779	Machine operators, n.e.c.	777	777	785	785	7850
		779	779	894	894	7855
		794	795	896	896	8940
		795				8965
783	Welders, solderers, and metal cutters	783	783	814	814	8140
		784	784			
785	Assemblers of electrical equipment	636	636	771	771	7710
		683	683	772	772	7720
		693	693	773	773	7730
		785	785	775	775	7750
789	Painting and decoration occupations	759	759	881	881	8810
		789	789			
799	Production checkers, graders, and sorters in manufacturing	689	689	874	874	3945
		796	796	941	941	8740
		797	797			9410
		798	798			
		799	799			
803	Supervisors of motor vehicle transportation	803	803	900	900	9000
		843	843			
			864			
804	Driver/sales workers and truck Drivers	804	804	913	913	9130
		805	806			
		806				
808	Bus drivers	808	808	912	912	9120
809	Taxi drivers and chauffeurs	809	809	914	914	9140
813	Parking lot attendants	813	813	935	935	9350
814	Motor transportation occupations, n.e.c.	814	814	915	911	9110
					915	9150
823	Railroad conductors and yardmasters	823	823	924	924	9240
824	Locomotive operators: engineers and firemen	824	824	920	920	9200
		826	826	926	926	9260
825	Railroad brake, coupler, and switch operators	825	825	923	923	9230
828	Ship and boat captains and operators	828	828	931	931	9310
829	Sailors and deckhands, ship/marine engineers	829	829	930	930	9300
		833	833	933		
834	Miscellanious transportation occupations	834	834	942	942	9420
844	Operating engineers of construction equipment	844	844	632	632	6320
		855	855			
848	Hoist and winch operators	848	848	956	956	9560
849	Crane and tower operators	845	845	951	951	9510
		849	849			
853	Excavating and loading machine operators	853	853	952	952	9520
856	Industrial truck and tractor operators	856	856	960	960	9600
859	Misc. material moving equipment operators	454	454	965	965	9650
		859	859	975	975	9750
865	Helpers, constructions	865	865	761	761	7610
866	Helpers, surveyors	866	866	660	660	6600
869	Construction laborers	869	869	626	626	6260
				673	673	6730
873	Production helpers	873	874	895	895	8950
		874				
875	Garbage and recyclable material collectors	875	875	972	972	9720
878	Machine feeders and offbearers	878	878	963	963	9630
885	Garage and service station related occupations	885	885	726	726	7260
				936	936	9360
887	Vehicle washers and equipment cleaners	887	887	961	961	9610
888	Packers and packagers by hand	888	888	964	964	9640
889	Laborers, freight, stock, and material handlers, n.e.c.	876	876	674	674	6740
		877	877	962	962	9620
		883	883			
		889	889			

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Theory Appendix

August 2015

1 Team Production and Trading Tasks Results

1.1 Distribution of P_{tn}

Let $P_{tn} = \min\{P_{tni}; i = 1, ..., N\}$. P_{tn} is distributed according to

$$G_{tn}(p) = Pr(P_{tn} \leq p) = 1 - \exp(-\phi_n p^{\theta})$$

where:

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

Proof:

$$\begin{aligned} G_{tn}(p) = \Pr(P_{tn} \leq p) &= 1 - \prod_{i=1}^{N} \Pr(P_{tni} > p) \\ &= 1 - \prod_{i=1}^{N} 1 - G_{tni}(p) \\ &= 1 - \prod_{i=1}^{N} \exp\left(-A_i^{\rho} (S_n S_i)^{\theta} p^{\theta}\right) \\ &= 1 - \exp\left(-\left(\sum_{i=1}^{N} A_i^{\rho} (S_n S_i)^{\theta}\right) p^{\theta}\right) \\ &= 1 - \exp\left(-\phi_n p^{\theta}\right) \end{aligned}$$

1.2 Probability that worker i provides the lowest price task trade to worker n

The probability that worker i provides the lowest price task trade to worker n is:

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

Proof:

Let $\pi_{ni} = Pr[P_{ni} \leq \min\{P_{nk}; k \neq i\}]$. If $P_{ni} = p$, the probability that worker i provides the lowest price task trade to worker n is equal to the probability that $P_{nk} \geq p$ for all $k \neq i$. This is equal to $\prod_{k \neq i} Pr(P_{nk} \geq p)$.

$$
\begin{aligned}
\pi_{ni} &= \prod_{k\neq i} Pr\left(P_{nk} \geq p\right) \\
&= \prod_{k\neq i} 1 - G_{nk}(p) \\
&= \int\limits_0^\infty \left(\prod_{k\neq i} 1 - G_{nk}(p)\right) dG_{ni}(p)
\end{aligned}
$$

since $G_{ni}(p)$ is the CDF of P_{ni}.

We know that

$$
\begin{aligned}
\prod_{k\neq i} 1 - G_{nk}(p) &= \prod_{k\neq i} \exp\left(-A_k^\rho \left(S_n S_k\right)^\theta p^\theta\right) \\
&= \exp\left(-\left(\sum_{k\neq i} A_k^\rho \left(S_n S_k\right)^\theta\right) p^\theta\right) \\
&= \exp\left(-\phi_n^{-i} p^\theta\right)
\end{aligned}
$$

where $\phi_n^{-i} = \sum_{k\neq i} A_k^\rho \left(S_n S_k\right)^\theta$. Subsitute $\exp\left(-\phi_n^{-i} p^\theta\right)$ for $\prod_{k\neq i} 1 - G_{nk}(p)$.

$$
\begin{aligned}
\pi_{ni} &= \int\limits_0^\infty \left(\prod_{k\neq i} 1 - G_{nk}(p)\right) \mathrm{d}G_{ni}(p) \\
&= \int\limits_0^\infty \exp\left(-\phi_n^{-i} p^\theta\right) \mathrm{d}G_{ni}(p) \\
&= \int\limits_0^\infty \exp\left(-\phi_n^{-i} p^\theta\right) \exp\left(-A_i^\rho \left(S_n S_i\right)^\theta p^\theta\right) \left(A_i^\rho \left(S_n S_i\right)^\theta \theta p^{\theta-1}\right) \mathrm{d}p \\
&= A_i^\rho \left(S_n S_i\right)^\theta \int\limits_0^\infty \exp\left(-\phi_n p^\theta\right) \theta p^{\theta-1} \mathrm{d}p \\
&= \frac{A_i^\rho \left(S_n S_i\right)^\theta}{\phi_n} \int\limits_0^\infty \exp\left(-\phi_n p^\theta\right) \phi_n \theta p^{\theta-1} \mathrm{d}p \\
&= \frac{A_i^\rho \left(S_n S_i\right)^\theta}{\phi_n} \int\limits_0^\infty \mathrm{d}G_n(p) \\
&= \frac{A_i^\rho \left(S_n S_i\right)^\theta}{\phi_n}
\end{aligned}
$$

2 Labor Market Equilibrium Results

2.1 Price Index Result

The exact price index for worker n's task trades, under Cobb-Douglas is:

$$
\bar{P}_n = \gamma \phi_n^{-1/\theta}
$$

where $\gamma = \exp\left(\frac{-\epsilon}{\theta}\right)$, with $\epsilon = 0.577...$ as Euler's constant.

Proof:

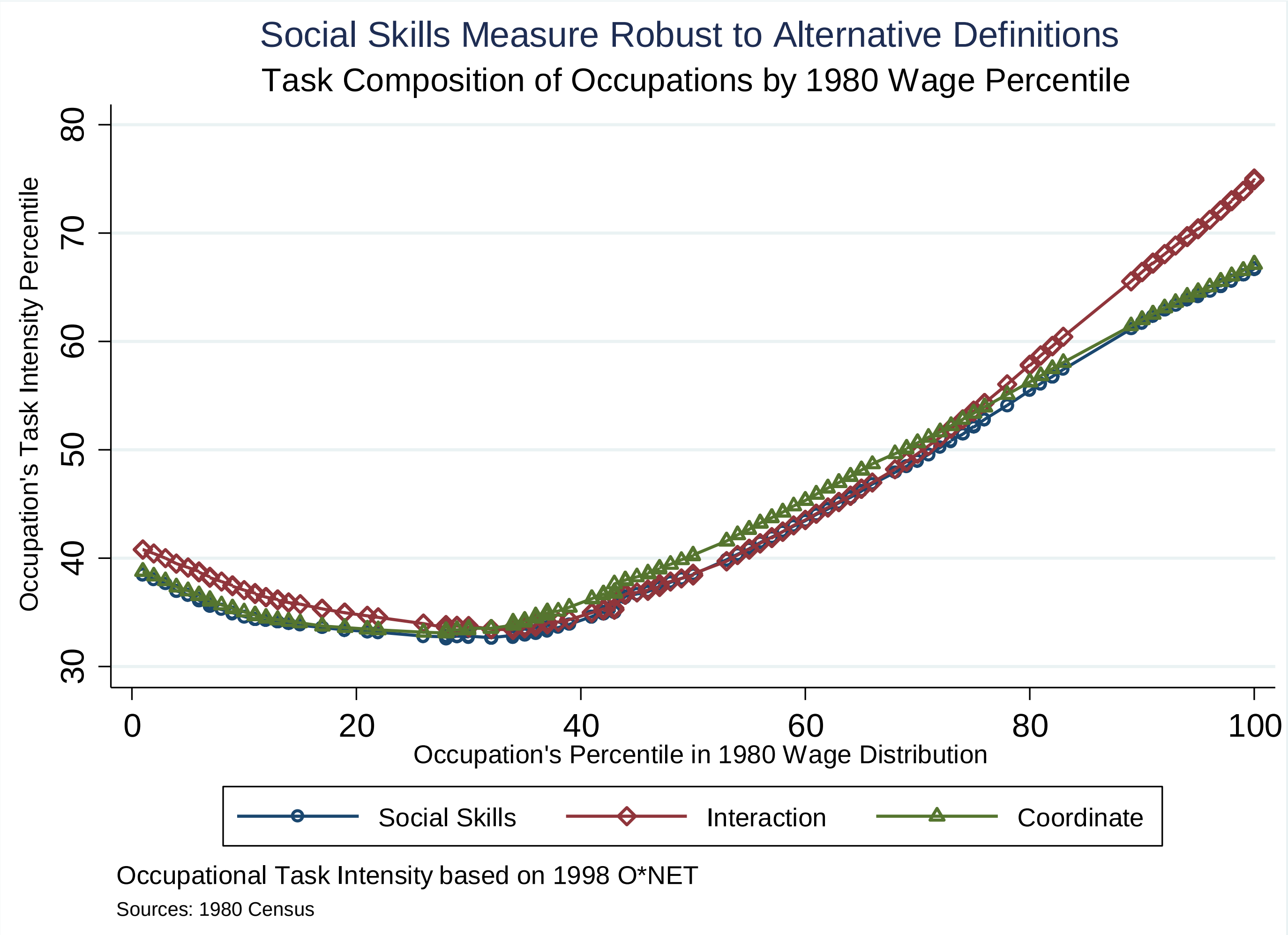
$$\begin{aligned}
\bar{P}_n &= \exp \int_0^1 \ln p_n(t)\, dt = \exp \int_0^\infty \ln p \, dG_n(p) \\
&= \exp \int_0^\infty \ln p \, \exp\left(-\phi_n p^\theta\right) \phi_n \theta p^{\theta-1} \, dp
\end{aligned}$$

Let $x = \phi_n p^\theta$, and $dx = \phi_n \theta p^{\theta-1}\, dp$. So $p = \left(\frac{x}{\phi_n}\right)^{1/\theta}$.

$$\begin{aligned}
\bar{P}_n &= \exp \int_0^\infty \ln \left[\left(\frac{x}{\phi_n}\right)^{1/\theta}\right] \exp(-x)\, dx \\
&= \exp \int_0^\infty \left[\ln\left(x^{1/\theta}\right) - \ln\left(\phi_n^{1/\theta}\right)\right] \exp(-x)\, dx \\
&= \exp\left(\frac{1}{\theta} \int_0^\infty \ln x \exp(-x)\, dx - \ln\left(\phi_n^{1/\theta}\right) \int_0^\infty \exp(-x)\, dx\right) \\
&= \exp\left(\frac{-\epsilon}{\theta} - \ln\left(\phi_n^{1/\theta}\right)\right) \\
&= \exp\left(\frac{-\epsilon}{\theta}\right) \phi_n^{-1/\theta} \\
&= \gamma \phi_n^{-1/\theta}
\end{aligned}$$

where ϵ is 0.577... Euler's constant.

Figure A1



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 A2

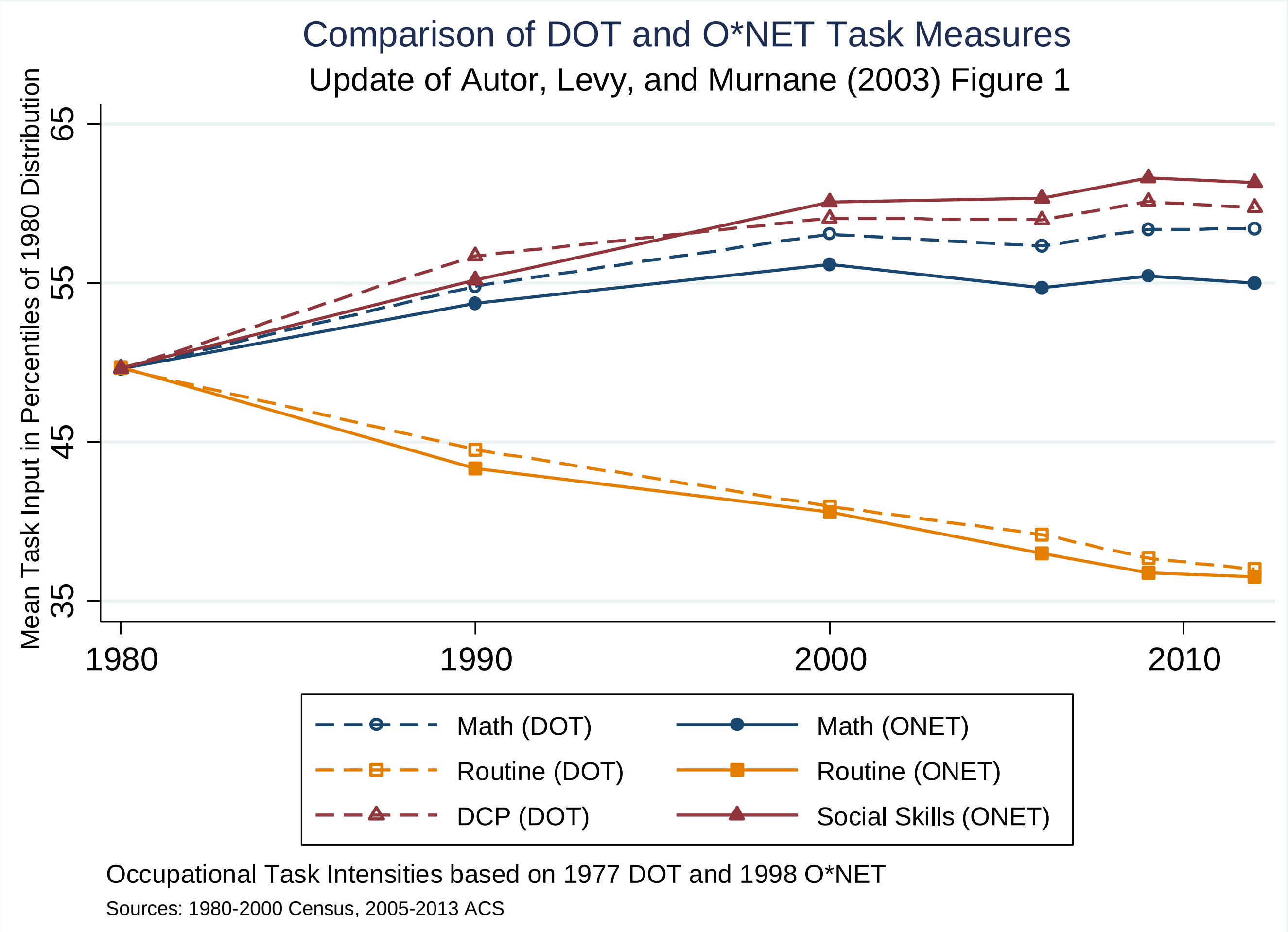
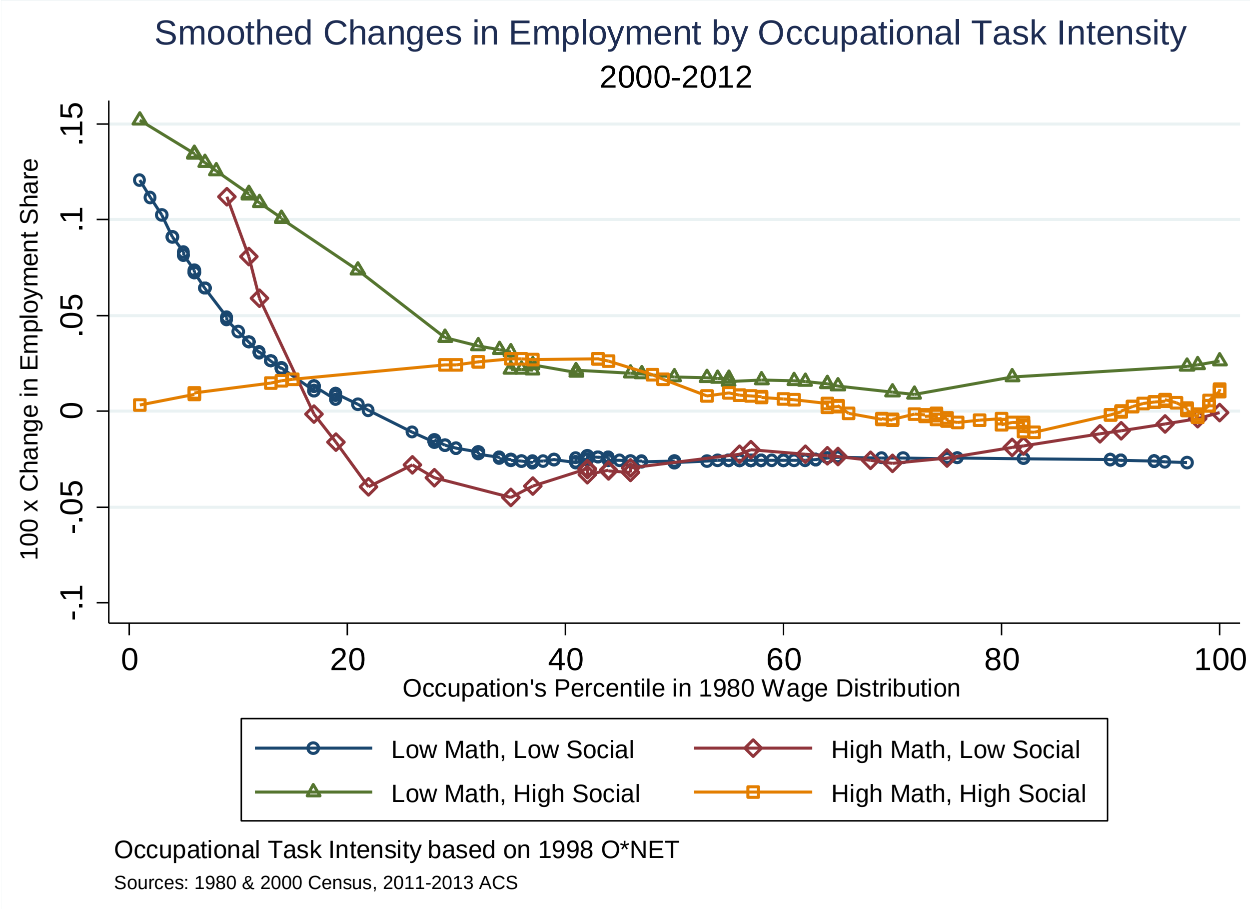


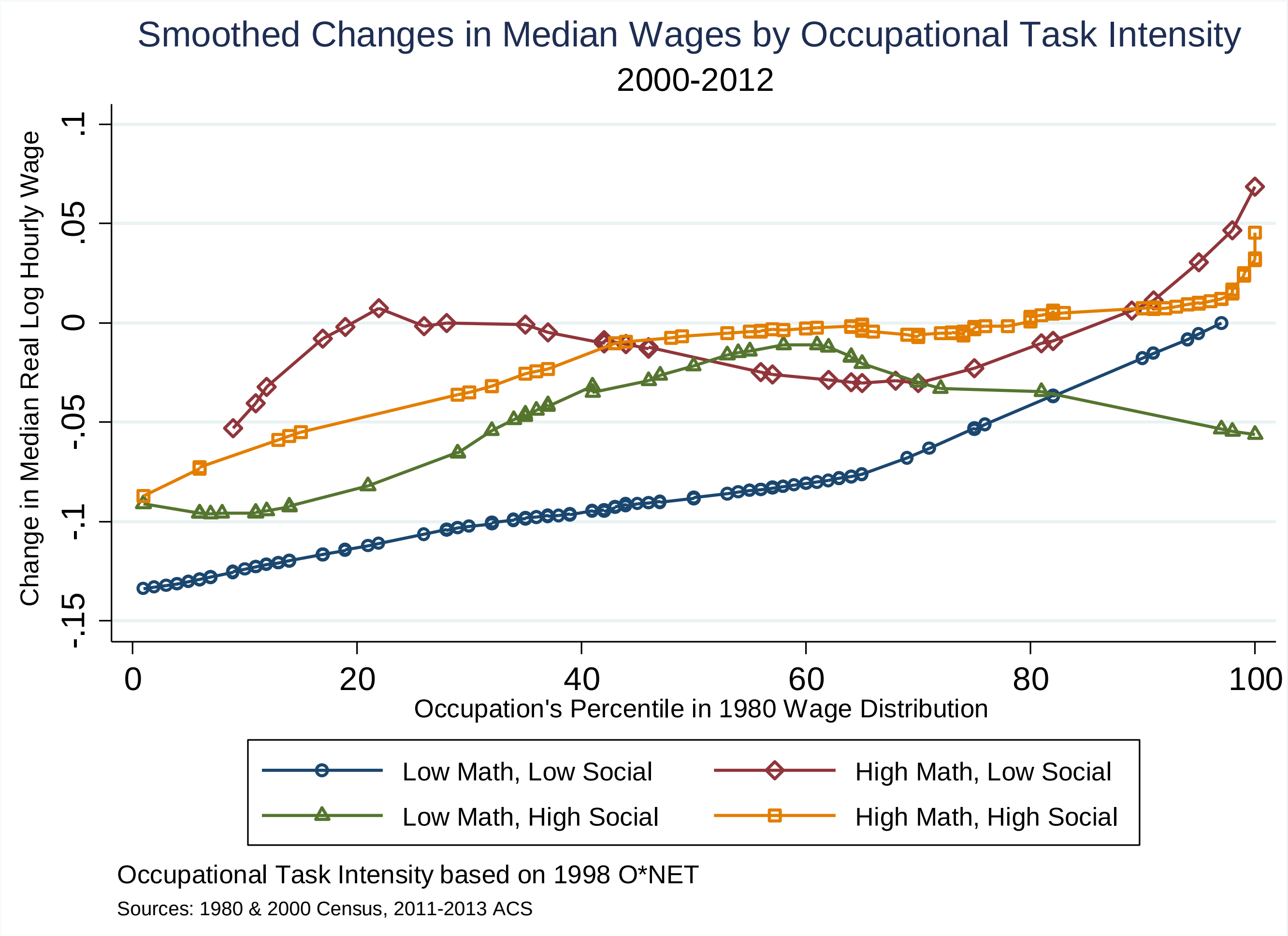
Figure A2 is constructed to parallel Figure I of Autor, Levy and Murnane (2003). O*NET 1998 and DOT 1977 task measures by occupation are paired with data from the IPUMS 1980-2000 Censuses and the 2005-2013 American Community Survey samples. Consistent occupation codes for 1980-2012 are updated from Autor 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 A3



Each line plots 100 times the change in employment share between 2000 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 A4



Each line plots 100 times the change in median log hourly real wages between 2000 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.

Table A1 - Returns to Skills by Subgroup

Outcome is Log Hourly Wage	(1)	(2)	(3)	(4)	(5)	(6)
	Males	*Females*	*White*	*Nonwhite*	*< BA*	*BA or more*
Cognitive Skills (AQT, standardized)	0.0477***	0.0638***	0.0552***	0.0575***	0.0563***	0.0705***
	[0.0091]	[0.0077]	[0.0078]	[0.0096]	[0.0062]	[0.0184]
Social Skills (standardized)	0.0250***	0.0125**	0.0246***	0.0030	0.0136***	0.0165
	[0.0070]	[0.0055]	[0.0061]	[0.0080]	[0.0048]	[0.0166]
Cognitive * Social	0.0058	0.0037	0.0093	-0.0080	-0.0038	0.0268**
	[0.0069]	[0.0057]	[0.0060]	[0.0086]	[0.0053]	[0.0131]
Rotter Locus of Control	0.0107*	0.0165***	0.0188***	0.0102*	0.0124***	0.0239**
	[0.0061]	[0.0054]	[0.0056]	[0.0060]	[0.0042]	[0.0121]
Rosenberg Self-Esteem Scale	0.0287***	0.0185***	0.0242***	0.0297***	0.0237***	0.0422***
	[0.0065]	[0.0055]	[0.0057]	[0.0063]	[0.0044]	[0.0128]
Years of completed education	X	X	X	X	X	X
Exclude government jobs	X	X	X	X	X	X
Occ-Ind-Region-Urban Fixed Effects	X	X	X	X	X	X
Observations	66,244	58,769	71,725	53,288	101,924	23,089
R-squared	0.7277	0.7286	0.7563	0.7081	0.6964	0.7504

Notes: Each column reports results from an estimate of equation (19) 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 regression also controls for race-by-gender indicator variables, fixed effects for years of completed education, and age, year, census region, and urbanicity fixed effects - plus additional controls as indicated. Standard errors are in brackets and clustered at the individual level. *** p<0.01, ** p<0.05, * p<0.10