Task reallocation: a cohort analysis

Carol A. Scotese[†]

Virginia Commonwealth University

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Abstract

Routine biased technological change lowers demand for routine tasks and increases demand for non-routine tasks. I construct a set of granular task measures that captures multiple types of routine and non-routine tasks and analyze task reallocation of individuals from the NLSY79 cohort who have exited routine work. Contrary to predictions from a sparse task framework, I find that low skill workers enter into abstract work at rates approximately 2.5 times higher than they enter non-routine physical work. Both low skill and high skill workers have similar rates of entry into occupations intensive in abstract tasks associated with wage gains. However, entry rates into tasks associated with wage declines is much higher for the lower skill group.

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[†]Email: cascotese@vcu.edu

1 Introduction

Autor et al. (2003)'s seminal study on computerization described tasks as production inputs. Labor and capital perform tasks to produce output. A standard task-based framework employs a sparse task set with tasks categorized by their amenability to automation. Routine tasks can be performed by either labor or machines while non-routine tasks describe activities for which labor maintains a comparative advantage. A sparse taxonomy broadly conceptualizes the themes in a stylized model of routine biased technological change. On the other hand, categorizing all occupations into just a few task groups limits the ability to observe reallocation more generally and to assess reallocation within those broad task groups. The analysis in this paper deploys a more granular taxonomy of tasks and permits a detailed characterization of task reallocation for the cohort of workers entering the labor market at the cusp of digital technological change revolution. The results indicate that a sizeable share of non-college educated individuals who exit routine intensive work move into occupations intensive in non-routine abstract tasks. This observation has been overlooked in most previous work and is different from the predominant view of lower-skilled task reallocation. The insight arises from the ability of the granular task measures to more precisely characterize the tasks performed *intensively* in each occupation.

More specifically, in a sparse task-based framework, it is common to consider only three task types: non-routine abstract, routine, and non-routine physical.[1] Within this framework, low skill workers who exit routine work will tend to sort into non-routine *physical* work while higher skill workers who exit routine work tend to enter non-routine *abstract* work.[2] The granular task division I implement uses occupation attributes from the O*NET to create measures for multiple types of routine and non-routine tasks. The non-routine tasks include different types of cognitive, interpersonal, managerial, technical, and physical tasks. The enhanced precision afforded by the granular task measures uncovers the pervasiveness of abstract tasks across occupations. Of course, college educated individuals are more likely to perform some abstract tasks and non-college educated individuals are more likely to perform others, but the relevance of abstract tasks performed

[1] The routine task may be divided into cognitive and physical types, yielding four task types. Spitz-Oener (2006), Atalay et al. (2020), and Atalay et al. (2018) use five task categories by dividing the non-routine cognitive task into analytical and interactive components. Also, note that abstract tasks are commonly referred to as cognitive tasks. In this study, abstract refers to tasks that are jointly non-physical and non-routine tasks. Cognitive tasks refer to a subset of the abstract tasks.

[2] See, for example, Acemoglu and Autor (2011) and Cortes (2016). Related models include Acemoglu and Restrepo (2020), Atalay et al. (2018), Atalay et al. (2020), Cortes et al. (2017), vom Lehn (2020), Böhm (2020), and Michaels et al. (2018).

by non-college educated labor has been largely overlooked in the empirical task-based literature.[3] Recognizing the ability of non-college labor to enter occupations intensive in the abstract task has implications for understanding the impact on wages, the allocation of talent, and public policies that might address education or training related to labor market issues.

Applying the granular task taxonomy to the occupation choices of individuals from the National Longitudinal Survey of Youth 1979 (NLSY79) cohort, confirms the broad trends associated with a more sparse task environment: non-college educated individuals who exit a routine task are more likely to enter an occupation intensive in a non-routine physical task relative to their college-educated counterparts. Only 4.7% - 5.6% of college exits from routine work enter a non-routine physical task compared to 16.8% - 22.7% of low-education exits from a routine work. (The range in percentages, here and throughout the paper, reflects differences across the specific exited routine task) However, roughly half of all non-college educated individuals who exit routine work enter into an occupation intensive in an abstract task. Specifically, 44.6% - 64.2% of non-college exits enter into occupations intensive in abstract work.

An occupation is designated as intensive in a task if the occupation's task score falls in the top decile for that task. This criteria, applied to a larger number of tasks, more precisely measures task intensity and helps to diminish confounding effects from other tasks that may occur in a sparser task setting. Using the top decile criteria also indicates that some occupations are not *intensive* in any of the measured tasks. These are mostly lower skill occupations and I designate these non-task intensive occupations with the acronym NTI. The NTI occupations absorb 13.2% - 22.4% of non-college exits from routine work, but only 3.0% - 5.6% of college exits from routine work.

The labor market outcomes of individuals who exit routine work, particularly non-college educated workers, are of particular interest because the displacement of routine labor by machines has been proffered as an explanation for the stagnation of employment and wages in the middle of the wage distribution.[4] Since this study uses a cohort of individuals, I do not directly quantify the impact of task reallocation on the overall wage or employment distributions, both of which depend on multiple cohorts. However, the cohort data permit direct tracking of individual occupation/task switches and allow me to leverage individual fixed effects when estimating the impact of switching tasks on wages.[5] I find that within the NLSY79 cohort, non-college educated individuals who

[3] College educated refers to individuals with at least 16 years of education. All others are referred to as non-college.

[4] See for example, Acemoglu and Autor (2011) and Autor and Dorn (2013).

[5] In Scotese (2022), I employ the granular task measures on a nationally representative repeated cross sections of the Census and ACS data to detail the impact of task reallocation on the overall wage distribution.

switch out of an occupation intensive in a routine task and into an occupation intensive in a general physical task or into an NTI occupation are associated with significant wage declines that have increased (in absolute value) over time. On the other hand, most non-college switches out of routine work and into non-routine abstract work are associated with wage increases. Moreover, the share of non-college educated individuals who switch into occupations intensive in tasks associated with declining wages is about the same as the share who switch into occupations intensive in abstract tasks with associated wage increases.[6]

I also examine task reallocation more generally, that is, not restricted to individuals who switch out of routine work. The granular task measures capture the broad pattern of declining labor shares in routine tasks and rising labor shares in non-routine tasks documented in existing research. But, in contrast to using a sparse task space, the granular task measures allow me to document task reallocation over more specific non-routine tasks. In particular, among the tasks captured by the granular measures are two tasks related to information gathering and information analysis, respectively, and another related to technology design. These tasks are complementary to digital technological change and, hence, relevant to the task-based framework, but have been empirically under-examined in existing research.[7] For the high education members of this cohort, I estimate that wage gains associated with these technology and information tasks have been among the largest and most persistent; however, there has not been a sizeable employment shift into those tasks. Scotese (2022) shows that in the representative cross section, the technology design task experienced one of the largest inflows among the college educated (particularly for men) and the information analysis task had a large inflow of college educated women. This difference between the cohort and nationally representative sample indicates that there may be important frictions impeding task reallocation. This cohort entered the labor market at the cusp of the digital technological revolution and crucial education decisions were likely made prior to the change in task demand.

I also find that non-college educated individuals in this cohort exhibit a pronounced shift away from tasks associated with personal service occupations prior to the early 2000s, with a rebound thereafter. In nationally representative samples, low education workers are shifting into service occupations (Autor and Dorn (2013)) and into service associated tasks (Scotese (2022)). This

[6]Note that the wage gains for those entering most abstract tasks in conjunction with the wage losses for those entering non-routine physical work and the NTI occupations present countervailing wage pressures that are consistent with observed wage stagnation in the middle and lower portion of the wage distribution over most of this period.

[7]Two notable exceptions are Deming (2017) who examines STEM jobs as a group and Harrigan et al. (2021) who show that in France employment in "techie" occupations has increased.

finding along with the cohort-specific results for the information and technology tasks suggest that new labor market entrants may be driving some of the observed task reallocation rather than labor market incumbents.

Finally, in constructing the granular task measures, I aim for a comprehensive set of measures guided by the task-based approach and assembled with as little subjectivity as possible. Toward that end I use 162 O*NET occupation attributes from the commonly employed O*NET subsets. The major decision I impose on the data is to group those attributes into broad task-based categories: cognitive, interpersonal, managerial, technical, and physical.[8] I do not decide which attributes measure which specific tasks within those groups. Instead, I employ factor analysis on each group to determine both the number of task measures within each group as well as the specific linear combination of the attributes that comprise each specific task measure. The task measures generate occupation-specific task scores for each task. Occupations scoring in the top decile for each task measure are designated as intensive in that task.

The work in this paper builds on an extensive body of work on the impact of routine biased technological change (RBTC) on employment patterns and wage structure. Employment polarization is linked to RBTC through the predominance of non-routine tasks in high and low wage occupations and the predominance of routine tasks in the middle of the wage distribution.[9] Studies that document employment polarization in the U.S. and abroad include Acemoglu (1999), Autor et al. (2006), Acemoglu and Autor (2011), Autor and Dorn (2013), Goos and Manning (2007), Goos et al. (2009), Goos et al. (2014), Spitz-Oener (2006), Green and Sand (2015), and Harrigan et al. (2021). Although Hunt and Nunn (2022) present an argument against rising employment in the lower portion of the wage distribution.[10] This study does not directly address employment polarization since the data are for a particular cohort of workers; however, a central part of the analysis addresses task reallocation differences between high and low education individuals, but using the finer task space division rather than a sparse task-based approach.

The foundations for this study also rest on research estimating the relationship between wages and tasks using O*NET or DOT data to measure occupation task intensity, including Autor and

[8] There is a sixth task group that O*NET denotes as structural characteristics. This is best explained in the next section.

[9] Employment polarization refers to employment growth at the high and low end of the wage distribution and the "hallowing out" of employment in the middle of the wage distribution.

[10] Related to the polarization literature, several studies have focused on the macroeconomic implications of RBTC, including Eden and Gaggl (2019), Gregory et al. (2021), Cortes et al. (2017), and Cavaglia and Etheridge (2020).

Dorn (2013), Beaudry et al. (2016), Beaudry and Lewis (2014), Caines et al. (2017), Firpo et al. (2011), Ross (2017), Yamaguchi (2018), and Yamaguchi (2012). It has also become common to deploy occupation groups as a proxy for tasks. Autor and Dorn (2013) characterize the managerial, professional, and technical occupations as intensive in non-routine cognitive tasks, the production, craft, operators, clerical, and retail sales occupations as routine intensive, and the personal service occupations as non-routine physical intensive.[11] Cortes (2016), Cortes et al. (2017), Ross (2017), Roys and Taber (2019), Cavaglia and Etheridge (2020), and Böhm (2020) are examples of research that employ occupations as proxies for task intensity to estimate the relationships between wages and tasks.[12]

The granular task measures capture more specifics task relative to the sparse task framework. The use of more specific task measures also occurs in Deming (2017), Cortes et al. (forthcoming), Bacolod and Blum (2010), Borghans et al. (2014), and Black and Spitz-Oener (2010), who construct specific measures for certain interpersonal tasks. Deming (2021) constructs a specific decision-making task and Caines et al. (2017) and Yamaguchi (2012) construct a measure for complex tasks. Those papers subjectively chose occupation attributes targeted for their specific needs and do not construct a comprehensive set of specific task measures as in this paper.

Cortes (2016) also uses panel data to isolate individual switches out of routine work in a study that is perhaps closest to the work in this paper.[13] He finds that, after exiting from routine work, higher ability workers are more likely to sort into non-routine cognitive work and lower ability workers are more likely to sort into non-routine physical work. Cortes (2016) examines switches between broad occupation groups where the personal service occupations proxy for the non-routine physical task. I show that while low education individuals are indeed more likely to switch into non-routine physical tasks, the entries into non-routine physical tasks comprise less than one-quarter of all low-education entries after exiting routine work.[14]

In the remainder of this paper, section 2 describes the factor analysis methodology for con-

[11] Autor and Dorn (2013) base their groupings on occupations' scores on the sparse task measures. Personal services should not be confused with the service industry more generally. Personal services are those provided to individuals such as haircuts, gardening, and cleaning. Acemoglu and Autor (2011) also use this occupation division to document employment polarization.

[12] A recent approach to measuring an occupation's exposure to digital technological change uses natural language processing to search words in job descriptions. See, Atalay et al. (2018), Atalay et al. (2020), Webb (2020), and Autor et al. (2021). Gaggl and Wright (2017) use U.K. tax incentive for ICT adoption targeted at small firms to detect exposure to ICT adoption.

[13] Cortes (2016) uses PSID data over the 1977-2005 period.

[14] And my measures of non-routine physical tasks comprise a wider array of occupations relative to the personal service occupations.

structing the granular task measures, section 3 describes the tasks captured by the granular task measures, section 4 analyzes the reallocation of labor over tasks as workers exit routine work, section 5 describes task reallocation in general within this cohort and compares the reallocation to a nationally representative sample, section 6 concludes with some suggestions for future research.

2 Task measure construction

In this section, I describe the construction of the granular task measures using O*NET occupation attributes. There are two objectives in the approach. The first is to divide the task space in a way that is both granular and relevant to the task-based research. The second is to minimize subjectivity in selecting which attributes are attached to each task measure.

To achieve a granular and relatively comprehensive set of task measures, I utilize all 162 relevant O*NET attributes.[15] To contextualize the measures within the task based approach, I begin by grouping the attributes into six *task groups*: cognitive, interpersonal, physical, technical, managerial, and a final group that O*NET labels structural characteristics.[16] Factor analysis is applied to each group of attributes separately to produce task measures based on the attributes from that group. For example, the cognitive group of attributes will be used to form the multiple specific cognitive task measures. The division of the attributes into groups is the major subjective step in constructing the task measures.

The cognitive, interpersonal and physical groups have conceptual antecedents in task-based framework. The technical group includes twenty attributes that fall into one of three O*NET defined categories: (i) technical skills involving machines or technological systems, (ii) identifying and evaluating information, and (iii) complex and technical activities. Maintaining these attributes as a separate group is motivated by a small but burgeoning research strand linking STEM or technical tasks to the RBTC framework. Deming (2017) shows that occupations that are jointly intensive in STEM and social skills have experienced both higher employment and wage growth. Beaudry et al. (2016), Harrigan et al. (2021) and vom Lehn (2020) discuss the intermediary role of technical tasks in developing and implementing new technologies.

The managerial group includes attributes from three O*NET categories: (i) resource manage-

[15] There are 183 attributes within the relevant O*NET subsets (ability, work activities, skills and work context subsets). I drop 21 of the work context attributes that describe physical work conditions such as degree to which work occurs indoors or outdoors, the physical temperature and noise level of the work environment, and exposure to hazardous conditions.

[16] The appendix presents the list of all attributes in each task group.

ment, (ii) administering, and (iii) responsibility. I group these attributes separately because they describe specific tasks that are neither strictly cognitive nor strictly interpersonal and the separate grouping ensures that administrative tasks will be disentangled from the strictly cognitive and interpersonal tasks.[17]

Finally, O*NET groups eleven attributes that describe the nature or context of the work into a category it calls "structural job characteristics." Some of these attributes are frequently used to measure routine tasks (degree of automation, importance of being exact, importance of repeating the same task, structured vs unstructured work, and work determined by pace of equipment). Other attributes in this group measure the freedom, flexibility, or consequentiality of decision-making. These decision-making attributes are distinct from the attributes for reasoning, problem-solving, or logic in the cognitive group since they describe the decision-making context rather than the cognitive process itself. It may seem, at first glance, incongruous to include attributes that may describe routine work together with attributes that describe non-routine work (e.g. freedom to make decisions), but recall that this is also true of other groupings. For example, cognitive tasks and physical tasks can be routine or non-routine.

As mentioned, the division of the attributes into the six groups is the major subjective assumption that guides the construction of the task measures. It is an alternative to subjectively selecting a few attributes for each task measure as is a common tactic in the sparse task approach. For example, when pulling from the more parsimonious DOT data, Autor et al. (2003) and Autor and Dorn (2013) select one or two attributes for each task measure and use the average of the attribute scores.[18] Empirical analyses using O*NET data have followed the precedent of selecting just a few occupation attributes despite the enlarged choice set.[19] Yet, it is not clear that the selected few attributes best reflect the task under scrutiny. Moreover, when attempting to examine specific tasks, a few selected attributes could be correlated with other omitted tasks and confound the analysis.

The O*NET attributes are matched to a set of time consistent occupation codes developed by Dorn (2009), deployed in Autor and Dorn (2013), and modified by Deming (2017).[20] To construct

[17]Some of the attributes in this group, or their DOT analogues, have been used in sparse task setting as part of a cognitive task measure. This strategy is more appropriate in a sparse setting when constructing a broad cognitive measure.

[18]DOT contains 44 attributes, but only about 22 with quantitative scores.

[19]Just to give a few examples: Deming (2017)'s social skill measure uses four attributes. Deming (2021) uses three attributes to measure decision-making. Acemoglu and Autor (2011) select three attributes per task measure. Cortes et al. (forthcoming) use two to six attributes per task measure.

[20]O*NET data are linked to SOC occupation codes. I follow Deming (2017) which involves using a crosswalk to assign SOC codes to 2000 occupation census codes and then another crosswalk to assign the 2000 census occupation codes to the 1990 consistent codes.

the task measures from each attribute pool, I employ a data-based methodology (factor analysis) for determining both the number of task measures within task groups and the weights assigned to occupation attributes within a task measure.[21] Factor analysis is useful when a large number of observed variables can be interpreted in terms of a smaller number of latent factors. In the current context, the latent factors are the task measures within each attribute group. Factor analysis guides the determination of the number of latent factors (task measures) in each task group and estimates the latent factors as a unique linear combination of all of the observed variables (occupation attributes in the group).[22] Heuristically, each latent factor groups the observed variables that "belong together." Each latent factor (task measure) is a linear combination of all the occupation attributes in that group, so the attributes that "belong together" will have larger weights in the linear combination. The computation relies on the covariance of the attributes between occupations and each task measure will have large weights on the attributes that tend to appear together within occupations. Therefore, each task measure has an economic interpretation guided by its heavily weighted occupation attributes.[23] Applying factor analysis separately on each *task group* yields a set of specific task *measures* for each group.

For example, applying factor analysis to the group of physical O*NET attributes yields four task measures. One linear combination gives heavy weights to attributes associated with general physical tasks such as gross body coordination, strength and stamina. A second linear combination assigns heavy weights to attributes associated with visual tasks. A third linear combination assigns heavy weights to attributes associated with manual dexterity and using one's hands. A fourth linear combination assigns heavy weights to attributes associated with a combination of hearing, finger dexterity and special visual tasks. The interpretation is that the the group of physical attributes describes four physical tasks (four latent variables): (1) general physical tasks, (2) visual tasks, (3) manual tasks, and (4) tasks that require eye-ear-hand coordination. Each of the four task measures is a unique linear combination of all attributes within that group.

Applying the methodology to each task group separately yields six cognitive task measures, five interpersonal task measures, three technical task measures, two managerial task measures, four physical task measures and four structural characteristics task measures.[24] Appendix tables A1

[21]Some previous work has used principal components analysis to determine the weights for a linear combination of *pre-selected* attributes. See, for example, Beaudry and Lewis (2014) and Bacolod and Blum (2010), Caines et al. (2017)), Yamaguchi (2012) and Yamaguchi (2018).

[22]The linear combinations will be orthogonal and have unit variance and zero mean.

[23]In the jargon of factor analysis, the weights on each attribute are called factor loadings.

[24]The appendix describes additional details of the factor analysis.

to A5 list the attributes with the heaviest weights for each task measure for expositional ease. Appendix tables A6 - A10 list the 15 occupations with the highest task score for each of the tasks in descending order by task score. Appendix tables A12 - A16 list the full set of factor loadings for each task measure by task group.

The groupings of heavily weighted attributes within each task measure yield sensible interpretations. Table 1 presents labels for each of the task measures based on their heavily weighted attributes. In the remainder of the analysis, an occupation with a task measure score in the top decile for that task will be designated as intensive in that task. Occupations that do not score in the top decile of any of the 24 task measures are designated as not task intensive (NTI). Maintaining a separate NTI designation enhances the precision of the task measures and allows a separate wage and employment analysis for the NTI occupations.[25] Of the 334 occupations, 43 occupations are not intensive in any of the above task measures. (Appendix table A11 lists all of the NTI occupations.) The NTI occupations are nearly all low-skill occupations. As will be seen below, the NTI occupations are associated with sizeable wage and employment share declines.

Table 1: Task measures

Cognitive	**Interpersonal**	**Technical**
Comprehnsion	External relationships	Repair & maintenance
Creativity & ideas	Coaching & guiding	Technology design
Logic	Conflictual interactions	Information recording
Mental agility	Instruction	
Information analysis	Team work	
Mathematics		
Managerial	**Physical**	**Structural Characteristics**
Resource control	General physical	Consequential decisions
Responsibility	Visual	Independent decision making
	Manual	Repetitive & exact
	Eye-ear-hand	Competition

[25]When there are fewer tasks measures, a larger percentage of occupations are typically designated as intensive. For example, Autor and Dorn (2013), using three task measures, define an occupation as intensive in a task if the score falls in the top third of all scores. Using a larger number of task measures necessitates a lower percentile cut-off to ensure that the designated occupations are intensive in the more specific task.

3 The tasks

In this section I describe the granular tasks reflected in each task measure and present the allocation of task hours between college and non-college educated individuals.[26]

Beginning with the cognitive task group, comprehension is the most general of the measures and captures tasks related to expression and critical thinking as well as comprehension. Table 2 presents the share of labor hours performed by non-college individuals by task.[27] The comprehension task has the lowest share of non-college educated labor and the comprehensive intensive occupations are predominantly professional and high skill. The creativity task is self-explanatory, but the mental agility task warrants a clarification. The task label does fit the tasks performed. For example, the occupation with with highest mental agility score are air traffic controllers. In practice, the occupations most intensive in the mental agility task tend to be those who operate moving equipment, including aircraft pilots, bus drivers, and ship captains.[28]

Within the cognitive task group, the math measure heavily weights the mathematical reasoning and number facility (arithmetic) attributes. Since math based tasks are easily translated into code, the math task is best considered a cognitive routine task. Another cognitive task, the logic task, heavily weights attributes describing decisions that use rules and methods for problem solving. These logic and rules-based tasks are distinct from subjective decision-making tasks and more amenable to automation. Machines that diagnose equipment malfunctions and computer automated design (CAD) software are examples of automation of some logic tasks. I will categorize the logic task as routine, but none of the analysis or conclusions rely on the specific categorization of the this task as routine or non-routine. Some of the logic intensive occupations are high-knowledge occupations such as engineers and scientists while others are lower-knowledge such as equipment operators and some repairers. Recall that occupations are bundles of tasks and an occupation can be simultaneously high-knowledge and contain both routine and non-routine tasks.

The relationship task in the interpersonal group captures tasks related to communication and maintaining relationships. The majority of hours devoted to this task come from college-educated individuals. The interpersonal instruction task heavily weights attributes that Deming (2017) uses to construct his social skills measure.[29] But occupations that that tend to score high in those attributes

[26]An individual is classified as non-college if their highest grade completed is less than 16.

[27]An individual contributes their hours worked to a task if they are employed in an occupation that is intensive in that task (i.e. the occupation falls in the top decile of scores for that task.

[28]Nurses and fire fighters are also mental agility intensive occupations.

[29]The attributes that comprise (Deming, 2017) social skill measure are coordination, negotiation, persua-

Table 2: Share of hours in each task by non-college individuals

	1982	1994	2006	2018
Routine tasks				
Math	0.872	0.696	0.703	0.627
Logic	0.938	0.791	0.779	0.713
Manual	0.959	0.867	0.883	0.892
Repetitive	0.927	0.818	0.817	0.740
Analytical tasks				
Comprehension	0.511	0.291	0.370	0.279
Creativity	0.865	0.624	0.618	0.529
Mental agility	0.875	0.747	0.779	0.702
Info Analysis	0.730	0.602	0.621	0.543
Relationships	0.576	0.442	0.464	0.481
Coaching	0.542	0.469	0.622	0.393
Conflictual	0.936	0.764	0.792	0.735
Instruction	0.714	0.369	0.484	0.309
Teams	0.786	0.666	0.686	0.638
Consequential decisions	0.850	0.654	0.603	0.516
Independent decisions	0.723	0.490	0.459	0.364
Technology design	0.752	0.504	0.506	0.423
Info Recording	0.671	0.522	0.585	0.490
Managerial resource	0.771	0.577	0.550	0.468
Managerial responsibility	0.926	0.813	0.756	0.658
Competition	0.877	0.655	0.663	0.653
Repair & physical tasks & NTI occupations				
Tech repair	0.993	0.949	0.957	0.942
General physical	0.949	0.875	0.870	0.847
Visual	0.973	0.934	0.950	0.926
Eye-ear-hand	0.850	0.691	0.697	0.597
NTI	0.973	0.907	0.932	0.886

Note: For each task, for each year, the shares in this table are calculated as the total hours worked by all non-college individuals in the sample employed in an occupation intensive in the task divided by the total hours worked by all individuals in the sample employed in an occupation intensive it the task. (See the appendix for sample definition.)

also tend to score high in the instruction attribute, the latter of which receives the heaviest weight in the instruction task measure.[30] Occupations intensive in the instruction task include most teaching occupations as well as clergy, tour guides, and some engineers and scientists. It is a task that is dominated by college-educated workers. The coaching task differs from the instruction task as the

sion, and social perceptiveness.

[30] A task measure constructed using the average of Deming (2017)'s attributes has a correlation coefficient of .68 with the instruction task measure used here.

former emphasizes guiding, advising, and development more than instruction. The occupations most intensive in the coaching task include compliance officers, clergy, medical health administrators, and coaches. Distinct from instructing and coaching, the conflictual task measure's heavily weighted attributes include: "deal with unpleasant or angry people," "deal with physically aggressive people," and "frequency of conflict situations." Parking lot attendants, detectives, criminal investigators, bailiffs, correctional officers, and jailers have the three highest task scores for that measure. Of the interpersonal tasks, the conflictual task has the highest share of labor hours from the non-college group. Finally, the team task measure's heavily weighted attributes include "work with group or team," and "coordinate or lead others". The occupations intensive in the team task are quite diverse and include operators, rail yard workers, scientists and engineers. The team task is a good (although not unique) example of an abstract task that is embedded in both low-skill and high-skill occupations.

The attributes in the technical group yield three task measures. The repair and maintenance measure heavily weights attributes relating to repairing, inspecting, installing and maintaining equipment and has one of highest shares of non-college educated labor. The technology design measure heavily weights the "technology design" and "operations analysis" attributes. These are defined by O*NET as "generating or adapting equipment and technology to serve user needs," and "analyzing needs and product requirements to create a design," respectively.[31] The occupations most intensive in this task tend to be scientists, analysts and engineers. Finally, the third technical task measure, information recording, heavily weights attributes describing the gathering, monitoring and recording of data, information, and processes. Many health and medical related occupations are intensive in this task.[32]

The attributes in the managerial group divide into two task measures. One measure heavily weights attributes that describe the management of material, financial, and personnel resources. The other heavily weights responsibility for outcomes and responsibility for the health and safety of others. I label these managerial task measures (1) resource control and (2) responsibility, respectively. Occupations intensive in the responsibility task tend to be supervisors while the occupations intensive in the resource control task tend to be managers and other professional occupations. Accordingly, Table 2 shows that the share of non-college educated labor is higher in the managerial

[31] Equipment selection, installation and programming are three other heavily weighted attributes.

[32] Note that the recording information task in this category is different from the analyzing information task in the cognitive task group. However, some occupations involve both data recording/gathering and data analysis. Seventeen occupations are intensive in both the cognitive information analysis and technical information recording task measures.

responsibility task.

The previous subsection described the four physical task measures (general physical, visual, manual, and eye-ear-hand). The manual task measure heavily weights the "manual dexterity," "wrist-finger speed," "using hands to control objects," "spend time making repetitive motions," and "control precision" attributes. These attributes describe precise and repetitive actions that a machine can perform. Therefore, the manual task measure is best categorized as describing physical routine tasks. Occupations intensive in this task include textile workers (much of fabric cutting and folding is automated), jewelry and metal workers, technicians, and operators.[33] Non-college educated workers dominate the hours devoted to most physical tasks.

The structural characteristic group of attributes yields four task measures although there are only eleven attributes in this group. The attributes in this grouping are more diverse with respect to tasks, so factor analysis requires a larger number of linear combinations relative to attributes to accurately group similar tasks. The four estimated measures capture the following tasks: (1) consequential decision making, (2) independent decision making, (3) repetitive and exact tasks, and (4) competitive pressures. Consequential decision making tends to occur in occupations where health and/or safety issues are prominent, while independent decision making occurs is a wider range of occupations. Importantly, factor analysis creates one task measure that heavily weights the three attributes typically used to measure routine task content (degree of automation, importance of being exact or accurate, and importance of repeating same tasks). Note that the data and methodology determined that these attributes belonged together in one task measure and confirms the subjective choices made in previous studies. While the logic and math task measures from the cognitive group describe specific tasks that can be automated, the repetitive and exact task is a more general rendering of routine tasks based on the repetitive nature of the work. Occupations intensive in this task tend to be clerks and administrative support occupations where the share of non-college workers is quite high.

Finally, the data and methodology also determined that there should be a separate task measure from the structural characteristics group whose only heavily weighted attribute is "level of competition."[34] There has been little attention paid to this sort of work in the task-based literature. Nonetheless, I retain the task measure to be consistent and to avoid potential omitted variables issues in regression results.

[33]However, the two occupations most intensive in this task (tailors/sewers and dental hygienists) may not be particularly routine since the environment in which they perform precise movements is not predictable.

[34]The attribute "time pressure" has a moderately high weight as well.

The task measures within each group are uncorrelated by construction and all task measures have zero mean and unit variance. However, since occupations are bundles of tasks, one would expect some correlation between tasks measures from different groups. The correlation matrix between all task measures is shown in appendix table A18. But recall that the task scores are only used to identify the top decile of scores for each task. Occupations in the top decile are denoted as intensive in that task.

The comprehension, external relationship, resource control, and independent decision making tasks are fairly highly correlated with each other (correlation coefficients ranging from .55 to .76). Despite the high correlation of the task scores, only one occupation (legislators) is intensive in all four tasks and only three occupations are intensive in three out of four of the tasks (medical scientists, dentists, and clergy). The logic task is correlated with both technical design (.69) and instruction (.51), but the correlation between technical design and instruction is quite low (.38). On the other hand, the logic task measure is not highly correlated with either of the decision-making tasks in the structural group, supporting the idea that the task measures distinguish between routine logic based analysis and the decision-making captured by the measures derived from the structural group. Finally, the general routine task (the repetitive task measure from the structural characteristics group) has a small negative correlation with the routine logic task (-.12) and a small positive correlation with the routine math task (.38).[35] Moreover, throughout this paper, the task scores are used only to identify the top decile of scores and to create indicator variables for task intensity. The correlation between indicator variables for task intensity is quite low.[36]

3.1 Distribution of skill hours across tasks

Table 2 presents the share of labor hours *within* each task contributed by individuals without a college degree. Non-college educated individuals contribute the plurality of labor hours for nearly every task which partly reflects the predominance of non-college educated labor.[37] Tables 3 and 4 present the distribution of education-specific labor hours *across* tasks.[38] Non-college labor hours

[35]The competition task measure is not highly correlated with any other task measure.

[36]The largest correlation coefficients occur for two pairs of tasks with correlation coefficients around .47: (1) information analysis and information recording, and (2) comprehension and instruction. Another two pairs have a correlation coefficient near .4: (1) information recording and logic, (2) resource control and coaching.

[37]In 1990, about 20% of the cohort is college educated, rising to about 24% in 2010.

[38]The actual shares will sum to number greater than one. I observe hours worked on the job but not the allocation of hours to different tasks. Therefore, for each individual, I allocate their hours worked at the job to each of the occupation intensive tasks. For example, a worker who works 8 hours in an occupation

are most concentrated in the repetitive routine task, the general and visual physical tasks, the interpersonal conflictual task and in the NTI occupations. College labor hours are most concentrated in the comprehensive and managerial resource control tasks. Tables 2, 3, and 4 together show that while college and non-college workers tend to concentrate hours in different tasks, non-college educated workers contribute a quantitatively sizeable share of labor hours to abstract tasks.

Tables 3 and 4 also offer the first glimpse within this paper of the decline in routine work. Both college and non-college individuals have shifted labor hours out of every routine task. In 1982, college educated workers devoted 19.1% of normalized labor hours to the four routine tasks combined. By 2018 the share had fallen to 8.5%. For non-college workers, 29.1% of normalized labor hours were devoted to routine tasks. By 2018, the share had fallen to 14.9%. Figure 1 also shows the shift out of routine work and into non-routine work by plotting the average number of routine and non-routine tasks per worker over time. Occupations are bundles of tasks, so an individual can be employed doing only routine work, only non-routine work, or a combination of both. Given the larger number of non-routine tasks, it is more likely for an occupation to be intensive in multiple non-routine tasks than for an occupation to be intensive in multiple routine tasks.[39] Figure 1 shows that on a per worker basis, both college and non-college educated workers have a similar propensity to be employed in routine work. The average college-educated individual is employed in an occupation with a larger number of non-routine tasks relative to their non-college educated counterpart. The propensity to be employed in a routine-intensive occupation has modestly declined over time for both education groups and labor effort has shifted in favor of non-routine work for both the average college and non-college educated individual.

The analysis in the next section examines the reallocation of labor hours and resulting wage changes for both low and high education individuals who exit a routine intensive occupation.

intensive in both the physical manual task and the interpersonal team task will contribute 8 hours to both tasks and 8 hours to total hours worked. Therefore, when aggregating over individuals, the actual share of total labor hours devoted to each will sum to a number greater than one. The normalized shares presented in Table 3 are the actual shares divided by the sum of all actual shares.

[39] Eighty-four occupations are intensive in both a routine and a non-routine task. The average occupation is intensive in approximately 2 non-routine tasks and .4 routine tasks.

Table 3: Normalized share of total non-college hours by task

	1982	1994	2006	2018
Routine tasks				
Math	0.056	0.045	0.035	0.034
Logic	0.035	0.024	0.018	0.019
Manual	0.075	0.041	0.024	0.021
Repetitive	0.125	0.094	0.079	0.075
Analytical tasks				
Comprehension	0.010	0.018	0.019	0.026
Creativity	0.018	0.032	0.046	0.041
Mental agility	0.018	0.032	0.038	0.036
Info Analysis	0.020	0.036	0.036	0.035
Relationships	0.007	0.021	0.022	0.025
Coaching	0.008	0.026	0.045	0.038
Conflictual	0.091	0.073	0.080	0.085
Instruction	0.022	0.017	0.018	0.025
Teams	0.026	0.037	0.032	0.028
Consequential decisions	0.017	0.023	0.024	0.029
Independent decisions	0.013	0.015	0.019	0.020
Technology design	0.016	0.016	0.023	0.021
Info Recording	0.010	0.022	0.024	0.023
Managerial resource	0.020	0.056	0.065	0.066
Managerial responsibility	0.018	0.032	0.046	0.038
Competition	0.020	0.026	0.024	0.019
Repair & physical tasks & NTI occupations				
Tech repair	0.048	0.039	0.036	0.034
General physical	0.134	0.091	0.081	0.085
Visual	0.045	0.058	0.061	0.066
Eye-ear-hand	0.020	0.024	0.026	0.023
NTI	0.130	0.101	0.080	0.088

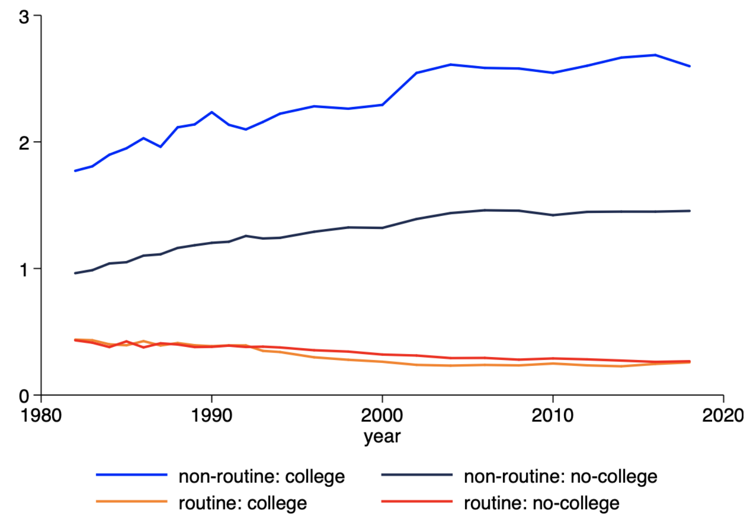
Note: For each task, for each year, "raw" shares are calculated as the total hours worked by all non-college individuals employed in an occupation intensive in the task divided by the total hours worked by all non-college individuals in the sample. The shares in this table for each year are the "raw" shares divided by the sum of the raw shares for that year. (See the appendix for sample definition.)

Table 4: Normalized share of total college hours by task

	1982	1994	2006	2018
Routine tasks				
Math	0.067	0.044	0.034	0.030
Logic	0.019	0.015	0.012	0.012
Manual	0.026	0.014	0.007	0.004
Repetitive	0.079	0.047	0.041	0.039
Analytical tasks				
Comprehension	0.074	0.098	0.076	0.102
Creativity	0.023	0.044	0.066	0.055
Mental agility	0.021	0.024	0.025	0.023
Info Analysis	0.058	0.054	0.051	0.044
Relationships	0.040	0.061	0.058	0.041
Coaching	0.055	0.065	0.063	0.090
Conflictual	0.050	0.051	0.049	0.046
Instruction	0.070	0.066	0.044	0.086
Teams	0.058	0.042	0.034	0.024
Consequential decisions	0.024	0.027	0.036	0.041
Independent decisions	0.041	0.035	0.051	0.052
Technology design	0.044	0.036	0.051	0.043
Info Recording	0.038	0.046	0.039	0.036
Managerial resource	0.049	0.092	0.123	0.113
Managerial responsibility	0.012	0.017	0.034	0.029
Competition	0.022	0.031	0.029	0.015
Repair & physical tasks & NTI occupations				
Tech repair	0.003	0.005	0.004	0.003
General physical	0.059	0.029	0.028	0.023
Visual	0.010	0.009	0.007	0.008
Eye-ear-hand	0.028	0.025	0.026	0.024
NTI	0.030	0.023	0.013	0.017

Note: For each task, for each year, "raw" shares are calculated as the total hours worked by all college individuals employed in an occupation intensive in the task divided by the total hours worked by all college individuals in the sample. The shares in this table for each year are the "raw" shares divided by the sum of the raw shares for that year. (See the appendix for sample definition.)

Figure 1: Average number of routine and non-routine tasks per worker



Notes: Any one occupation can be intensive in multiple tasks. This figure presents the average number of routine and non-routine tasks performed per worker for all college and non-college individuals in the sample. College is defined as having at least 16 complete years of education.

4 Exiting routine work

This section focuses on the task reallocation of non-college and college educated individuals who exit a routine-intensive occupation and their associated wage changes. As a preliminary, Table 5 presents the normalized share of exits from each routine task into an occupation also intensive in a routine task. For both college and non-college groups, a sizeable share of exits out of a routine-intensive occupation entered into another routine-intensive occupation. Non-college individuals exiting an occupation intensive in the repetitive or the math task are more likely to enter into a routine intensive occupation than their college educated counterparts.

In the remainder of this section, the analysis will focus on the set of individuals who exit a routine intensive occupation and enter into an occupation that is not routine intensive. Within that set, the data indicate that non-college individuals are more likely to enter non-routine physical work relative to their higher education counterparts after exiting routine work, consistent with the sparse task framework. However, non-college workers enter into non-routine abstract work at a higher rate than they enter non-routine physical work. Moreover, many of those switches into abstract tasks are associated with wage increases. The details are presented below.

Table 5: Entry rates into routine tasks
after exit from routine task (1982-2018)

	Exited task			
	Logic	Math	Manual	Repetitive
(A) Non-college individuals				
Logic	0.028	0.016	0.036	0.009
Math	0.034	0.087	0.044	0.090
Manual	0.060	0.039	0.080	0.039
Repetitive	0.041	0.177	0.096	0.172
Total	**0.162**	**0.319**	**0.255**	**0.310**
Observations	3214	6042	5538	12026
(B) College individuals				
Logic	0.030	0.028	0.031	0.010
Math	0.079	0.091	0.058	0.087
Manual	0.027	0.017	0.051	0.018
Repetitive	0.033	0.094	0.075	0.125
Total	**0.169**	**0.230**	**0.215**	**0.240**
Observations	569	1881	640	2424

Note: Shares are normalized shares of all exits from the column's routine task.

4.1 Task reallocation from routine work

Tables 6 and 7 present normalized entry rates into each non-routine task for the non-college and college groups, respectively. The entry rates are calculated by identifying individuals who exit an occupation intensive in a routine task and recording their subsequent occupation's task intensity.[40] Each column displays the entry rates associated with exits from that column's routine task.[41] For example, the entry in the first row and first column of Table 6 (0.008) indicates that, for non-college individuals, of all exits from an occupation intensive in the logic task that are not entries into a routine task, .8% enter an occupation intensive in the comprehension task. The entry rates associated with leaving each routine task are tracked and reported separately to show that the reallocation of the non-college group into abstract tasks is not dependent on a specific routine task measure. On the contrary, the task reallocation patterns are broadly similar regardless of the exited routine task with some quantitative differences.

[40]Or task intensities, since an occupation can be intensive in more than one task. The entry rates are calculated for all exits from a routine intensive occupation over the entire time period.

[41]As with the labor shares, the entry rates reported in each column of Tables 6 and 7 are the raw entry rates divided by the sum of the raw entry rates.

Table 6: Normalized entry rates after exit from routine work
Non-college work (1982 - 2018)

	Task exited			
	Logic	Math	Manual	Repetitive
Comprehension	0.008	0.041	0.018	0.044
Creativity	0.045	0.046	0.043	0.042
Mental agility	0.032	0.017	0.029	0.019
Info Analysis	0.028	0.050	0.032	0.047
Sub-total: Non-routine cognitive	0.114	0.154	0.122	0.151
Relationships	0.014	0.040	0.011	0.038
Coaching	0.035	0.032	0.029	0.035
Conflictual	0.040	0.106	0.063	0.105
Instruction	0.019	0.019	0.031	0.021
Teams	0.067	0.073	0.064	0.073
Sub-total: Interpersonal	0.174	0.270	0.198	0.273
Managerial resource	0.029	0.082	0.036	0.075
Managerial responsibility	0.059	0.029	0.045	0.027
Sub-total: Managerial	0.088	0.111	0.081	0.102
Consequential decisions	0.016	0.022	0.022	0.025
Independent decisions	0.015	0.037	0.023	0.037
Sub-total: Tech (non-repair)	0.031	0.059	0.045	0.062
Technology design	0.026	0.034	0.028	0.027
Info Recording	0.013	0.014	0.008	0.011
Sub-total: Tech (non-repair)	0.039	0.048	0.036	0.038
Total share into abstract tasks	**.446**	**.642**	**.482**	**.626**
General physical	0.106	0.141	0.103	0.119
Visual	0.089	0.020	0.063	0.030
Eye-ear-hand	0.032	0.017	0.039	0.019
Sub-total: Non-routine physical	0.227	0.178	0.205	0.168
Competition	0.032	0.024	0.034	0.027
Tech repair	0.070	0.025	0.073	0.022
NTI	0.224	0.132	0.205	0.158

Note: Shares are normalized shares of all non-college entries into non-routine tasks.

Table 7: Normalized entry rates after exit from routine work
College group (1982 - 2018)

	Task exited			
	Logic	Math	Manual	Repetitive
Comprehension	0.047	0.058	0.065	0.093
Creativity	0.047	0.051	0.052	0.048
Mental agility	0.020	0.017	0.012	0.014
Info Analysis	0.070	0.068	0.053	0.065
Sub-total: Non-routine cognitive	0.184	0.194	0.181	0.219
Relationships	0.087	0.071	0.051	0.068
Coaching	0.046	0.056	0.043	0.068
Conflictual	0.017	0.035	0.025	0.055
Instruction	0.043	0.045	0.060	0.059
Teams	0.122	0.092	0.104	0.072
Sub-total: Interpersonal	0.316	0.299	0.283	0.322
Managerial resource	0.097	0.153	0.090	0.127
Managerial responsibility	0.025	0.043	0.025	0.034
Sub-total: Managerial	0.123	0.195	0.114	0.161
Consequential decisions	0.016	0.016	0.028	0.020
Independent decisions	0.054	0.074	0.064	0.077
Sub-total: Tech (non-repair)	0.070	0.090	0.091	0.097
Technology design	0.117	0.083	0.161	0.044
Info Recording	0.067	0.028	0.024	0.020
Sub-total: Tech (non-repair)	0.185	0.111	0.185	0.064
Total share into abstract tasks	**0.877**	**0.889**	**0.855**	**0.863**
General physical	0.022	0.030	0.023	0.037
Visual	0.004	0.003	0.007	0.006
Eye-ear-hand	0.026	0.014	0.018	0.013
Sub-total: Non-routine physical	0.052	0.047	0.048	0.056
Competition	0.023	0.029	0.029	0.030
Tech repair	0.013	0.006	0.012	0.004
NTI	0.034	0.030	0.056	0.048

Note: Shares are normalized shares of all college entries into non-routine tasks.

Of those who exit a routine task and enter into a non-routine task, the broad trends are consistent with the sparse task framework in the following two ways. First, college educated individuals enter into the non-routine abstract tasks at higher rates than their non-college educated counterparts with over 85% of college exits yielding entries into abstract tasks. (See Table 7). Second, the non-college group enters non-routine physical tasks at much higher rate than their college educated counterparts: 16.8% - 22.7% compared to 4.7% - 5.6% for the non-college and college groups, respectively.

The granular task measures also uncover the non-college group's significant inflow into occupations intensive in the abstract task. More specifically, over 60% of non-college exits from the repetitive and math routine tasks and around 45% of non-college exits from the logic and manual routine tasks yield entries into abstract tasks. (See Table 6). The reallocation is fairly broad-based across the abstract tasks. The tasks with two of the largest inflows are the interpersonal conflictual task (with 4.0% - 10.6% of entries) and the team task (with 6.4% - 7.3% of entries).

Occupations most intensive in the conflictual task include parking lot attendants, detectives, correctional officers, detectives and their managers, nurses, transportation attendants, and hotel/motel desk clerks. (See Appendix Table A7 which lists the 15 occupations most intensive in the conflictual task. The remaining 18 conflictual intensive occupations include other occupations that deal with the public such as counter clerks, waiters, security guards, bus drivers and lobby attendants. Also on the list are physicians, physician assistants, and special education teachers.) Occupations intensive in the team task tend to be either either engineers/scientists or operators. Table A7 lists the top 15 occupations intensive in the team task, the other 18 occupations also intensive in the team task include operators, some clerks, human resource assistants, and other occupations most likely requiring college degrees (e.g., public relations specialists, broadcast and news occupations, and one engineering occupation).

So, switching from a routine intensive occupation to an occupation intensive in abstract work does not necessarily mean switching into a "better" job. In fact, one of the major points apparent from the granular task measures is that many types of occupation are intensive in abstract tasks.

Another key distinction between the two education groups is their flow into the NTI occupations. Only about 5% of college educated workers exiting routine work enter into the low-skill NTI occupations, while approximately 15% - 20% (depending on the exited routine task) of non-college entries flow to the NTI occupations. Therefore, within this cohort, non-college exits from routine-intensive work flow into non-routine physical intensive occupations and lower skill NTI occupations at similar rates and together comprise approximately 30% - 40% of entries after exiting routine work. Recall that about 45% - 64% of non-college exits enter into occupations intensive in the abstract task.

Finally, one might expect the non-college group exiting the routine cognitive tasks to have a different allocation pattern relative to their counterparts exiting the routine manual task. Indeed, non-college workers exiting the manual routine task have lower propensities to enter non-routine cognitive, interpersonal, and decision-making tasks relative to those exiting from the math and the general repetitive tasks. Also, non-college workers who exit the manual task are more likely to enter the non-routine physical and repair tasks and the NTI occupations. However, exits from the logic task yield entry propensities more similar to the manual task than than to math or general repetitive task. This pattern arises because the high knowledge occupations intensive in the logic task are very different from the lower knowledge occupations intensive in the logic task. The former are dominated by engineers, scientists, analysts, and similar occupations while the latter contain many operators. Therefore, the non-college workers who exit the logic task, likely have skills that are more similar to the skill set of those exiting the manual task.

4.2 Wage changes

As individuals exit routine intensive occupations and enter non-routine intensive occupations, to what extent are those switches associated with wage gains or wage losses? Toward addressing that question, equation (1) describes an individual fixed effects estimator for the association between wages and the task intensity of the entered occupation. The coefficient estimates associated with the task intensity indicator variables (the α_k's) describe the wage effect from switching out of a routine-intensive occupation and into an occupation intensive in task k (or into an NTI occupation for α_{25}). The wage equation is estimated over the set of individuals who exited a routine-intensive occupation and is estimated separately on the college and non-college educated switchers. The combination of the cohort specific sample, individual fixed effects, and the separation of college from non-college individuals diminishes the impact of composition and selection effects on the wage estimates. Conditioning variable include individual demographic data that can vary over time and indicator variables for the routine task exited in the previous period. Specifically, the estimated wage equation is

$$w_{ijt} = \sum_{k=1}^{25} \alpha_k T_{jk} + \sum_{p=1}^{4} \theta_p RT_{jp} + X_i' \beta + \gamma_i + \tau' \delta_t + \epsilon_{it} \tag{1}$$

where w_{ijt} is the log of the time t real hourly wage for worker i in occupation j. T_{jk} is an indicator variable that equals one if individual i switches into occupation j at time period t and occupation j is intensive in task k, for $k = 1, ..., 24$. $T_{j,25}$ is an indicator variable that equals one if individual i shifts into an NTI occupation at time t. RT_{jp} is an indicator variable that equals one if the individual exited occupation j and occupation j is intensive in the p_{th} routine task. There need not be an omitted T_{jk} or RT_{jp} indicator because an occupation can be intensive in multiple tasks, eliminating perfect co-linearity between the indicator variables. τ is a vector of year effects, γ_i are individual fixed effects, and X_i is a vector of individual demographic information that includes indicator variables for education, marital status, rural versus urban location, and union membership.[42]

The NLSY79 surveys were conducted annually until 1994 and biennially thereafter. Also, as shown in Figure 2 and discussed in the next section, the change in task allocation is not evenly divided over the entire time period. The non-college educated group's task reallocation occurs more in the period prior to the early 1990s relative to later periods and the college educated group's task reallocation occurs mostly prior to the early 2000s relative to later periods.[43] Therefore, for both the college and non-college groups, I estimate equation (1) separately over three time periods: 1982-1993, 1994-2004, and 2006-2018. The first period is given by the time when the data are annual. The second two periods divide the remaining years (nearly) in half and help to eliminate potential biased introduced by the observed change in the frequency of occupation/task switching.[44]

Tables 8 - 10 report the estimates of α_k and θ_p for the non-college group and tables 11 - 13 report the same estimates for the non-college group. Switching into the information analysis,

[42]For the college educated group the education indicator equals one if the individual has 16 or more years of education. For the non-college educated group, there is an indicator variable for 12 years of education, and another for 13-15 years of education, the omitted indicator is less than 12 years of education. Additional details on the individual level covariates are given in the appendix. Standard errors are robust.

[43]The sample periods presented in Figures 2 differ slightly from the sample periods in the wage regressions. The latter were constructed, in part, around the change in survey frequency. However, because that break is not crucial for looking at changes in task shares, Figure 2 divides the sample more evenly into three 10-year periods and the remaining 6 years.

[44]The fixed effects estimator de-means the data. The time period over which the average is calculated will matter. When the average is calculated over the entire sample and if individual wages trend up, then if switches are concentrated during a period when deviations from the mean are high (low) the coefficients on the task indicators may be biased to upward (downward). Breaking the sample into time periods alleviates this bias.

technology design, or either of the managerial tasks is generally associated with wage gains for both education groups. However, while 22.5% - 30.7% of college switches enter into those tasks, only 11.8% - 16.0% from the non-college group do so. [45] But the non-college educated group also has wage gains, over some periods, associated with switching into occupations intensive in the comprehension, relationships, coaching, and teams tasks. Adding the share of entrants from these additional tasks results in 22.2% - 30.5% of non-college switches are into occupations intensive in abstract tasks that experience wage gains. That is, both the college and non-college educated groups have similar shares of exits from a routine intensive occupation that enter into an abstract intensive occupation associated with wage gains.

For both education groups, switching into the interpersonal conflictual or general physical tasks is associated with wage losses as is switching into the NTI occupations. However, again there are key differences in the reallocation shares between education groups. Only 7.3% - 14.0% of college educated switches out of routine work enter into conflictual or general physical intensive occupations or the NTI occupations compared to 37.0% - 38.1% of non-college switches.

In summary, roughly similar shares of college and non-college switchers out of routine work enter into an abstract intensive occupation with associated wage gains. However, a much larger share of non-college switchers enter into occupations intensive in non-routine tasks or the NTI occupations associated with losses relative to their college educated counterparts.

The analysis thus far has indicated that switching into occupations intensive in the conflictual or the non-routine general physical task is associated with wage losses. Moreover, other than the NTI occupations, those two tasks absorb the largest shares of non-college exits out of routine work, for a combined 11.0% - 24.7% of all entries. Autor and Dorn (2013) have highlighted the employment rise in personal service occupations accompanying the decline in routine work. The data used in this paper include 35 personal service occupations and 26 are intensive in either the interpersonal conflictual task or the general physical task. Therefore, the work in this paper is consistent with the notion that the personal service occupations have absorbed exits out of routine work. However, evidence presented here also shows that shifts into abstract tasks and the NTI occupations are a quantitatively important part of the reallocation.[46]

While low education workers exiting routine work shift into the general physical and conflictual

[45]Refer to Tables 6 and 7 for the disaggregated entry rates. As before, the range in rates reflects the different rates associated with exiting the different routine tasks.

[46]Other studies have used personal service occupations as a proxy for occupations intensive in the non-routine physical task. See, for example, Cortes (2016), Böhm (2020), and Cavaglia and Etheridge (2020).

tasks and the NTI occupations, within the full sample of non-college workers labor share hours for those tasks and the NTI occupations decline. The next section discusses the more general task reallocation for both education groups in more detail.

Table 8: Wage impact of switching into abstract task from a routine task for non-college individuals
Dependent variable: log hourly real wage

	(1982-1993)	(1994-2004)	(2006-2018)
Comprehension	0.026*	0.071**	-0.038
	(0.015)	(0.032)	(0.050)
Creativity	-0.003	0.048*	0.054
	(0.017)	(0.029)	(0.050)
Mental agility	0.025	0.003	-0.050
	(0.025)	(0.053)	(0.065)
Info analysis	0.039**	0.070**	0.054
	(0.016)	(0.030)	(0.041)
Relationships	0.074***	0.092***	0.073
	(0.021)	(0.033)	(0.049)
Coaching	0.052***	-0.001	0.024
	(0.020)	(0.029)	(0.048)
Conflictual	-0.143***	-0.184***	-0.154***
	(0.012)	(0.025)	(0.032)
Instruction	-0.135***	-0.260***	-0.162*
	(0.023)	(0.044)	(0.085)
Teams	0.025**	0.048**	0.046
	(0.011)	(0.021)	(0.034)
Tech design	0.106***	0.226***	0.330***
	(0.016)	(0.035)	(0.057)
Info recording	0.099***	-0.018	0.080
	(0.031)	(0.051)	(0.070)
Mgr resource control	0.074***	0.103***	0.194***
	(0.015)	(0.024)	(0.039)
Mgr responsibility	0.072***	0.090***	0.118**
	(0.019)	(0.033)	(0.057)
Consequential decisions	-0.004	0.066	0.080
	(0.022)	(0.060)	(0.068)
Independent decisions	0.011	-0.051	-0.025
	(0.020)	(0.040)	(0.064)
Competition	-0.048**	0.002	0.032
	(0.019)	(0.032)	(0.055)
Observations	11156	3258	1697

Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Includes individual fixed effects and time effects. Conditioned on binary variables for education level (less than high school, high school, some college), marital status, union membership, and urban residence and all variables in Tables 9 and 10.

Table 9: Wage impact of switching into another routine task after exiting routine task for non-college individuals
Dependent variable: log hourly real wage

	(1982-1993)	(1994-2004)	(2006-2018)
(A) Wage effect entered routine task			
Logic	0.037*	0.132***	-0.150*
	(0.022)	(0.038)	(0.078)
Mathematics	-0.024***	-0.021	-0.007
	(0.009)	(0.019)	(0.028)
Manual	-0.029**	-0.036	-0.066
	(0.012)	(0.023)	(0.054)
Repetitive-exact	-0.016*	-0.071***	-0.045
	(0.010)	(0.020)	(0.027)
(B) Wage effect of exited routine task			
Logic	0.074***	0.099***	-0.005
	(0.010)	(0.021)	(0.031)
Math	-0.054***	-0.047***	-0.065***
	(0.007)	(0.014)	(0.022)
Manual	-0.030***	-0.095***	-0.091***
	(0.008)	(0.016)	(0.031)
Repetitive	-0.067***	-0.080***	-0.114***
	(0.007)	(0.015)	(0.022)
Observations	11156	3258	1697

Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Includes individual fixed effects and time effects. Conditioned on binary variables for education level (less than high school, high school, some college), marital status, union membership, and urban residence and all variables in Tables 8 and 10

Table 10: Wage impact of switching from a routine task: non-college
Dependent variable: log hourly real wage

	(1982-1993)	(1994-2004)	(2006-2018)
Tech repair	-0.004	-0.060	0.073
	(0.020)	(0.040)	(0.070)
General physical	-0.090***	-0.183***	-0.283***
	(0.013)	(0.029)	(0.037)
Visual	0.025	-0.052	-0.070
	(0.019)	(0.034)	(0.063)
Eye-ear-hand	0.044*	0.033	-0.046
	(0.023)	(0.046)	(0.068)
NTI	-0.053***	-0.112***	-0.119***
	(0.011)	(0.022)	(0.037)
Observations	11156	3258	1697

Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Includes individual fixed effects and time effects. Conditioned on binary variables for education level (less than high school, high school, some college), marital status, union membership, and urban residence and all variables in Tables 8 and 9

Table 11: Wage impact of switching into abstract task from a routine task for college individuals
Dependent variable: log hourly real wage

	(1982-1993)	(1994-2004)	(2006-2018)
Comprehension	0.038	-0.030	-0.025
	(0.027)	(0.052)	(0.078)
Creativity	0.002	0.085	-0.191**
	(0.032)	(0.059)	(0.089)
Mental agility	0.014	-0.122	0.217
	(0.052)	(0.099)	(0.204)
Info analysis	0.074***	0.096*	0.161**
	(0.025)	(0.054)	(0.081)
Relationships	0.054*	0.061	0.033
	(0.033)	(0.066)	(0.073)
Coaching	-0.036	-0.212***	0.031
	(0.031)	(0.055)	(0.087)
Conflictual	-0.167***	-0.200**	-0.362***
	(0.039)	(0.082)	(0.114)
Instruction	-0.079**	-0.093	-0.090
	(0.036)	(0.064)	(0.103)
Teams	-0.003	-0.025	-0.110
	(0.024)	(0.049)	(0.078)
Tech design	0.128***	0.225***	0.227***
	(0.026)	(0.047)	(0.078)
Info recording	0.024	0.077	0.048
	(0.036)	(0.071)	(0.111)
Mgr resource control	0.046**	0.142***	0.125*
	(0.022)	(0.043)	(0.066)
Mgr responsibility	0.068	0.203**	0.365**
	(0.046)	(0.086)	(0.145)
Consequential decisions	-0.042	0.145	0.380**
	(0.049)	(0.120)	(0.177)
Independent decisions	0.020	0.081*	-0.102
	(0.027)	(0.049)	(0.106)
Competition	-0.048	-0.074	0.299**
	(0.048)	(0.069)	(0.137)
Observations	2403	769	514

Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Includes individual fixed effects and time effects. Conditioned on binary variables for education level (less than high school, high school, some college), marital status, union membership, and urban residence and all variables in Tables 12 and 13.

Table 12: Wage impact of switching into another routine task after exiting routine task for college individuals
Dependent variable: log hourly real wage

	(1982-1993)	(1994-2004)	(2006-2018)
(A) Wage effect of entered routine task			
Logic	-0.004	-0.105	0.087
	(0.034)	(0.066)	(0.183)
Mathematics	0.002	0.035	0.038
	(0.022)	(0.044)	(0.071)
Manual	-0.015	-0.012	-0.180
	(0.038)	(0.107)	(0.140)
Repetitive-exact	-0.077***	-0.173***	-0.225***
	(0.025)	(0.046)	(0.058)
(B) Wage effect of exited routine task			
Logic	0.077***	0.018	0.137*
	(0.026)	(0.047)	(0.077)
Math	0.010	0.039	0.066
	(0.018)	(0.036)	(0.054)
Manual	0.006	-0.034	-0.118
	(0.020)	(0.059)	(0.095)
Repetitive	-0.130***	-0.208***	-0.164***
	(0.018)	(0.040)	(0.054)
Observations	2403	769	514

Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Includes individual fixed effects and time effects. Conditioned on binary variables for education level (less than high school, high school, some college), marital status, union membership, and urban residence and all variables in Tables 11 and 13

Table 13: Wage impact of switching into non-routine physical, repair, & NTI from a routine task for college individuals
Dependent variable: log hourly real wage

	(1982-1993)	(1994-2004)	(2006-2018)
Tech repair	0.017	0.114	-0.079
	(0.066)	(0.161)	(0.287)
General physical	-0.126***	-0.297**	-0.704***
	(0.047)	(0.145)	(0.128)
Visual	-0.185**	-0.161	-0.413
	(0.094)	(0.144)	(0.271)
Manual	-0.015	-0.012	-0.180
	(0.038)	(0.107)	(0.140)
Eye-ear-hand	0.025	0.030	0.035
	(0.054)	(0.099)	(0.182)
NTI	-0.092***	-0.166**	-0.306***
	(0.034)	(0.072)	(0.087)
Observations	2403	769	514

Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Includes individual fixed effects and time effects. Conditioned on binary variables for education level (less than high school, high school, some college), marital status, union membership, and urban residence and all variables in Tables 8 and 9

5 Task reallocation in general

Figure 2 illustrates the change in normalized labor shares for the entire samples of college educated (panel (a)) and non-college educated (panel (b)) individuals. The shift away from routine tasks (math, logic, manual, and repetitive-exact) is clearly evident in both groups with the college group exhibiting a larger shift out of the math task and the non-college group exhibiting a larger shift out of the manual task. The non-college group increased labor share hours over a broad range of non-routine tasks, similar to the sub-sample of those who exit routine tasks. The college educated group exhibits a different task reallocation pattern characterized by positive "reallocation spikes" in comprehension, creativity, coaching, and managerial resource control tasks, with an especially large increase in the latter.[47] Also note that there is a tendency for the bulk of reallocation to occur during the 1980s for the non-college group and during the 1990s for the college group.

The reallocation pattern of this cohort has some interesting differences relative to repeated cross sections of representative samples. In Scotese (2022), I apply the granular task measures to repeated cross sections from the 1980, 1990, 2000 decennial censuses and the 3-year 2007 American Community Survey (ACS). In contrast to this cohort, college educated workers in the repeated cross sections exhibit *declining* labor shares in the comprehension, coaching and instruction tasks and increasing labor shares in the information and technology design tasks.[48] Appendix figures A1 and A2 illustrate task reallocation in the census/ACS representative samples. Of course the major difference between the two samples is that the repeated cross-sections include young adults newly entering the job market in every observed time period.

Therefore, the reallocation differences between this cohort and the nationally representative data may arise from new college-educated entrants who are more likely to flow into tasks that are directly complementary to digital technology (the information and technology design tasks) relative to their college-educated incumbents in this cohort. The college educated incumbents in this cohort instead flow into non-routine tasks with a focus on interpersonal, cognitive or managerial tasks despite the fact that the technology design and information tasks are associated with sizeable and persistent wage gains.[49] As Figure 2 indicates, this cohort does exhibit modest labor flows into the

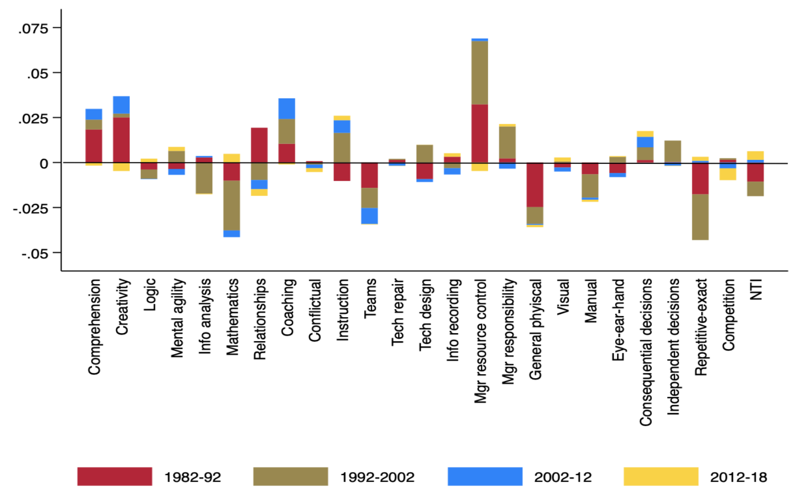
[47] A few tasks exhibit differential allocation patterns between time periods. Labor flowed into the relationship task during the 1980s, but out of the task during the subsequent periods. Labor flowed out of the technology design and instruction tasks during the 1980s, but into those tasks in subsequent periods.

[48] In both the census/ACS and the cohort samples, college educated labor flows into the creativity task and out of the team task.

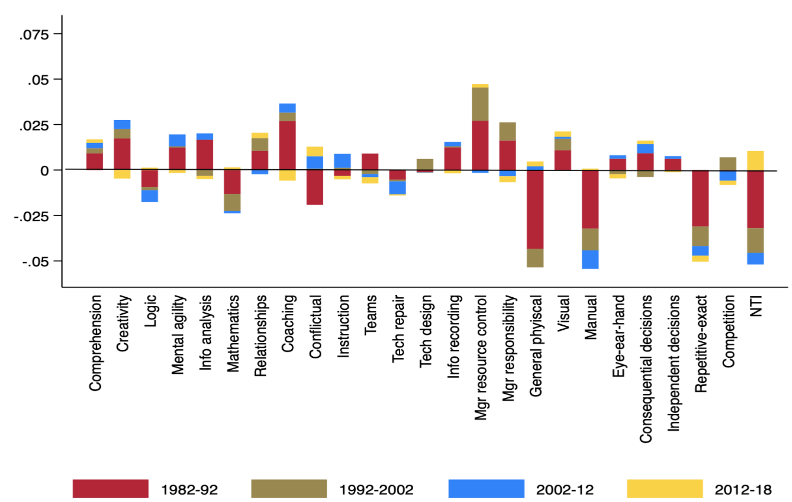
[49] The regression results from the wage equation applied to the full college and non-college samples are presented in the appendix.

Figure 2: Change in hours share by education: 1982-2018

(a) College educated



(b) Non-college educated



Notes: The change in hour shares are calculated from the normalized hour shares. The normalized hours share for any one task in a given year is the "raw" hours share divided by the sum of the "raw" hours shares over all tasks in that year.

technology design and information recording tasks in later periods. This may reflect some degree of retraining in response to the increasing returns to switching into those tasks.

There is also a contrast between the cohort and the nationally representative task allocations for the non-college group. As presented in the previous section, following exit from routine work, 11.0% - 24.7% of entries go to occupations intensive in the general physical or conflictual tasks. However, for the entire non-college group in this cohort, labor shares *decrease* for the general physical and conflictual task between 1982 and the early 2000s, modestly rebounding thereafter. (See Figure 2.) In the census/ACS data, labor shares *increase* for the general physical and conflictual tasks between 1980 and 2007 for non-college educated individuals. Personal service occupations tend to be intensive in the general physical and conflictual tasks and exhibit a well-documented employment rise since the 1980s, consistent with the task labor flows documented with the granular task measures in the census/ACS data.[50] Figure 3 plots the personal service employment shares by gender and education for the NLSY79 cohort. Among the college group, women tend to have slightly higher hour shares in the personal service occupations relative to men. In the non-college group, the gap is much larger. For all groups, employment shares in personal service occupations *fall* until about the early 2000s. Subsequently, only the non-college group reallocates labor toward the personal service occupations. This suggests that the shift into personal service occupations in the nationally representative data may be driven by younger labor market entrants rather than a reallocation of task effort by this cohort (at least prior to the early 2000s).[51]

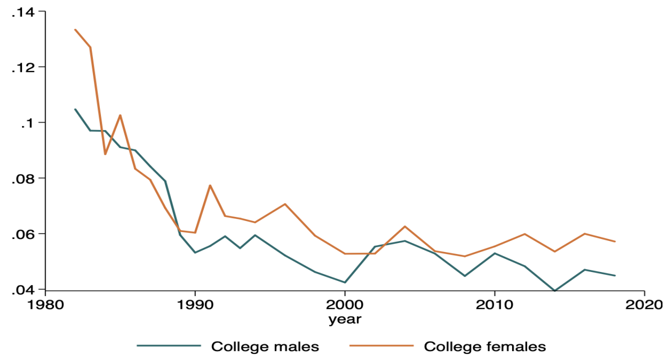
In summary, the general pattern of task reallocation in the cohort is similar to the population as whole in the broadest sense: they exit the routine tasks and enter non-routine tasks. However, using the granular task measures, key distinctions emerge. First, college educated workers in the cohort exhibit a lower propensity to enter technology and information tasks and a higher propensity to enter into resource control, comprehension, creativity and coaching tasks relative to the population as a whole over a similar time frame. Second, non-college educated individuals shift out of general physical and interpersonal conflictual tasks (and personal service occupations which tend to be intensive in those tasks) until the early 2000s, again, in contrast to the non-college educated populace as a whole. There are several candidate factors that may contribute to the differences. First, cohort task reallocation could be influenced by life-cycle specific choices, including the impact of aging on performing physical tasks. This may suppress the move into personal service occupations. However, ageing is unlikely to be the decisive factor in explaining the decline since labor shares increased in the physical tasks (and personal service occupations) in the later periods when individuals in the cohort were older. Second, the cohort of individuals in this study were 18-25 years old in 1982 and, therefore, made formative education decisions prior to or in the very early stages of the computer

[50]See, for example,Acemoglu and Autor (2011) and Autor and Dorn (2013) for evidence on the personal service employment patterns.

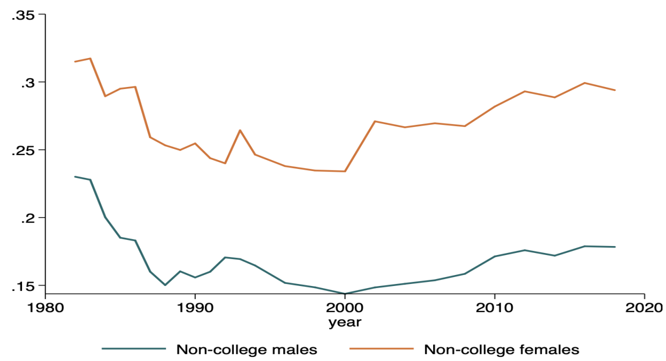
[51]In a related point, Cortes et al. (2020) show that a decline in the "inflow" rates was a key factor in the overall decline in routine employment. This, in part, reflects the decisions of new entrants.

Figure 3: Hours share in personal service occupations

(a) College educated



(b) Non-college educated



Notes: Panel (a) shows the share of labor hours worked in personal service occupations separately for college educated males and females in the sample. Panel (b) shows the share of labor hours worked in personal service occupations separately for males and females in the sample without a college degree. See the appendix for the sample definition.

and automation revolution. As the impact of digital technological change on labor markets unrolled, newer entrants into the labor market could adjust their education decisions accordingly and enter into technology design and information analysis tasks at a higher rate. Also, if task-specific human capital raises the cost of switching into a new task/occupation, this cohort would be less likely to switch into tasks directly related to the new technology. Members of this cohort continued to return to formal education throughout the period, but the ability to switch careers or skills can be fairly "sticky." Alternatively, it could be that attrition from the cohort sample was biased toward those who might have a propensity to move into tasks complementary to the new technology. These are all interesting questions which merit further research.

6 Conclusion

The advancement of digital technological change and its propensity to displace people performing routine tasks with machines has altered the pattern of employment and the wage structure. The sparse task approach, and the associated link to broad occupation groups, has been extremely useful in documenting broad employment patterns such as polarization. However, a major motivation for this paper's approach is that a more refined task space helps to uncover key details and dynamics driving the broader trends. Determining which groups of workers are most impacted, defining their choices, and how those choices affect wage and employment patterns is a key element for not only understanding the process, but also in developing and analyzing policy propositions.

I have presented a set of granular task measures and used those task measures to analyze task reallocation within a cohort of workers from the NLSY79. The paper presents some novel findings that contribute to our understanding of who is affected by the changing labor market conditions, their relevant choices, and the impact on wages and employment. Clearly, there are also details not examined in this paper, limitations to the findings, and further work to do.

The contributions presented in this paper include using the granular task measures to reveal that abstract tasks are embedded in both high-skill and low-skill occupations. Therefore, non-college educated workers who shift out of a routine intensive occupation may sort into non-routine physical tasks or sort into abstract tasks. More specifically, for this cohort, roughly one-half of non-college exits from routine work yield entry into occupations intensive in an abstract task. Recognizing the expanded task choice set for those potentially displaced by RBTC matters both for how we understand the impact of RBTC and for any policy propositions that may be considered. For example, given the high cost of a college education or post-graduate training, and additional opportunity costs for individuals already in the work-force, retraining opportunities outside of college attendance may offer an alternative policy option. In fact, news reports indicate a burgeoning trend among employers to eliminate or diminish the college degree requirement and/or establish apprenticeship programs. The trend appears to be most relevant for tech-related jobs.[52] None of these related policy issues was directly addressed in this paper.

The refined task space analysis also showed that, within this cohort, college educated workers tended to shift hours into a few cognitive, interpersonal and managerial tasks, in contrast to the non-college educated group whose allocation into abstract work was more broad-based. Moreover,

[52]For example, see Lanahan (2022) and Lohr (2022).

shifts into tasks that are likely more closely aligned with digital technological change (information and technology based tasks) were modest despite the relatively large wage gains linked to those tasks. The reallocation patterns of the college educated group in the cohort differ from those documented in Scotese (2022) using nationally representative repeated cross sections of the Census and ACS where there are larger shifts into the information and technology tasks. The NLSY79 cohort entered the labor market at the cusp of RBTC's influence on task demand. It is probable that many in this cohort made formative education decisions before understanding the impact of digital technological change on task demand.

The difference in task reallocation between this cohort and the nationally representative samples points to both strengths and limitations of this analysis. A key limitation of focusing on one cohort is that the impact of young entrants into the labor market is absent. On the other hand, focusing on one cohort, along with the ability to compare the results to a nationally representative sample, highlights the potential relevance of distinguishing between the task allocation decisions of incumbents and new entrants. Another significant advantage of the cohort panel structure is the ability to condition on individual effects and, of course, not have to disentangle time and cohort effects. While this study has indicated the relevance of differences between cohorts, and provided some detail on this cohort, additional research on this point would be helpful. Issues related to human capital specificity, the costs of retraining, and staggered entry of new entrants, as applied to the impact of RBTC, warrant more consideration.

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A Appendix

Not intended for publication in its entirety

Available online

A.1 O*NET data and task construction

The analysis uses consistent occupation categories across all years. The occupation codes are based on a set of consistent 1990 occupation codes developed by Meyer and Osborne (2005) and modified by Dorn (2009) and Deming (2017). The O*NET uses SOC occupation codes. I map the O*NET SOC codes to 2000 census codes and apply Deming (2017)'s crosswalks to the consistent 1990 codes. The NLSY79 reports occupation using 1980 census codes until the 2002 survey year and uses 2000 census codes thereafter. Again, I use Deming (2017)'s crosswalks to map the 1980 and 2000 census codes to the 1990 consistent occupation codes.

Dorn/Deming consistent occupation code crosswalks appear to be based on the census 2000 1% sample codes. The NLS uses the census 2000 5% sample occupation codes and this census sample has additional occupation codes. I have mapped the following codes used in the 2000 5% sample to the 1990 consistent codes based on the census 2000 to census 1990 crosswalk and then employing the 1990 census to 1990 consistent code crosswalk. The following assignments were made:

Census 2000 (5%) code	1990 consistent code
134	59
383	423
416	444
521	326
631	844
650	597
692	614
693	617
705	523
802	684
812	684
843	749
887	779
890	779
950	859

The above procedure produces a pool of 334 consistently coded occupations.

The 162 O*NET occupation attributes used in this study are pulled from the skills, work activities, abilities, and work context subsets. The attributes from the first three subsets have numerical values for both their level and importance in the occupation. Those are combined into one number using a Cobb-Douglas specification with an exponents of .67 on the importance and .33 on the level as in Firpo et al. (2011). In practice, there is a very high correlation between the importance and level values.

After pooling the attributes into the task groups (cognitive, interpersonal, managerial, technical, physical, and structural characteristics), factor analysis is performed on each group separately on the 334 consistently coded occupations. The number of task measures is determined by first examining the number of factors with eigenvalues greater than one. Then that number of factors was extracted using principal components, the factors were rotated and the weights on the attributes inspected. If the last factor (i.e. the one that explained the least variance) had no attributes with a heavy factor loading, the number of factors was reduced. Only for the physical group of attributes was the number of factors reduced beyond the first round. In that instance, only the attribute "climbing ladders" was heavily weighted in the fifth factor. That factor was dropped, by extracting only four factors using principle components, yielding four physical task measures.

Tables A1 - A5 report the attributes with the heaviest load for each task measure, tables A6 - A10 report the 15 occupations most intensive in each task, and a set of tables reporting all of the weights on each occupation attribute for each task measure. Each set of tables includes a separate table for each task group.

Table A1: Attributes in the cognitive task measures with large weights

Comprehension & Expression		**Logic**	
Active Listening	0.8743	Science	0.7346
Speaking	0.8589	Systems Analysis	0.6958
Oral Expression	0.8426	Systems Evaluation	0.6789
Oral Comprehension	0.8252	Complex Problem Solving	0.662
Reading Comprehension	0.7965	Active Learning	0.6115
Writing	0.7829	Mathematics	0.5937
Written Expression	0.7294		
Written Comprehension	0.7132	**Mental agility**	
Critical Thinking	0.6783	Selective Attention	0.8285
Active Learning	0.628	Time Sharing	0.8156
Getting Information	0.6253	Speed of Closure	0.7651
Monitoring	0.6147	Perceptual Speed	0.7237
Inductive Reasoning	0.5983	Flexibility of Closure	0.6967
Learning Strategies	0.5806	Spatial Orientation	0.5394
Deductive Reasoning	0.5734	Memorization	0.5013
Problem Sensitivity	0.5397		
Judgment and Decision Making	0.5344	**Information**	
		Evaluating Information	0.6934
Creativity & ideas		Information	0.5827
Thinking Creatively	0.7866	Processing Information	0.5744
Originality	0.7456	Updating and Using Relevant Knowledge	0.5179
Fluency of Ideas	0.7144		
Scheduling Work and Activities	0.6851	**Mathematics**	
Developing Objectives and Strategies	0.67	Mathematical Reasoning	0.793
Organizing, Planning, and Prioritizing Work	0.5685	Number Facility	0.7858
Judging the Qualities	0.5137	Category Flexibility	0.5639
		Mathematics	0.5623

Table A2: Attributes in the interpersonal task measures with large weights

External relationships		**Conflictual**
Communicating with Persons Outside Organization	0.8594	Deal With Unpleasant or Angry People
Communicating via phone, email or memo	0.8238	Deal With Physically Aggressive People
Establishing and Maintaining Interpersonal Relationships	0.7229	Frequency of Conflict Situations
Selling or Influencing Others	0.6869	Contact With Others
Deal With External Customers	0.6821	Assisting and Caring for Others
Persuasion	0.6047	Performing for or Working Directly with the Public
		Deal With External Customers
Guiding-Coaching		**Instruction**
Coaching and Developing Others	0.8853	Instructing
Guiding, Directing, and Motivating Subordinates	0.8728	Coordination
Training and Teaching Others	0.8555	Persuasion
Developing and Building Teams	0.843	
Coordinating the Work and Activities of Others	.7989	**Teams**
Provide Consultation and Advice to Others	0.733	Work With Work Group or Team
		Coordinate or Lead Others

Table A3: Attributes in the technical and managerial task measures with large weights

Technical task measures		Managerial task measures	
Repair & Maintenance		**Resource Control**	
Repair/Maintain Mech Equipment	0.9224	Management of Financial Resources	0.8508
Inspecting Equipment	0.8959	Monitoring and Controlling Resources	0.8081
Equipment Maintenance	0.8654	Management of Personnel Resources	0.7935
Repairing	0.8302	Staffing Organizational Units	0.7737
Operation Monitoring	0.7934	Performing Administrative Activities	0.7672
Operation and Control	0.7921	Time Management	0.7657
Repair/Maintain Elect Equipment	0.7496	Management of Material Resources	0.5907
Troubleshooting	0.6996		
Installation	0.6328		
Drafting Tech Devices/Equipment	0.5082		
Design		**Responsibility**	
Operations Analysis	0.8892	Responsible for Others' Health /Safety	0.9221
Technology Design	0.8232	Responsibility for Outcomes/Results	0.7916
Equipment Selection	0.7217		
Programming	0.7061		
Installation	0.6514		
Troubleshooting	0.597		
Quality Control Analysis	0.5711		
Information			
Identifying Objects, Actions, Events	0.8698		
Documenting/Recording Information	0.8048		
Monitor Processes, Materials, Surroundings	0.789		
Estimating Quantifiable Characteristics	0.6738		
Interacting With Computers	0.5588		

Table A4: Attributes in the physical task measures with large weights

General physical		**Visual**	
Spend Time Standing	0.8671	Night Vision	0.8854
Stamina	0.8518	Peripheral Vision	0.884
Spend Time Walking/Running	0.849	Glare Sensitivity	0.8564
Trunk Strength	0.8369	Sound Localization	0.8293
Gross Body Coordination	0.8343	Operating Vehicles/Equipment	0.8148
Extent Flexibility	0.7594	Response Orientation	0.6135
Dynamic Strength	0.7509	Depth Perception	0.6015
Performing General Physical Activities	0.7431	Reaction Time	0.5728
Static Strength	0.741	Rate Control	0.5374
Speed of Limb Movement	0.7025		
Gross Body Equilibrium	0.7021	**Manual**	
Bending or Twisting the Body	0.7018	Use Hands on Objects/Controls	0.7828
Kneeling, Crouching, Crawling	0.6724	Repetitive Motions	0.744
Keeping/Regaining Balance	0.6566	Wrist-Finger Speed	0.6488
Handling and Moving Objects/Controls	0.6539	Manual Dexterity	0.6471
Multilimb Coordination	0.5791	Arm-Hand Steadiness	0.5934
Dynamic Flexibility	0.5622	Control Precision	0.5823
Explosive Strength	0.4972	Controlling Machines/Processes	0.574
		Eye-ear-hand	
		Visual Color Discrimination	0.7655
		Hearing Sensitivity	0.7552
		Finger Dexterity	0.7159
		Auditory Attention	0.671
		Far Vision	0.6354

Table A5: Attributes in the structural characteristics task measures with large weights

Consequential decisions		**Repetitive & exact**	
Consequence of Error	0.8514	Importance of Repeating Same Tasks	0.876
Impact of Decisions on Co-workers or Company	0.8052	Degree of Automation	0.7617
Frequency of Decision Making	0.7783	Importance of Being Exact or Accurate	0.7153
Time Pressure	0.4256		
Independent decision making		**Competition**	
Structured versus Unstructured Work	0.8196	Level of Competition	0.8922
Freedom to Make Decisions	0.7217	Time Pressure	0.4046

Table A6: Occupations intensive in the cognitive tasks

Comprehension & Expression	Creativity & ideas	Logic
Public Relations Specialists	Dancers and Choreographers	Plasterers and Stucco Masons
Postsecondary Teachers	Artists and Related Workers	Aerospace Engineers
Lawyers	Writers and Authors	Electrical Engineers
Counselors	Architects, Except Naval	Sales Engineers
Physicians and Surgeons	Advertising/Promotions Mgrs	HVAC Mechanics
Veterinarians	Producers and Directors	Chemists and Materials Scientists
Air Traffic Controller	Designers	Medical Scientists
Medical Scientists	Clergy	Aircraft Pilots and Flight Engineers
Psychologists	Public Relations Specialists	Chemical Engineers
Bill and Account Collectors	Musicians, Singers, and Related	Material Moving Workers
Podiatrists	Occupational Therapists	Elevator Installers and Repairers
Audiologists	Legislators	Shoe Machine Operators
Interviewers, Except Eligibility and Loan	Religious Workers	FLS/Mgrs, Landscaping
News Reporters	Advertising Sales Agents	Rolling Machine Operators
Clergy	Medical/Health Services Managers	Plant and System Operators
Mental agility	**Information**	**Mathematics**
Air Traffic Controllers	Pharmacists	Mathematicians
Aircraft Pilots and Flight Engineers	Chiropractors	Astronomers and Physicists
Ship and Boat Captains and Operators	Computer Operators	Statistical Assistants
Packaging Operators	Medical/Health Services Managers	Actuaries
Taxi Drivers and Chauffeurs	Compliance Officer	Bookkeeping and related
Bus Drivers	Physical Therapists	Mechanical Engineers
Parking Lot Attendants	Physician Assistants	Civil Engineers
Detectives and Criminal Investigators	Occupational Therapists	Marine Engineers and Naval Architects
FLS/Mgrs: Police, Detectives	Actuaries	Surveyors and related
Locomotive Engineers	Construction Inspectors	Accountants and Auditors
Automotive Technicians	Management Analysts	Billing clerks and related
Plant and System Operators	Chemical Technicians	Tellers
Registered Nurses	Registered Nurses	Order Clerks
Clergy	Clinical Laboratory Techs	Office Clerks, General
Derick Operators, Oil/Gas	Packaging Operators	Operations Research Analysts

Table A7: Occupations intensive in the interpersonal tasks

External relationships	**Coaching**	**Conflictual**
Insurance Sales Agents	Compliance Officers	Parking Lot Attendants
Public Relations Specialists	Clergy	Detective/Investigators
Financial Services Sales Agents	Medical/Health Managers	Bailiffs, Correctional Officers
Advertising Sales Agents	Dietitians and Nutritionists	Registered Nurses
Agents of Performers and Artists	Athletes, Coaches, Umpires	FLS/Mgrs, Police and Detectives
Telemarketers	FLS/Mgrs, Constr/Extraction	Transportation Attendants
Lawyers	Human Resources Managers	Hotel Desk Clerks
Writers and Authors	Civil Engineers	Licensed Practical Nurses
Information and Record Clerks	FLS/Mgrs, Production/Operation	Gaming Cage Workers
Market and Survey Researchers	Education Administrators	Social Workers
Advertising and Promotions Mgrs	Religious Workers	Dispatchers
Urban and Regional Planners	Pharmacists	Community/Social Service Speclst
Construction-Bldg Inspectors	Chemical Engineers	Counter and Rental Clerks
Travel Agents	FLS/Mgrs, Police/Detectivs	Bartenders
Legislators	Purchasing Managers	FLS/Mgrs, Food Prep/Servers

Instruction	**Team**
Secondary School Teachers	Computer Operators
Recreation and Fitness Workers	Technical Writers
Tour and Travel Guides	Railroad Conductors and Yardmasters
Clergy	Computer Programmers
Audiologists	Air Traffic Controllers/Airfield Speclst
Sales Engineers	Petroleum Engineers
Crane and Tower Operators	Mechanical Engineers
Elementary/Middle School Teachers	Financial Managers
Librarians	Other Transportation Workers
Plasterers and Stucco Masons	Power Plant Operator and related
Aerospace Engineers	Urban and Regional Planners
Postsecondary Teachers	Chemists and Materials Scientists
Special education teachers	Hoist and Winch Operators
FLS/Mgrs, Personal Service Workers	Electrical and Electronics Engineers
Religious Workers	Drafters

Table A8: Occupations intensive in the technical and managerial tasks

	Technical task intensive occupations	
Repair and maintenance	**Design**	**Information**
Aircraft Mechanics /Technicians	Computer Programmers	Environmental Scientists
Hoist and Winch Operators	Sales Engineers	Registered Nurses
Boilermakers	Electrical Engineers	Respiratory Therapists
Mining Machine Operators	Management Analysts	Pharmacists
Stationary Engineers amd related	Chemical Engineers	FLS/Mgs, Police and Detectives
Derrick operators, oil/gas	Actuaries	Environmental Engineers
Sailors and Marine Oilers	Atmospheric and Space Scientists	Clinical Laboratory Techs
HVAC mechanics	Astronomers and Physicists	LPNs/Vocational Nurses
Elevator Installers/Repairers	Mathematicians	Physician Assistants
Heavy Vehicle/Equipment Techs	Chemists/Materials Scientists	Physical Therapists
Millwrights	Computer Support Specialists	Podiatrists
Maintenance Workers, Machinery	Operations Research Analysts	Occupational Therapists
Helpers–Install/Repair	Marine Engineers/Naval Architects	Power Plant Opers and related
Motion Picture Projectionists	Petroleum Engineers	Civil Engineers
Small Engine Mechanics	Legislators	Medical Scientists

Managerial task intensive occupations	
Resource control	**Responsibility**
Education Administrators	Roofers
Clergy	Legislators
Medical/Health Managers	FLS/Mgs, Production/Operating
Legislators	FLS/Mgs, Fire Fighting
FLS/Mgs, Office/ Adm Support	Derrick operators, oil/gas
Religious Workers	Plasterers and Stucco Masons
Podiatrists	FLS/Mgs, Landscaping
Sales Engineers	Power-Line Install/Repair
Dentists	FLS/Mgs, Construction/Extraction
Purchasing Managers	FLS/Mgs, Mechanics/Repairers
Farmers and Ranchers	Explosives Workers and related
Architects, Except Naval	FLS/Mgs, Farming, Fishing, Forestry
Management Analysts	Operating Engineers and related
Property/Association Managers	Dentists
FLS/Mgs, Personal Service	FLS/Mgs, Housekeeping/Janitorial

Table A9: Occupations intensive in the physical tasks

General physical	**Visual**
Waiters and Waitresses	Bus Drivers
Maids, Housekeeping, Cleaners	Taxi Drivers and Chauffeurs
Recreation and Fitness Workers	Aircraft Pilots and Flight Engineers
Porters, Bellhops, and Concierges	Locomotive Engineers
LPN's and Vocational Nurses	Ship/Boat Captains/Operators
Bartenders	Driver/Sales Workers and Truck Drivers
Janitors and Building Cleaners	Crane and Tower Operators
Roofers	Hoist and Winch Operators
Physical Therapists	FLS/Mgrs, Police and Detectives
Flooring Installers and Finishers	Refuse/Recyclable Collectors
Athletes, Coaches, Related Workers	Industrial Truck and Tractor Operators
Combined Food Prep/Serving	Dredge operators and related
Plasterers and Stucco Masons	Railroad Conductors and Yardmasters
Drywall Installers and related	Railroad Brake, Signal, and Switch Operators
Food Preparation Workers	Parking Lot Attendants
Manual	**Eye-ear-hand**
Tailors, Dressmakers, and Sewers	Clinical Laboratory Techs
Dental Hygienists	Veterinarians
Jewelers and related	Air Traffic Controllers
Computer Operators	Podiatrists
Shoe Machine Operators and Tenders	Registered Nurses
Pressers, Textile, other related	Audiologists
Sewing Machine Operators	Aircraft Pilots/Flight Engineers
Proofreaders and Copy Markers	Dentists
Barbers	Cabinetmakers and Bench Carpenters
Earth Drillers, Except Oil and Gas	Medical, Dental, Ophthalmic Lab Techs
Cutting Workers	Respiratory Therapists
Prepress Technicians/Workers	Precision Instrument/Equipment Repairers
Etchers and Engravers	Computer Control Programmers/Operators
Packers and Packagers, Hand	Jewelers and related
Technical Writers	Optometrists

Table A10: Occupations intensive in the structural characteristics tasks

Consequential decisions	**Independent decision making**
Railroad Conductors and Yardmasters	Dietitians and Nutritionists
Taxi Drivers and Chauffeurs	Recreation and Fitness Workers
Hoist and Winch Operators	Barbers
Railroad Brake, Signal, and Switch Operators	Insurance Sales Agents
LPN's and Vocational Nurses	Podiatrists
Veterinarians	Vendors and related
Physician Assistants	Compliance Officers
Bus Drivers	Hairdressers and related
Dentists	Bartenders
Physicians and Surgeons	Agents of Artists and related
Legislators	Audiologists
Crossing Guards	Postsecondary Teachers
Pharmacists	Purchasing Agents, Farm Products
Pest Control Workers	Astronomers and Physicists
Crane and Tower Operators	Clergy
Repetitive & exact tasks	**Competition**
Bookkeeping and related	Advertising Sales Agents
Computer Operators	Etchers and Engravers
Eligibility Interviewers (Gov't)	Insurance Sales Agents
Atmospheric and Space Scientists	Plasterers and Stucco Masons
Payroll and Timekeeping Clerks	Financial Serv Sales Agents and related
Air Traffic Controllers	Agents of Artists and related
Purchasing Agents	Drywall Installers and related
Dispatchers	Announcers
Office and Administrative Support	Computer/ATM/Office Machine Repair
Data Entry Keyers	Sewing Machine Operators
Bill and Account Collectors	Furniture Finishers
Information and Record Clerks	Public Relations Specialists
Human Resources Assistants	Pest Control Workers
Interviewers	Earth Drillers, Except Oil and Gas
Insurance Claims/Processing Clerks	FLS/Mgrs, Production and Operating

Table A11: Occupations not intensive in any task measure

HR Specialists and related	Structural Iron/Steel Workers
Medical Records/Health Info Techs	Shoe and Leather Repairers
EMTs and Paramedics	Molders & related,Excpt Metal,Plastic
Biological Technicians	Butchers and related
Other Science/Social Science Techs	Bakers
Models and related	Cutting Machine Oper & related, metal
Word Processors and Typists	Forging Machine Opers & related, Metal & Plastic
Receptionists and Information Clerks	Molders/Molding Machine Opers & related, Metal & Plastic
Mail Clerks/Operators, Except Postal	Sawing Machine Operators & related
Cargo and Freight Agents	Bookbinders and Bindery Workers
Procurement Clerks	Textile Bleaching/Dyeing Machine Operators & related
Meter Readers, Utilities	Extruding and Drawing Machine Operators & related
Laundry and Dry-Cleaning Workers	Chemical Processing Machine Operators & related
Cooks	Food and Tobacco Machine Operators & related
Grounds Maintenance Workers	Electrical Assemblers & related
Nonfarm Animal Caretakers	Painting Workers
Agricultural Inspectors	Inspectors/Testers/Sorters/Sampler/Weighers
Industrial/Refractory Mechanics	Helpers–Production Workers
Electrical Repairers, Industrial/Utility	Misc Vehicle Mechanics & related
Riggers	Cleaners of Vehicles and Equipment
Plumbers and related	Rail-Track Laying Operators & related
Glaziers	

Table A12: Factor loadings on cognitive attributes

	(1)	(2)	(3)	(4)	(5)	(6)
Oral Comprehension	0.8252	-0.3315	-0.2665	0.0316	0.1202	-0.0333
Written Comprehension	0.7132	0.2609	0.0748	0.0904	0.3571	0.4234
Oral Expression	0.8426	0.2568	-0.0919	0.1029	0.2464	0.1609
Written Expression	0.7294	0.3394	0.0436	0.029	0.3624	0.3146
Fluency of Ideas	0.5042	0.7144	0.1501	0.2175	0.0592	0.2777
Originality	0.4787	0.7456	0.1546	0.19	0.0364	0.2483
Problem Sensitivity	0.5397	0.2494	0.1772	0.4474	0.4952	0.064
Deductive Reasoning	0.5734	0.3098	0.223	0.2527	0.4836	0.3275
Inductive Reasoning	0.5983	0.3085	0.2143	0.2519	0.4772	0.2597
Information Ordering	0.4233	0.1867	0.2453	0.3422	0.3969	0.4475
Category Flexibility	0.3885	0.3366	0.1586	0.2699	0.2805	0.5639
Mathematical Reasoning	0.3133	0.1719	0.1998	0.1813	0.2165	0.793
Number Facility	0.2143	0.1757	0.1056	0.2807	0.117	0.7858
Memorization	0.4934	0.3519	0.0007	0.5013	0.0815	0.3155
Speed of Closure	0.3086	0.2229	0.078	0.7651	0.1878	0.2779
Flexibility of Closure	0.0912	0.1032	0.2935	0.6967	0.3199	0.2814
Perceptual Speed	-0.2005	-0.0909	0.2952	0.7237	0.211	0.2798
Spatial Orientation	-0.4642	-0.0199	0.1439	0.5394	-0.0281	-0.2829
Visualization	-0.3423	0.4393	0.4672	0.482	-0.0669	0.1208
Selective Attention	0.0994	-0.0043	0.1418	0.8285	0.1272	0.1116
Time Sharing	0.2648	0.1839	-0.0736	0.8156	-0.0254	-0.0381
Reading Comprehension	0.7965	0.1233	0.3378	0.0268	0.2069	0.2352
Active Listening	0.8743	0.1731	0.2119	0.0803	0.044	0.0473
Writing	0.7829	0.2375	0.2441	-0.0481	0.2354	0.2211
Speaking	0.8589	0.2795	0.1461	0.051	0.0093	0.0447
Mathematics	0.1595	0.0118	0.5937	-0.0145	0.0172	0.5623
Science	0.1955	0.044	0.7346	0.1117	0.1417	0.1163
Critical Thinking	0.6783	0.2752	0.4987	0.1851	0.1976	0.1567
Active Learning	0.628	0.2682	0.6115	0.0919	0.1014	0.1472
Learning Strategies	0.5806	0.1527	0.5696	0.1324	-0.0584	-0.0627
Monitoring	0.6147	0.3262	0.5122	0.1403	0.0925	-0.0067
Complex Problem Solving	0.4416	0.311	0.662	0.1665	0.2464	0.2263
Judgment and Decision Making	0.5344	0.3703	0.5116	0.1825	0.2029	0.0426
Systems Analysis	-0.0211	0.1876	0.6958	0.2196	0.3317	0.1912
Systems Evaluation	0.103	0.2395	0.6789	0.1774	0.2983	0.1821
Getting Information	0.6253	0.2751	0.1149	0.0914	0.5162	0.2615
Judging the Qualities of Things, etc.	0.2639	0.5137	0.303	0.1567	0.3603	-0.0942
Processing Information	0.4996	0.1324	0.1923	0.1313	0.5744	0.4583
Evaluating Info for Compliance	0.2598	0.1475	0.2582	0.2979	0.6934	0.1244
Analyzing Data or Information	0.4525	0.2733	0.2737	0.1498	0.5827	0.4226
Making Decisions and Solving Problems	0.4012	0.4718	0.3332	0.314	0.4755	0.1245
Thinking Creatively	0.3284	0.7866	0.2551	0.0113	0.1329	0.1475
Updating and Using Relevant Knowledge	0.4972	0.3697	0.238	0.1674	0.5179	0.2303
Developing Objectives and Strategies	0.4265	0.67	0.1743	0.0936	0.3803	0.0757
Scheduling Work and Activities	0.3701	0.6851	0.145	0.0439	0.3758	0.0468
Organizing, Planning, and Prioritizing Work	0.5133	0.5685	0.0951	0.004	0.3869	0.1805

Columns refer to the task measures (1) Comprehension, (2) Creativity, (3) Logic, (4) Mental Agility, (5) Information Analysis, (6) Math

Table A13: Factor loadings on interpersonal attributes

	(1)	(2)	(3)	(4)	(5)
Social Perceptiveness	0.5468	0.205	0.4116	0.5692	0.0296
Coordination	0.196	0.3829	-0.0568	0.6658	0.3447
Persuasion	0.6047	0.2969	0.0776	0.6136	0.1075
Negotiation	0.53	0.2991	0.1462	0.5971	0.1787
Instructing	-0.0412	0.4385	0.0038	0.7357	0.1197
Service Orientation	0.5141	0.1056	0.5064	0.5113	0.0227
Interpreting the Meaning of Information for Others	0.5504	0.5646	-0.0898	0.184	0.2122
Communicating with Supervisors, Peers, or Subordinates	0.4064	0.5373	0.0221	0.198	0.4439
Communicating with Persons Outside Organization	0.8594	0.265	0.1931	0.0971	0.0563
Establishing and Maintaining Interpersonal Relationships	0.7229	0.4106	0.2557	0.1854	0.0857
Assisting and Caring for Others	0.0537	0.4017	0.6519	0.1505	-0.1379
Selling or Influencing Others	0.6869	0.2979	0.1446	0.172	-0.2845
Resolving Conflicts and Negotiating with Others	0.5584	0.5405	0.4508	0.1196	0.035
Performing for or Working Directly with the Public	0.5463	0.117	0.6289	0.0417	-0.3121
Coordinating the Work and Activities of Others	0.2275	0.7989	0.1161	0.1535	0.2689
Developing and Building Teams	0.2404	0.843	0.1531	0.1523	0.1638
Training and Teaching Others	0.034	0.8555	0.0879	0.2034	0.0835
Guiding, Directing, and Motivating Subordinates	0.1917	0.8728	0.1455	0.1321	0.0861
Coaching and Developing Others	0.1614	0.8853	0.1689	0.1911	0.0461
Provide Consultation and Advice to Others	0.4952	0.733	-0.0548	0.1686	0.0877
Public Speaking	0.4068	0.3616	0.1592	0.3369	0.1735
Telephone	0.8238	0.1206	0.1917	0.072	0.2557
Electronic Mail	0.7624	0.2161	-0.1351	0.1258	0.3802
Letters and Memos	0.7342	0.2329	0.1083	0.1794	0.4076
Face-to-Face Discussions	0.3304	0.2518	0.1727	0.166	0.5628
Contact With Others	0.4593	-0.0048	0.6551	0.118	0.2778
Work With Work Group or Team	0.1351	0.2575	0.317	0.2082	0.6958
Deal With External Customers	0.6821	-0.0241	0.6103	0.0581	0.0156
Coordinate or Lead Others	0.2402	0.3713	0.2333	0.2096	0.6534
Frequency of Conflict Situations	0.2036	0.223	0.6733	0.1223	0.4119
Deal With Unpleasant or Angry People	0.1085	0.0076	0.8517	-0.0377	0.2092
Deal With Physically Aggressive People	-0.0945	0.2636	0.757	0.0385	0.1206

Columns refer to the task measures (1) External relationships, (2) Coaching, (3) Conflictual, (4) Instruction, (5) Team

Table A14: Factor loadings on technical attributes

	(1)	(2)	(3)
Operations Analysis	0.0497	0.8892	0.075
Technology Design	0.3584	0.8232	0.2036
Equipment Selection	0.531	0.7217	-0.0914
Installation	0.6328	0.6514	-0.1788
Programming	-0.0084	0.7061	0.3133
Operation Monitoring	0.7934	0.1915	0.2894
Operation and Control	0.7921	0.2644	0.1296
Equipment Maintenance	0.8654	0.3588	-0.1757
Troubleshooting	0.6996	0.597	0.1465
Repairing	0.8302	0.4255	-0.1896
Quality Control Analysis	0.4234	0.5711	0.3387
Monitor Processes, Materials, or Surroundings	0.4144	0.0132	0.789
Identifying Objects, Actions, and Events	0.0199	0.0447	0.8698
Inspecting Equipment, Structures, or Material	0.8959	-0.0036	0.2428
Estimating the Quantifiable Characteristics of Products, Events, or Information	0.2749	0.2983	0.6738
Interacting With Computers	-0.5538	0.3658	0.5588
Drafting, Laying Out, and Specifying Technical Devices, Parts, and Equipment	0.5082	0.4543	0.2596
Repairing and Maintaining Mechanical Equipment	0.9224	0.098	-0.0276
Repairing and Maintaining Electronic Equipment	0.7496	0.2298	0.1814
Documenting/Recording Information	-0.2811	0.0569	0.8048

Columns refer to the task measures (1) Maintenance and repair, (2) Technical design (3) Information gathering

Table A15: Factor loadings on managerial attributes

	(1)	(2)
Time Management	0.7657	-0.0829
Management of Financial Resources	0.8508	0.107
Management of Material Resources	0.5907	0.4832
Management of Personnel Resources	0.7935	0.3784
Performing Administrative Activities	0.7672	-0.2776
Staffing Organizational Units	0.7737	0.2392
Monitoring and Controlling Resources	0.8081	0.2702
Responsible for Others' Health and Safety	-0.0789	0.9221
Responsibility for Outcomes and Results	0.3558	0.7916

Columns refer to the task measures (1) Resource control, (2) Responsibility

Table A16: Factor loadings on structural job attributes

	(1)	(2)	(3)	(4)
Consequence of Error	0.8514	-0.1982	0.0168	-0.0308
Impact of Decisions on Co-workers or Company Results	0.8052	0.4129	0.1052	0.1633
Frequency of Decision Making	0.7783	0.3581	0.1581	0.1166
Freedom to Make Decisions	0.3561	0.7217	-0.1223	0.3298
Degree of Automation	-0.074	-0.2382	0.7617	0.1103
Importance of Being Exact or Accurate	0.2964	0.1425	0.7153	0.1907
Importance of Repeating Same Tasks	0.0909	-0.0393	0.876	-0.1743
Structured versus Unstructured Work	0.1873	0.8196	0.0303	0.2829
Level of Competition	0.0786	0.1349	-0.0233	0.8922
Time Pressure	0.4256	-0.1881	0.3765	0.4046
Pace Determined by Speed of Equipment	0.0588	-0.8504	0.1172	0.2058

Columns refer to the task measures (1) Consequential decisions, (2) Independent decisions, (3) Repetitive, (4) Competition

Table A17: Factor loadings on physical attributes

	(1)	(2)	(3)	(4)
Arm-Hand Steadiness	0.4918	0.2202	0.5934	0.4817
Manual Dexterity	0.4842	0.2661	0.6471	0.4181
Finger Dexterity	0.2162	0.1192	0.4725	0.7159
Control Precision	0.3227	0.4429	0.5823	0.5248
Multilimb Coordination	0.5791	0.4758	0.3795	0.42
Response Orientation	0.369	0.6135	0.3469	0.5056
Rate Control	0.3696	0.5374	0.4913	0.4635
Reaction Time	0.394	0.5728	0.415	0.468
Wrist-Finger Speed	0.271	0.1639	0.6488	0.4727
Speed of Limb Movement	0.7025	0.5107	0.2223	0.2618
Static Strength	0.741	0.3829	0.3159	0.3228
Explosive Strength	0.4972	0.4335	0.048	0.1739
Dynamic Strength	0.7509	0.3886	0.3002	0.2821
Trunk Strength	0.8369	0.231	0.2755	0.2385
Stamina	0.8518	0.346	0.2095	0.1852
Extent Flexibility	0.7594	0.3662	0.376	0.2481
Dynamic Flexibility	0.5622	0.3122	0.361	0.0082
Gross Body Coordination	0.8343	0.3925	0.1569	0.2003
Gross Body Equilibrium	0.7021	0.5194	0.1873	0.2224
Near Vision	-0.5712	-0.151	-0.0454	0.3242
Far Vision	0.0323	0.5234	-0.2543	0.6354
Visual Color Discrimination	0.1906	0.2755	0.1532	0.7655
Night Vision	0.2315	0.8854	0.1399	0.1816
Peripheral Vision	0.2776	0.884	0.1495	0.2006
Depth Perception	0.2939	0.6015	0.2553	0.5428
Glare Sensitivity	0.2803	0.8564	0.2153	0.1927
Hearing Sensitivity	0.182	0.4251	0.0666	0.7552
Auditory Attention	0.2715	0.4185	0.0351	0.671
Sound Localization	0.2759	0.8293	0.1379	0.2953
Speech Recognition	-0.3837	-0.2261	-0.733	0.0576
Speech Clarity	-0.3886	-0.187	-0.7753	0.0048
Performing General Physical Activities	0.7431	0.4299	0.2546	0.2533
Handling and Moving Objects	0.6539	0.329	0.4892	0.304
Controlling Machines and Processes	0.3526	0.3328	0.574	0.494
Operating Vehicles, Mechanized Devices, or Equipment	0.3189	0.8148	0.2138	0.231
Spend Time Sitting	-0.8781	-0.042	-0.2536	-0.1618
Spend Time Standing	0.8671	-0.0096	0.2932	0.1446
Spend Time Climbing Ladders, Scaffolds, or Poles	0.3979	0.4929	0.1967	-0.0186
Spend Time Walking and Running	0.849	0.1499	0.1482	0.032
Spend Time Kneeling, Crouching, Stooping, or Crawling	0.6724	0.385	0.2642	0.0253
Spend Time Keeping or Regaining Balance	0.6566	0.4646	0.2192	-0.0195
Spend Time Using Your Hands to Handle, etc.	0.3504	0.2206	0.7828	0.2405
Spend Time Bending or Twisting the Body	0.7018	0.3027	0.4914	0.1404
Spend Time Making Repetitive Motions	0.2025	0.0105	0.744	-0.0923

Columns refer to the task measures (1) General physical, (2) Visual, (3) Manual, (4) Eye-ear-hand

Table A18: Correlation between task measures

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)
(1)	1.00																							
(2)	0.00	1.00																						
(3)	0.00	0.00	1.00																					
(4)	0.00	0.00	0.00	1.00																				
(5)	0.00	0.00	0.00	0.00	1.00																			
(6)	0.00	0.00	0.00	0.00	0.00	1.00																		
(7)	0.59	0.36	-0.18	-0.16	0.19	0.31	1.00																	
(8)	0.06	0.48	0.24	0.19	0.42	-0.04	0.00	1.00																
(9)	0.27	-0.08	-0.46	0.24	-0.04	-0.38	0.00	0.00	1.00															
(10)	0.48	0.09	0.51	0.04	-0.31	-0.21	0.00	0.00	0.00	1.00														
(11)	0.22	-0.13	0.14	0.17	0.22	0.20	0.00	0.00	0.00	0.00	1.00													
(12)	-0.61	-0.12	0.39	0.38	-0.03	-0.35	-0.65	0.08	-0.10	-0.05	-0.09	1.00												
(13)	0.14	0.13	0.69	-0.14	-0.18	0.30	0.16	0.02	-0.51	0.38	0.13	0.00	1.00											
(14)	0.30	0.19	0.25	0.37	0.65	0.18	0.25	0.54	-0.02	0.06	0.33	0.00	0.00	1.00										
(15)	0.55	0.52	0.25	-0.02	0.17	0.18	0.63	0.50	-0.01	0.36	0.05	-0.37	0.35	0.40	1.00									
(16)	-0.32	0.07	0.37	0.36	0.07	-0.28	-0.47	0.38	0.12	0.07	0.21	0.62	0.00	0.17	0.00	1.00								
(17)	-0.42	-0.07	-0.04	-0.01	-0.18	-0.41	-0.57	0.08	0.29	-0.04	-0.25	0.42	-0.31	-0.30	-0.37	0.43	1.00							
(18)	-0.27	0.03	0.17	0.43	0.04	-0.28	-0.22	0.10	0.01	-0.03	0.11	0.48	-0.02	0.03	-0.11	0.37	0.00	1.00						
(19)	-0.57	-0.36	0.14	-0.19	-0.09	-0.03	-0.45	-0.37	-0.33	-0.23	-0.18	0.45	0.08	-0.34	-0.50	0.03	0.00	0.00	1.00					
(20)	-0.15	0.15	0.24	0.66	0.02	0.13	-0.19	0.22	-0.03	0.09	0.04	0.46	0.04	0.41	0.05	0.35	0.00	0.00	0.00	1.00				
(21)	0.10	0.04	0.16	0.47	0.32	-0.30	-0.04	0.27	0.30	0.06	0.29	0.34	-0.14	0.42	0.09	0.46	0.00	0.42	-0.14	0.30	1.00			
(22)	0.61	0.36	-0.09	-0.08	0.11	0.18	0.76	0.13	0.11	0.14	0.03	-0.58	0.13	0.23	0.63	-0.32	-0.40	-0.20	-0.50	-0.16	0.00	1.00		
(23)	0.17	-0.36	-0.12	0.03	0.18	0.38	0.16	-0.23	-0.01	-0.17	0.31	-0.22	0.08	0.17	0.00	-0.22	-0.43	-0.21	0.24	0.00	0.00	0.00	1.00	
(24)	-0.10	0.34	0.20	0.02	-0.08	0.15	0.12	0.13	-0.20	-0.01	0.01	0.10	0.22	0.04	0.21	0.20	-0.08	0.08	0.02	0.16	0.00	0.00	0.00	1.00

Rows and columns refer to the task measures as follows
Cognitive tasks: (1) Comprehension, (2) Creativity, (3) Logic, (4) Mental agility, (5) Info analysis, (6) Math
Interpersonal tasks: (7) External relationships, (8) Coaching, (9) Conflict, (10) Instruction, (11) Team,
Technical and managerial tasks: (12) Tech repair, (13) Tech design, (14) Info recording, (15) Resource control, (16) Responsibility,
Physical tasks: (17) Genl physical, (18) Visual, (19) Manual, (20) Eye-ear-hand
Structural characteristics tasks: (21) Consequential decisions, (22) Independent decisions, (23) Repetitive, (24) Competition

A.2 NLSY79 data and summary statistics

NLSY79 begins in 1979 with 12,686 individuals. The following criteria for employment and wage data were used to define the sample selection:

- worked between 10 and 100 hours per week
- real hourly wage between $3.60 and $250.00 in 1992 dollars. $3.60 is one-half the minimum wage in 1992. (The 1992 PCE price index was used to deflate wages.)

Table A19 lists the number of observations in the sample, gender counts and the overall median wage in all sample years. Table A20 displays the median wage by task in select sample years.

Table A19: Summary statistics

Year	Observations	Male	Female	Median wage
1982	8068	4293	3775	2.22
1983	8231	4383	3848	2.30
1984	8416	4503	3913	2.35
1985	8154	4306	3848	2.42
1986	8295	4340	3955	2.48
1987	8275	4300	3975	2.58
1988	8404	4418	3986	2.65
1989	8338	4422	3916	2.66
1990	8296	4383	3913	2.70
1991	7047	3776	3271	2.70
1992	7020	3726	3294	2.72
1993	6966	3736	3230	2.73
1994	6899	3685	3214	2.76
1996	7124	3768	3356	2.80
1998	7011	3615	3396	2.85
2000	6769	3474	3295	2.94
2002	5899	2970	2929	2.96
2004	5474	2742	2732	2.99
2006	5427	2774	2653	2.99
2008	5712	2819	2893	3.01
2010	5402	2651	2751	3.01
2012	5098	2458	2640	3.02
2014	4693	2281	2412	3.03
2016	4490	2165	2325	3.07
2018	4287	2083	2204	3.07

Table A20: Median hourly real wage (2012 dollars)

	1983	**1994**	**2006**	**2018**
Comprehension	2.48	2.97	3.38	3.33
Creativity	2.56	2.95	3.34	3.47
Logic	2.52	2.88	3.12	3.29
Mental agility	2.53	2.99	3.26	3.29
Info Analysis	2.60	3.09	3.35	3.48
Math	2.27	2.72	2.94	3.14
Relationships	2.58	3.17	3.53	3.65
Coaching	2.56	2.90	3.27	3.43
Conflictual	2.17	2.55	2.81	2.86
Instruction	2.32	2.81	3.05	3.15
Teams	2.63	3.00	3.15	3.37
Tech repair	2.44	2.78	3.05	3.11
Technology design	2.70	3.26	3.53	3.81
Info Recording	2.82	3.14	3.39	3.53
Managerial resource	2.62	3.02	3.42	3.53
Managerial responsibility	2.57	2.85	3.16	3.47
General physical	2.14	2.55	2.68	2.67
Visual	2.39	2.76	2.90	2.93
Manual	2.39	2.74	2.89	2.99
Eye-ear-hand	2.56	3.03	3.27	3.37
Consequential decisions	2.56	3.00	3.42	3.51
Independent decisions	2.43	2.89	3.45	3.49
Repetitive	2.30	2.67	2.84	2.88
Competition	2.44	2.92	3.25	3.29
NTI	2.23	2.60	2.70	2.82

A.3 Task entry rates

Tables 6 and 7 display the normalized entry rates into each task for exits from each of the routine tasks. The "raw" entry rates are calculated as follows: (i) total the number of individuals who exit an occupation intensive in routine task, (ii) the tasks in which the entering occupation is intensive each count as an entry from the exiting task, (iii) the "raw" entry shares are number of entries into the task divided by the total number of exits. Since the "raw" entry rates out of any individual task will sum to a number greater than one, the "raw" entry rates, I normalize the entry rates by dividing the entry rates out of each task by the sum of the "raw" entry rates for that task.

Panel (B) in Tables A21 and A22 present the normalized entry rates as a share of the entries into all non-routine tasks. To arrive at the entry rates in panel (B) of Tables A21 and A22, take the sum of the normalized entry rates for all tasks in the row item and divide it by one minus the sum of the normalized entry rates into the routine task. For example, for non-college individuals, 11.4% of exits from the logic task into non-routine tasks entered into one of the "other cognitive" tasks (comprehension, creativity, mental agility, information analysis): (.007 + .038 + .027 + .024)/(1-.162) = .114.

An individual is put into the college category if highest grade completed is equal to 16 or higher.

A.4 Wage regressions

The covariates in the wage regressions based on equation (1) are:

- an indicator variable that equals one if the individual resides in a standard metropolitan statistical area
- an indicator variable that equals one if the individual is married and the spouse is present
- an indicator variable for race with three categories: African-American, Hispanic, and other. The "other" category is the omitted indicator.
- five indicator variables for education using the highest grade completed: (1) less than 12th grade, (2) completed 12th grade, (3) completed 16th grade, (4) completed higher than 16th grade.
- an indicator variable that equals one if the respondent was a union member or covered by a collective bargaining agreement

Tables A23 and A24 report the estimates for α_k from equation (1) for the entire non-college and college groups, respectively. That is, the sample is not limited to only those individuals who switched out of an occupation intensive in a routine task, so the indicator variables for previous routine occupation are not included in the regression.

Table A21: Entry rates by task after exit from routine task
Non-college (1982-2018)

	Exited task			
	Logic	Math	Manual	Repetitive
(A) Entry rate as a share of all entrants				
Logic	0.028	0.016	0.036	0.009
Math	0.034	0.087	0.044	0.090
Manual	0.060	0.039	0.080	0.039
Repetitive	0.041	0.177	0.096	0.172
Total	**0.162**	**0.319**	**0.255**	**0.310**
(B) Entry rate as a share of non-routine entrants				
Non-routine cognitive	0.114	0.154	0.122	0.151
Interpersonal	0.174	0.270	0.198	0.273
Managerial	0.088	0.111	0.081	0.102
Decision-making	0.031	0.059	0.045	0.062
Non-repair tech	0.039	0.048	0.036	0.038
Subtotal	**.446**	**.642**	**.482**	**.626**
Repair	0.070	0.025	0.072	0.022
NTI	0.224	0.132	0.205	0.158
Non-routine physical				
General phys	0.106	0.141	0.103	0.119
Visual	0.089	0.020	0.063	0.030
Eye-ear-hand	0.032	0.017	0.039	0.019
Subtotal	**0.228**	**0.178**	**0.205**	**0.168**
Observations	3214	6042	5538	12026

Note: Each row of panel (A) shows the share of entries into that row's routine task when exiting an occupation intensive the column's routine task. The panel (A) shares are normalized shares of all exits from the column's routine task. Each row of panel (B) shows the share of entries into that row's task category when exiting an occupation intensive in the column's routine task. The panel (B) shares are normalized shares of all exits from the routine task that did not enter a routine task. That is, each row is a share the of all non-routine entries. The non-routine cognitive row is the sum of the entries into the comprehension, creativity, information analysis, and mental agility tasks. The interpersonal row is the sum of all interpersonal tasks. The Non-repair tech row is the sum of information recording and technology design tasks. The managerial row is the sum of the resource control and responsibility tasks. The decision-making row is the sum of the consequential and independent decision-making tasks. The competition task is omitted from the table. All of the above are calculated on the sub-sample of individuals without a college degree.

Table A22: Entry rates by task after exit from routine task
College (1982-2018)

	Exited task			
	Logic	Math	Manual	Repetitive
(A) Entry rate as a share of all entrants				
Logic	0.030	0.028	0.031	0.010
Math	0.079	0.091	0.058	0.087
Manual	0.027	0.017	0.051	0.018
Repetitive	0.033	0.094	0.075	0.125
Total	**0.169**	**0.230**	**0.215**	**0.240**
(B) Entry rate as a share of non-routine entrants				
Non-routine cognitive	0.184	0.194	0.181	0.219
Interpersonal	0.316	0.299	0.283	0.322
Managerial	0.123	0.195	0.114	0.161
Decision-making	0.070	0.090	0.091	0.097
Non-repair tech	0.185	0.111	0.185	0.064
Subtotal	**0.877**	**0.889**	**0.855**	**0.863**
Repair	0.013	0.006	0.012	0.004
NTI	0.034	0.030	0.056	0.048
Non-routine physical				
General phys	0.022	0.030	0.023	0.037
Visual	0.004	0.003	0.007	0.006
Eye-ear-hand	0.026	0.014	0.018	0.013
Subtotal	**0.053**	**0.047**	**0.048**	**0.056**
Observations	569	1881	640	2424

Note: Each row of panel (A) shows the share of entries into that row's routine task when exiting an occupation intensive the column's routine task. The panel (A) shares are normalized shares of all exits from the column's routine task. Each row of panel (B) shows the share of entries into that row's task category when exiting an occupation intensive in the column's routine task. The panel (B) shares are normalized shares of all exits from the routine task that did not enter a routine task. That is, each row is a share the of all non-routine entries. The non-routine cognitive row is the sum of the entries into the comprehension, creativity, information analysis, and mental agility tasks. The interpersonal row is the sum of all interpersonal tasks. The Non-repair tech row is the sum of information recording and technology design tasks. The managerial row is the sum of the resource control and responsibility tasks. The decision-making row is the sum of the consequential and independent decision-making tasks. The competition task is omitted from the table. All of the above are calculated on the sub-sample of individuals with a college degree.

Table A23: Wage effect from switching tasks: no-college
Dependent variable: log hourly real wage

	(1982-1993)	(1994-2004)	(2006-2018)
Comprehension	0.014	0.027*	0.016
	(0.010)	(0.016)	(0.022)
Creativity	0.030***	0.030**	0.041**
	(0.008)	(0.013)	(0.017)
Logic	0.028***	−0.010	0.013
	(0.009)	(0.017)	(0.023)
Mental agility	0.009	−0.017	0.015
	(0.012)	(0.019)	(0.025)
Info analysis	0.044***	0.038***	0.063***
	(0.009)	(0.013)	(0.020)
Mathematics	−0.032***	−0.039***	−0.027*
	(0.006)	(0.011)	(0.015)
Relationships	0.032***	0.019	0.022
	(0.012)	(0.018)	(0.024)
Coaching	0.015	−0.011	−0.023
	(0.010)	(0.013)	(0.018)
Conflictual	−0.056***	−0.054***	−0.050***
	(0.005)	(0.011)	(0.015)
Instruction	−0.049***	−0.036*	−0.046**
	(0.010)	(0.019)	(0.023)
Teams	0.021***	0.012	0.007
	(0.007)	(0.012)	(0.017)
Tech repair	−0.008	0.025*	0.014
	(0.009)	(0.015)	(0.020)
Tech design	0.067***	0.060***	0.089***
	(0.010)	(0.017)	(0.024)
Info recording	0.100***	0.016	0.048
	(0.016)	(0.021)	(0.032)
Mgr resource control	0.058***	0.035***	0.078***
	(0.007)	(0.011)	(0.016)
Mgr responsibility	0.067***	0.049***	0.092***

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	(1982-1993)	(1994-2004)	(2006-2018)
	(0.008)	(0.014)	(0.018)
General physical	-0.015^{***}	-0.051^{***}	-0.078^{***}
	(0.006)	(0.011)	(0.015)
Visual	0.028^{***}	-0.007	0.030
	(0.008)	(0.013)	(0.021)
Manual	0.019^{***}	0.023^{*}	0.020
	(0.006)	(0.012)	(0.021)
Eye-ear-hand	0.030^{***}	0.019	0.011
	(0.011)	(0.022)	(0.026)
Consequential decisions	-0.029^{**}	0.028	-0.040
	(0.012)	(0.021)	(0.030)
Independent decisions	0.003	0.000	-0.018
	(0.011)	(0.020)	(0.021)
Repetitive-exact	-0.006	-0.020^{**}	-0.015
	(0.005)	(0.009)	(0.014)
Competition	-0.007	0.035^{**}	0.045^{**}
	(0.010)	(0.015)	(0.022)
NTI	-0.019^{***}	-0.025^{**}	-0.025^{*}
	(0.005)	(0.010)	(0.014)
Observations	71718	26909	25476

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Includes individual fixed effects and time effects. Conditioned on binary variables for education level (less than high school, high school, some college), marital status, union membership, and urban residence. Standard errors are robust.

Table A24: Wage effect from switching tasks: college
Dependent variable: log hourly real wage

	(1982-1993)	(1994-2004)	(2006-2018)
Comprehension	0.061***	0.042	0.013
	(0.015)	(0.027)	(0.032)
Creativity	0.026*	0.037	0.009
	(0.015)	(0.025)	(0.024)
Logic	−0.010	−0.003	−0.018
	(0.022)	(0.030)	(0.048)
Mental agility	0.004	0.015	0.059
	(0.026)	(0.060)	(0.054)
Info analysis	0.045***	0.055*	0.065**
	(0.015)	(0.029)	(0.031)
Mathematics	−0.017	−0.005	−0.070**
	(0.012)	(0.024)	(0.033)
Relationships	0.012	−0.021	0.054
	(0.016)	(0.031)	(0.033)
Coaching	−0.060***	−0.080***	−0.061**
	(0.018)	(0.029)	(0.027)
Conflictual	−0.069***	−0.077***	−0.018
	(0.017)	(0.030)	(0.032)
Instruction	−0.002	−0.034	−0.034
	(0.021)	(0.032)	(0.031)
Teams	−0.023*	0.008	0.016
	(0.013)	(0.027)	(0.029)
Tech repair	−0.039	0.036	0.141
	(0.042)	(0.070)	(0.088)
Tech design	0.068***	0.068***	0.090***
	(0.016)	(0.026)	(0.030)
Info recording	0.059***	0.039	−0.001
	(0.020)	(0.035)	(0.039)
Mgr resource control	0.008	0.012	0.077***
	(0.011)	(0.018)	(0.019)
Mgr responsibility	0.064***	0.091**	0.097**

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	(1982-1993)	(1994-2004)	(2006-2018)
	(0.023)	(0.037)	(0.039)
General physical	-0.068^{***}	-0.093^{***}	-0.165^{***}
	(0.017)	(0.035)	(0.040)
Visual	-0.011	-0.122^{*}	-0.211^{**}
	(0.033)	(0.066)	(0.098)
Manual	0.020	-0.059	-0.037
	(0.019)	(0.041)	(0.054)
Eye-ear-hand	0.028	0.035	0.069
	(0.031)	(0.065)	(0.059)
Consequential decisions	-0.008	0.036	-0.036
	(0.032)	(0.053)	(0.053)
Independent decisions	-0.011	-0.021	-0.079^{***}
	(0.014)	(0.025)	(0.030)
Repetitive-exact	-0.047^{***}	-0.050^{**}	-0.046
	(0.013)	(0.024)	(0.030)
Competition	-0.001	0.003	0.059
	(0.024)	(0.037)	(0.043)
NTI	-0.092^{***}	-0.079^{***}	-0.070^{*}
	(0.017)	(0.031)	(0.039)
Observations	13442	7043	8507

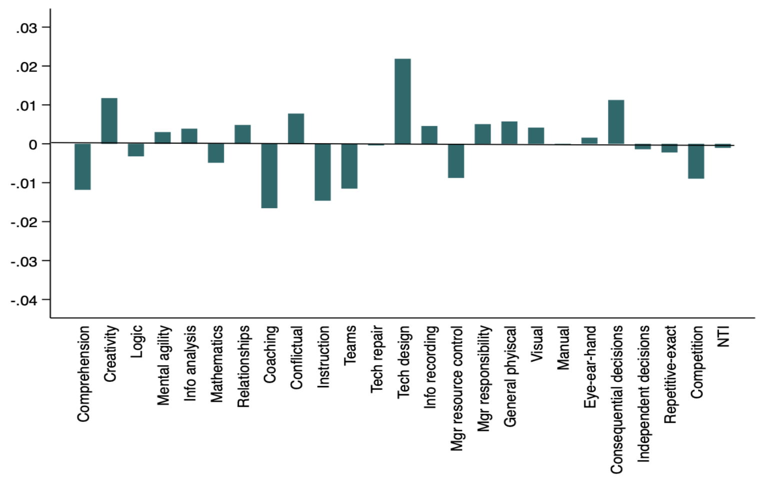
Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Includes individual fixed effects and time effects. Conditioned on binary variables for education level (college and greater than college), marital status, union membership, and urban residence. Standard errors are robust.

A.5 Comparison to Census/ACS sample

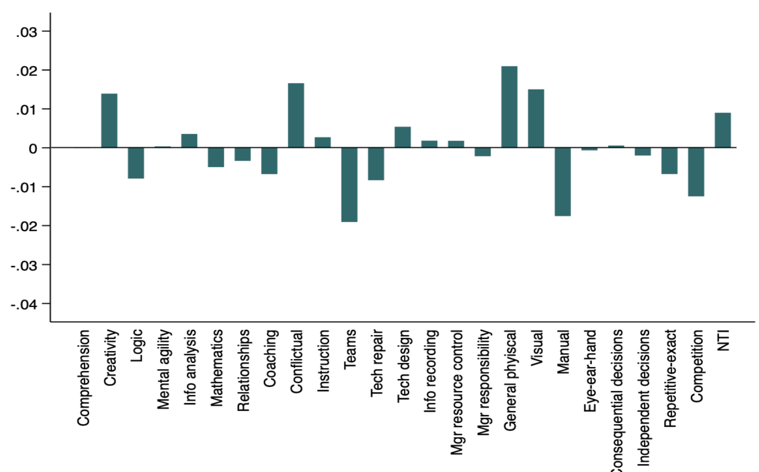
Figures A1 and A2 are from Scotese (2022) and present the change in task shares computed on the nationally representative repeated cross-sections from the 1980, 1990, and 2000 decennial censuses and the 3-year 2007 ACS.

Figure A1: Change in hours share by education: Census/ACS Males: 1980-2007

(a) College educated



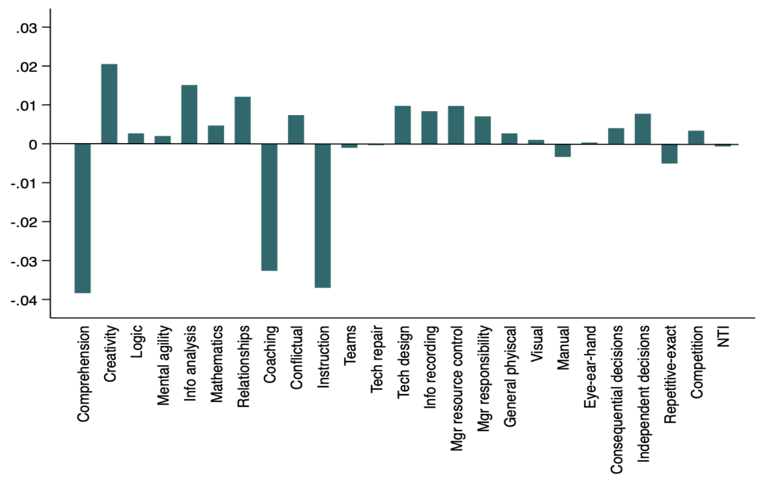
(b) Non-college educated



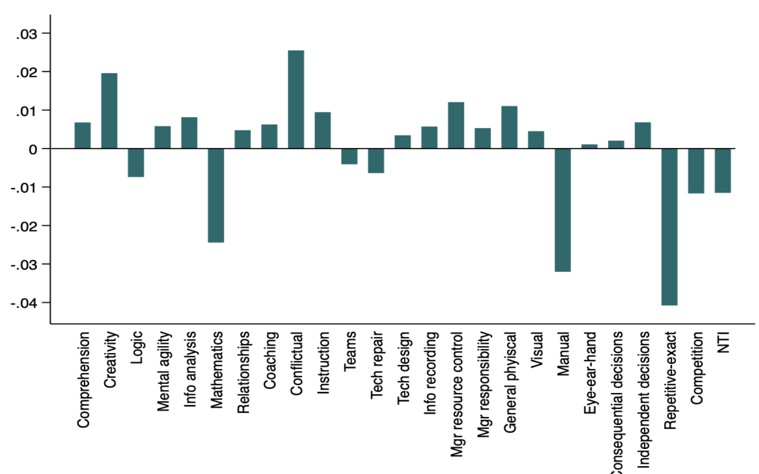
Note: The change in hour shares are calculated from the normalized hour shares. The normalized hours share for any one task in a given year is the "raw" hours share divided by the sum of the "raw" hours shares over all tasks in that year.

Figure A2: Change in hours share by education: Census/ACS Females: 1980-2007

(a) College educated



(b) Non-college educated



Note: The change in hour shares are calculated from the normalized hour shares. The normalized hours share for any one task in a given year is the "raw" hours share divided by the sum of the "raw" hours shares over all tasks in that year.