The Evolution of Work in the United States

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Abstract

Using the text from job ads, we introduce a new data set to describe the evolution of work from 1950 to 2000. We show that the transformation of the U.S. labor market away from routine cognitive and manual tasks and toward nonroutine interactive and analytic tasks has been larger than prior research has found, with a substantial fraction of total changes occurring within narrowly defined job titles. We provide narrative and systematic evidence on changes in task content within job titles and on the emergence and disappearance of individual job titles.
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1 Introduction

The dramatic technological innovations of the 20th century and the rise of international offshoring have transformed labor markets (Autor, 2015; Brynjolfsson and McAfee, 2014; Firpo, Fortin, and Lemieux, 2014). The ensuing decline in the real earnings of low-skilled workers, the widening earnings distribution, and the hollowing out of middle-skilled jobs have turned the attention of policymakers and researchers to a detailed study of the activities workers do on the job. Despite substantial recent progress, however, measuring changes in available jobs and their associated tasks remains a challenge.

One approach to measuring the changing nature of work that is widely used in the literature is to study the occupational shares of U.S. employment. Using this approach, the literature

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has identified a dramatic transformation in the U.S. labor market. For example, occupations that are intensive in routine tasks have shrunk as a share of total employment, while those that emphasize nonroutine tasks, as well as social and cognitive skills, have grown (Autor, Levy, and Murnane, 2003; Autor, Katz, and Kearney, 2005; Autor and Dorn, 2013; Deming, 2017).[1] The evidence is largely silent, however, on whether the occupations themselves have changed. Data sources that are widely used to study the labor market in the U.S. are not well suited for studying task changes within occupations over time. Meanwhile, case studies—including those of managers (National Research Council, 1999), production workers (Bartel, Ichniowski, and Shaw, 2007), and cashiers (Basker, Klimek, and Van, 2012)—document substantial transformations within individual occupations. These findings raise the question of whether these occupations are unique in experiencing changes in tasks, or whether comparable changes have occurred elsewhere in the labor market.

In this paper, we introduce a new data source to document the transformation of job tasks in the U.S. We construct our data set from the text content of approximately 7.8 million job ads appearing in three major metropolitan newspapers: the *Boston Globe,* the *New York Times*, and the *Wall Street Journal*. We then map the words contained in the job descriptions to tasks. Our main strategy uses a mapping of words into routine and nonroutine tasks introduced by Spitz-Oener (2006), but for robustness we consider alternative mappings, including one discussed by Deming and Kahn (2018). Since job ads that appear in newspapers do not contain Standard Occupational Classification (SOC) codes, we use machine-learning methods to map job titles—which we observe directly in the ads—to their corresponding SOCs.

To demonstrate that our job descriptions contain valuable information, we validate our new data set in several ways. We show that our cross-sectional measures of occupations' task and skill measures correlate with those in the widely used Dictionary of Occupational Titles (DOT) and Occupational Information Network (O*NET). We further show that our new data are able to replicate, with broad concurrence, the key between-occupation trends in tasks documented by Autor, Levy, and Murnane (2003). We perform several checks on the data to provide evidence that neither the selection of ads into newspapers nor the fact that our data originate in metropolitan areas biases our results.[2]

We next show that substantial changes in job tasks have occurred since 1950. Using our database of newspaper ads, we demonstrate that words related to nonroutine tasks have been increasing in frequency, while words related to routine tasks (especially routine manual tasks) have declined in frequency between 1950 and 2000. The frequency of words related to routine cognitive tasks has declined by more than one-half over the sample period, from 2.0 mentions

[1] Acemoglu and Autor (2011), among others, emphasize that skills and tasks refer to different work concepts: "A *task* is a unit of work activity that produces output (goods and services). In contrast, a skill is a worker's endowment of capabilities for performing various tasks" (p. 1045, emphasis in the original). We adopt these definitions of skills and tasks throughout our paper.

[2] First, we document that there are no trends over time in ad length or in the number of words that do not appear in the dictionary (Appendix C.1). Second, we show that trends in the propensity of unemployed workers to search for jobs through help wanted ads does not vary with the task content of their prior occupation (Appendix C.2). And third, we find evidence against these results being driven by the fact that most of our ads come from a selected number of large metro areas (Appendix C.3).

per 1,000 job ad words to 0.9 mentions per 1,000 words. The frequency of routine manual tasks has declined even more starkly. The frequency of words related to nonroutine analytic tasks, on the other hand, has increased from 2.9 to 5.5 mentions per 1,000 job ad words. Mentions of nonroutine interactive tasks have increased from 5.0 to 7.1 mentions per 1,000 job ad words. Since tasks have no natural unit of measurement, we consider an alternative measure of task changes that decomposes each job into its composite task shares. Both approaches lend support to these overall trends.

Our main finding is that a large share of the aggregate change in both nonroutine and routine tasks over our sample period has occurred *within* occupations, rather than through changes in occupations' employment shares. In our benchmark decompositions, 88 percent of the overall changes in task content have occurred within rather than between job titles. We emphasize that the predominance of the within-occupation margin holds regardless of how finely one defines an occupation: 4-digit SOC codes, 6-digit SOC codes, or job titles. This finding is robust to alternative mappings between words and tasks and to alternative weighting methods and normalizations. Our finding is important because it implies that the transformation of the U.S. labor market has been far more dramatic than previous research has found. It also suggests that fixing the task content of jobs at a point in time misses important features of the evolving nature of work in the U.S., and that standard data sources are unable to fully characterize this evolution.

We next provide new descriptive evidence on the evolution of individual job titles, a level of granularity unavailable in standard data sources. We confirm the finding of the National Research Council (1999) that managerial jobs in the U.S. have become much more interactive, emphasizing team building, coaching, and interactions with customers. We find similar changes for machinists and cashiers, along the lines of Bartel, Ichniowski, and Shaw (2007) and Basker, Klimek, and Van (2012). Next, we document the rise and fall of individual job titles. We find substantial turnover in the mix of job titles within 6-digit SOCs. Further, we show that newer vintage job titles mention nonroutine analytic and interactive tasks more frequently and routine tasks less frequently. Taken together, these findings illustrate the many margins of change within occupations in the SOC classification—margins we could not observe before.

Our paper builds on two literatures. The first examines the causes and consequences of the evolution of occupations. Autor, Levy, and Murnane (2003) and Acemoglu and Autor (2011) develop the hypothesis that technological advances have reduced the demand for routine tasks, which, in turn, has led to a reduction in the wages of low- and middle-skill workers. Deming (2017) documents that employment and wage growth has been confined to occupations that are intensive in both social and cognitive skills. Michaels, Rauch, and Redding (2019) studies changes in employment shares by task content over a longer time horizon. They adopt a methodology related to ours, using verbs from the DOT's occupational descriptions and their thesaurus-based meanings. With the exception of Autor, Levy, and Murnane (2003), none of this prior work directly measures within-occupation variation across different editions of the DOT.[3]

[3] Autor, Levy, and Murnane (2003) use the 1977 and 1991 versions of the DOT to compare changes in occupations'

Relative to this first literature, our paper contributes with a new measurement of time-varying characteristics of U.S. occupations over the second half of the 20th century. We introduce a new, publicly available data set at the occupation-year level. This data set includes measures of tasks, skill requirements, and other job characteristics between 1950 and 2000. Because they are built from newspaper text, our data rely on a continuously updated source and have the advantage over survey-based data of being collected in the field: Firms post these ads while they are actively searching for workers. We view this new data set as complementary to data sources currently used to study the evolution of the U.S. labor market. In particular, we extend what can be accomplished by linking across editions of the DOT or O*NET (Ross, 2017). We also make our data available at the job title-year level, which measures tasks at a finer unit of analysis than the occupational level available in other data sets.[4]

Outside the U.S. context, one paper that focuses on within-occupation changes is Spitz-Oener (2006), which uses survey data from four waves of German workers to track task changes within and between occupations, from the late 1970s to the late 1990s. A comparable analysis in the U.S. cannot be achieved with existing surveys, and hence one of the contributions of this paper is to undertake the construction and validation of a new data set that allows for such an analysis. Our newly constructed data set not only covers a substantially longer period than the data set used by Spitz-Oener (2006), but also does so continuously throughout our sample and includes a much wider set of task and skill measures. The key takeaway from our analysis, resulting from our new measurement and framework, is that the evolution of job tasks in the U.S. has been even more dramatic than previously thought.[5]

The second literature our paper builds on uses the text from online help wanted ads to study the labor market: how firms and workers match with one another, how firms differ in their job requirements, and how skill requirements have changed since the beginning of the Great Recession.[6] Using data from CareerBuilder, Marinescu and Wolthoff (2019) document substantial variation in job ads' skill requirements and stated salaries within narrowly defined occupation codes. Also using online job ads, Hershbein and Kahn (2018) and Modestino, Shoag, and Ballance (2019) argue that jobs' skill requirements have increased during the post-Great Recession period; Deming and Kahn (2018) find that firms that post ads with a high

task content and computer adoption rates. As they and Autor (2013) note, the update of the DOT was not exhaustive across occupations, potentially leading to status quo bias (Miller, Treiman, Cain, and Roose, 1980). We contrast occupational change measured in our data to what is possible using the DOT in Appendix B.3, and also conclude that the DOT's ability to measure time-varying occupational tasks is limited.

[4]Our new data set can be found at `https://occupationdata.github.io`. Even though our job measures extend back to 1940, many of the exercises in this paper rely on mapping occupation codes across vintages of the decennial census, which is difficult to do for earlier periods. Our data set has recently been applied by Anastasopoulos, Borjas, Cook, and Lachanski (2018), Cortes, Jaimovich, and Siu (2018), and Deming and Noray (2018).

[5]While an exploration of the mechanisms that drive task changes is beyond the scope of this paper, we explore one such mechanism in related work (Atalay, Phongthiengtham, Sotelo, and Tannenbaum, 2018). In that paper, we extract additional information from vacancy postings: mentions of 48 distinct information and communication technologies. Based on the patterns of task and technology mentions, we argue that technologies tend to increase the demand for worker-performed nonroutine analytic tasks relative to other tasks (though exceptions, like the Microsoft Office Suite, exist).

[6]Gentzkow, Kelly, and Taddy (2018) summarize recent applications of text analysis in economic research.

frequency of words related to social and cognitive skills have higher labor productivity and pay higher wages.[7] Our contribution relative to this second literature is to extend the analysis of job ad text to the pre-internet era, spanning a much longer horizon and a key period of occupational change. We also apply tools from natural language processing—which to our knowledge have had limited use in economics research—to extend our word-based task categories to include synonyms for task-related words and to limit our analysis' sensitivity to changes in word meaning over time.

The rest of the paper is organized as follows. Section 2 outlines the construction of our data set of occupations and their content, then compares this new data set to existing data sources. In Section 3, we document changes in occupational tasks in the aggregate and conclude that a large share has occurred within, rather than between, occupations. Section 4 provides new descriptive evidence on the changing nature of work, through a discussion of a few selected job titles. Section 5 concludes and suggests areas for future research.

2 A New Data Set of Occupational Characteristics

In this section, we discuss the construction of our structured database of occupational characteristics. The primary data sets are raw text files, purchased from ProQuest and were originally published in the *New York Times* (from 1940 to 2000), *Wall Street Journal* (from 1940 to 1998), and *Boston Globe* (from 1960 to 1983).[8] The first step in our approach is to clean and process the raw newspaper data. We then map job ad titles to Standard Occupational Classification (SOC) codes and map job ad text into task categories. Once we describe these procedures, we illustrate the performance of our approach using a set of ads from the April 10, 1960, *New York Times* and present some simple descriptive statistics from our data set. Lastly, we describe several checks we perform on the data to test for selection and time-varying measurement error.

2.1 Processing the Newspaper Text Files

The newspaper data are stored as raw text files, which ProQuest has produced using an algorithm that converts images of newspapers into text files. The raw text files ProQuest has provided allow us to isolate the subset of text that comes from advertisements, but do not allow us to directly identify job ads from other types of advertisements. Nor does the text indicate where one job ad ends and another begins. Therefore, in processing the ProQuest text files, we

[7] Our paper also relates to work by Abraham (1987). Using the Help Wanted Index, she documents that frequencies of newspaper job ad postings track reasonably well with administrative data on total labor market vacancies. A more recent paper that uses newspaper job ads is DeVaro and Gurtler (2018), which studies worker-firm matching. They document that before 1940, both job seekers and firms posted advertisements to match with one another. Since 1940, firms have been the primary party posting ads.

[8] In addition to the newspaper text files, we use a data set purchased from Economic Modeling Specialists International (EMSI); these data include the full text of the near-universe of online job ads for selected months between 2012 and 2017. As described below, we use the EMSI data to identify word synonyms and to study the geographic selection of job ads.

must (i) identify which advertisements comprise vacancy postings, (ii) discern the boundaries between vacancy postings, and (iii) identify the job title of each vacancy posting. In addition, as much as possible, we attempt to undo the spelling mistakes induced by ProQuest's imperfect transcription of the newspaper text. Appendix D.1 describes our procedure for performing (i). Appendix D.2 describes steps (ii) and (iii). Overall, our procedure allows us to transform unstructured text into a set of 8.3 million distinct job ads linking job titles to job ad text.[9]

2.2 Grouping Occupations by SOC Code

Our next step is to consolidate the information in our vacancy postings to characterize occupations and their corresponding attributes into a small number of economically meaningful categories. In the newspaper text, postings for the same occupation appear via multiple distinct job titles. For example, vacancy postings for registered nurses will be advertised using job titles that include "iv nurse," "icu nurse," or "rn coordinator." These job titles should all map to the same occupation—291141 using the SOC system.

From our list of job titles, we apply a *continuous bag of words* (CBOW) model to identify the ad's SOC code. Roughly put, this CBOW model allows us to find synonyms for words or phrases. The model is based on the idea that words or phrases are similar if they themselves appear (in text corpora) near similar words. For example, to the extent that "iv nurse," "icu nurse," and "rn coordinator" all tend to appear next to words like "patient," "care," or "blood" one would conclude that "rn" and "nurse" have similar meanings. For additional background on CBOW models and details of our implementation, see Appendix D.3. EMSI has provided us with a data set of the text from online job ads originally posted between October 2011 and March 2017. These ads contain a job title and text describing the job characteristics and requirements. We use online job postings from two of these months, January 2012 and January 2016, plus all of the text from our newspaper data to construct our CBOW model.

Our CBOW model is useful for our purposes when applied in combination with O*NET's Sample of Reported Titles and list of Alternate Titles. Once we have estimated the CBOW model, for each job title $\mathcal{N}$ in our newspaper text, we search for the job title $\mathcal{O}$ among those in the O*NET Sample of Reported Titles and list of Alternate Titles that is most similar to $\mathcal{N}$.[10] Since each of the job titles in the O*NET Sample of Reported Titles and list of Alternate Titles has an associated SOC code, we can obtain the SOC code for any job title in our newspaper text. As an example, the job title "rn coordinator"—a title from our newspaper data—is closest to the O*NET Title "Registered Nurse Supervisor," which has an associated SOC code of 291141. Based on this, we identify 291141 as the SOC code for "rn coordinator." In this manner, we retrieve these SOC codes on all of the job titles that appear in our newspaper

[9]This 8.3 million figure excludes vacancy postings for which we cannot identify the job title or that contain a substantial portion (35 percent or greater) of misspelled words. We also exclude ads with fewer than 15 words.

[10]The CBOW model associates each word and phrase with a vector, with elements in the vector describing the contexts in which the word or phrase appears. The similarity between job titles $\mathcal{O}$ and $\mathcal{N}$ equals the cosine similarity of the vectors associated with these two titles.

text.[11] This procedure yields SOC codes for 7.8 million job ads.[12]

2.3 Eliciting Job-Related Information

Within the body of our job ads, we map similar words to a common task or skill. For example, mathematical skills could appear in job ads using the words "mathematics," "math," or "quantitative." To study occupations' evolving skill requirements and task content, it is necessary to categorize these occupational characteristics into a manageable number of groups. We follow three approaches, which we explain next.[13]

Our main classification follows that of Spitz-Oener (2006), who, in her study of the changing task content of German occupations, groups survey questionnaire responses into five categories: *nonroutine analytic, nonroutine interactive, nonroutine manual, routine cognitive,* and *routine manual.*[14] In our main application of these categories, we begin with the list of words related to each of her five tasks. For each task, we augment the list with words whose meanings are similar to those in the original list, where similarity is determined by the same CBOW model introduced in Section 2.2. This is our primary classification, and we use it in each empirical exercise that follows in the paper. In addition, as a robustness check, we consider a narrower mapping between categories and words, one that only relies on Spitz-Oener's (2006) definitions as enumerated in footnote 14. Including similar words based on our CBOW model has its advantages and disadvantages. On the one hand, the CBOW model has the advantage of accounting for the possibility that employers' word choice may differ within the sample period.[15] On the other hand, there is a danger that the CBOW model will identify words as

[11] For our 1950-2000 sample period, we cannot directly evaluate the accuracy of our SOC assignment algorithm. However, the online job ad data we have procured from EMSI contain an SOC code, which allows us to assess the performance of our method to assign SOC codes in a more recent data set. To do so, we compare the results from our procedure to the SOC code available in the EMSI data. Our procedure assigns the same 4-digit SOC code 53 percent of the time and the same 6-digit SOC code 36 percent of the time. As there are 110 unique 4-digit SOC codes and 840 unique 6-digit SOC codes, these rates suggest our algorithm has a high degree of precision.

[12] We do not find an associated SOC code for certain job titles, such as "trainee" or "personnel secretary," for which the title is either uninformative (in the case of trainee) or refers to the person to whom job applications are usually sent (in the case of personnel secretary). For this reason, our main data set includes fewer than the 8.3 million ads mentioned at the end of Section 2.1.

[13] Throughout this paper, we interpret the words as accurate representations of the positions firms seek to fill. We cannot measure the extent to which firms may misrepresent or perhaps euphemize the tasks of the job to attract workers. A similar consideration, however, is also relevant for survey-based measures of tasks, where respondents may or may not accurately answer questions about their job's tasks (Autor, 2013). Our analysis is unaffected by level differences in job descriptions' accuracy, and would only be affected by trends in the representation of jobs over time.

[14] The data set used by Spitz-Oener (2006) is a questionnaire given to West German workers. Building on her mapping from survey question titles to task categories, we search for the following sets of words for each category: (1) nonroutine analytic: analyze, analyzing, design, designing, devising rule, evaluate, evaluating, interpreting rule, plan, planning, research, researching, sketch, sketching; (2) nonroutine interactive: advertise, advertising, advise, advising, buying, coordinate, coordinating, entertain, entertaining, lobby, lobbying, managing, negotiate, negotiating, organize, organizing, presentation, presentations, presenting, purchase, sell, selling, teaching; (3) nonroutine manual: accommodate, accommodating, accommodation, renovate, renovating, repair, repairing, restore, restoring, serving; (4) routine cognitive: bookkeeping, calculate, calculating, correcting, corrections, measurement, measuring; (5) routine manual: control, controlling, equip, equipment, equipping, operate, operating.

[15] For instance, even though "creative" and "innovative" largely refer to the same occupational skill, it is possible that their relative usage among potential employers may differ within the sample period. This is indeed the case: Use of the

synonymous even if they are not.

We also consider alternative and complementary task classifications for the purpose of (i) exploring the robustness of our results to our primary choice of classification; (ii) comparing our text-based measures with widely used survey-based measures; and (iii) connecting our main results to those in the literature. Our second classification draws on the groups of skills that Deming and Kahn (2018) have defined in their study of the relationship between firms' characteristics and the skill requirements in their vacancy postings.[16] Finally, with the aim of validating our data set, we map our text to O*NET's work styles, skills, knowledge requirements, and work activities (corresponding to O*NET Elements 1C, 2A and 2B, 2C, and 4A, respectively). As with our Spitz-Oener (2006)-based measures, we append synonymous words—using our CBOW model—to Deming and Kahn's (2018) and to O*NET's lists of skill-related words and phrases.

2.4 An Example from the April 10, 1960, *New York Times*

Having delineated our procedure for cleaning and extracting information from our newspaper text, we next illustrate the performance of our procedure with an example. Figure 1 presents a snippet of digitized text from a page of display ads in the April 10, 1960, *New York Times*. This text refers to multiple vacancy postings, including one for an Accountant position, a second for a Mechanical Engineer position, a third for a Methods Engineer position, and so on. Each ad describes, in varying levels of detail, the sets of tasks that workers will perform, experience requirements, and aspects of the work environment. Some but not all of the ads contain the identity of the posting firm. Some ads contain a posted salary; others do not. As Figure 1 makes clear, while the text contains a high frequency of transcription errors, due to the imperfect performance of ProQuest's optical character recognition technology, much of the information contained in the ad is preserved.

Figure 2 presents the output from our approach. First, on the basis of strings that tend to appear at the beginning and end of job ads, our algorithm successfully finds the boundary between the Accountant and Mechanical Engineer job ad, and the Transportation Advertising Supervisor ad and the Performance Engineer ad. However, some of the text from the Methods

word "innovative" has increased more quickly than "creative" over the sample period. If our classification included only one of these words, we would be mischaracterizing trends in the O*NET skill of "Thinking Creatively." The advantage of the continuous bag of words model is that it will identify "creative" and "innovative" as synonyms because they appear in similar contexts within job ads. Hence, even if employers start using "innovative" as opposed to "creative" part way through our sample, we will be able to consistently measure trends in "Thinking Creatively" throughout the entire period. A second advantage of our CBOW model is that it allows us to partially undo the transcription errors generated by ProQuest's image scanning. Our CBOW algorithm, for example, identifies "adverhslng" as synonymous with "advertising."

[16] See Table 1 of Deming and Kahn (2018) for their list of words and their associated skills. Building on their definitions, we use the following rules. (1) cognitive: analytical, cognitive, critical thinking, math, problem solving, research, statistics; (2) social: collaboration, communication, negotiation, presentation, social, teamwork; (3) character: character, energetic, detail oriented, meeting deadlines, multi-tasking, time management; (4) writing: writing; (5) customer service: client, customer, customer service, patient, sales; (6) project management: project management; (7) people management: leadership, mentoring, people management, staff, supervisory; (8) financial: accounting, budgeting, cost, finance, financial; (9) computer (general): computer, software, spreadsheets.

Figure 1: Unprocessed Ads from the April 10, 1960, *New York Times*.

TIMES ACCOUNTANTS Due to staff promotions, openings have developed in our Cost and Auditing Divisions of parent company. We are looking for men with 2 to 5 years of experience with a large public accounting firm. Good opportunities for growth. Excellent salary. Send resume to Personnel Department Johnson &Johnson. New Brunswick, New Jersey MECHANICAL ENGINEER Specialist In selection of pumps, compressors &general mechanical equipment. 4 te 6 yrs exp. with pump mfr.. engineering contractor. o or public utility, etc. o . . Good starting salary o . Ercellent conditions ark Area BOX 219, Large New England sheet metal fabricating plant manufacturing extensive line of InstItutional furniture has good opportunity for Methods Engineer with comprehensive knowledge of ope,ations and layout. Include resume and salary. requirements. X7548 TIMES u RESUMES PRINTED S3.50 lst5Goiviesfnciudiiw type. Si ch - add. 100 copIes. I Add 35c to mall ord (P1AE) Open DiSh td6 P.M. DAY The PRESS 42Wust 33 SI4E6Y.C. OX 5.3658 Major Oil Company Needs A TRANSPORTATION ADVERTISING SUPERVISOR With Specific experience in creating advertising for: truck-bus, aviation, marine or construction industries. Understanding of advertising media, creative functions, agency relationships and organization procedures. College degree with a background in advertising and sales promotion. Versatility, initiative and a good personality. Some knowledge of the, petroleum requirements and their application to the transportation industries desirable. OPPORTUNITY FOR ADVANCEMENT ? by letter only, submitting detailed resume of education, experience and salary requirements. Socony Mobil Oil Company, Inc. 150 East 42 Street, N. Y. (at Lexington) PERFORMANCE ENGINEERS Aircraft &Space Vehicle Systems Evaluation Diversified projects include the evaluation of advanced propulsion concepts for subsonic, hypersonic and space vehicles in terms of system performance capabilities. Sustained program with excellent support from services from the largest industrial computing efforts by experienced component specialists. Minimum qualifications for these positions include a M.S. degree in aeronautical engineering plus 3 related experience. UNITED AIRCRAFT CORPORATION 400 Main Street . East Hartford, Conn. Please write to Mr. W. M. Walsh RESEARCH LABORATORIES

Notes: This figure presents the digitized text, obtained from ProQuest, from a portion of page F13 of the April 10, 1960, *New York Times*.

Engr ad was erroneously appended to that of the preceding ad.

Further, our algorithm extracts task-related words: The Transportation Advertising Supervisor ad includes three mentions of nonroutine interactive tasks—"advertising," "media," and "sales"—and a single mention of a nonroutine analytic task—"creating." Of the task words in Spitz-Oener, only "advertising" appears in the raw text presented in Figure 1. The others are included on the basis of our CBOW algorithm. This algorithm identifies "media" as close to "advertising," "sales" as close to "selling," "creating" as close to "designing," and "evaluation" as close to "evaluating." Within the figure, we also highlight words corresponding to Deming and Kahn's (2018) lists of skills: "cost," "auditing," and "accounting" correspond to their Financial skill category; "engineering," "construction," and "projects" correspond to their Project Management skill; and so on.

Finally, our algorithm reasonably identifies SOC codes for each job title. It assigns the Accountant job title to the SOC code for Accountants and Auditors, the Mechanical Engineer job title to the SOC code for Mechanical Engineers, and the Performance Engineer job title to the SOC code for Other Engineering Technicians. The Transportation Advertising Supervisor job title, which we have classified in the First-Line Supervisors of Transportation Operators SOC, presents an ambiguous case: It could reasonably be classified among advertising-related or transportation-related occupations. Overall, our text processing procedure satisfactorily retrieves information on jobs' titles, their associated tasks, and their occupational codes.

2.5 Descriptive Statistics

Using the newspaper text, our algorithm from Sections 2.1, 2.2, and 2.3 results in a data set with 7.8 million vacancy postings. Table 1 lists the top occupations in our data set. The first two columns list the most common job titles and the last four columns present the the most common SOC codes.[17] Across the universe of occupations, our newspaper data represent a broad swath of Management, Business, Computer, Engineering, Life and Physical Science, Healthcare, Sales, and Administrative Support occupations, but it underrepresents Construction occupations and occupations related to the production and transportation of goods.

To systematically assess the representativeness of our newspaper data, in Appendix B.1 we compare the share of workers across occupations in the decennial census to the share of vacancies in our new data set (Ruggles, Genadek, Goeken, Grover, and Sobek, 2015). Perhaps unsurprisingly, our newspaper text underrepresents certain blue-collar occupations. Nevertheless, there are still a considerable number of ads that we can map to each 6-digit SOC code throughout our sample period, including broad coverage of blue collar occupations. In the same appendix, we establish that occupations the decennial census measures as having a large share of educated workers also tend to have newspaper ads with a large share of stated

[17] Marinescu and Wolthoff (2019) document that many job titles contain multiple words. Even though the top job titles in Table 1 are single word, most job ads—73 percent—contain multi-word job titles. To the extent that newspaper space is scarcer than space within online job ads, newspaper job titles will be shorter than the job ads within Marinescu and Wolthoff's analysis.

Figure 2: Processed Ads from the April 10, 1960, *New York Times*.

ACCOUNTANT [[132011]] Due to staff promotions, openings have developed in our Cost and Auditing Divisions of parent company. We are looking for men with 2 to 5 years of experience with a large public accounting firm. Good opportunities for growth. Excellent salary. Send resume to Personnel Department Johnson &Johnson. New Brunswick, New Jersey

MECHANICAL ENGINEER [[172141]] Specialist In selection of pumps, compressors &general mechanical equipment. 4 te 6 yrs exp. with pump mfr. engineering contractor. o or public utility, etc. o . . Good starting salary o . Ercellent conditions ark Area BOX 219, Large New England sheet metal fabricating plant manufacturing extensive line of InstItutional furniture has good opportunity for Methods Engineer with comprehensive knowledge of ope,ations and layout. Include resume and salary. requirements. X7548 TIMES u RESUMES PRINTED S3.50 lst5Goiviesfnciudiiw type. Si ch - add. 100 coples. I Add 35c to mall ord (P1AE) Open DiSh td6 P.M. DAY The PRESS 42Wust 33 SI4E6Y.C. OX 5.3658 Major Oil Company Needs A

TRANSPORTATION ADVERTISING SUPERVISOR [[531031]] With Specific experience in creating advertising for: truck-bus, aviation, marine or construction industries. Understanding of advertising media, creative functions, agency relationships and organization procedures. College degree with a background in advertising and sales promotion. Versatility, initiative and a good personality. Some knowledge of the, petroleum requirements and their application to the transportation industries desirable. OPPORTUNITY FOR ADVANCEMENT ? by letter only, submitting detailed resume of education, experience and salary requirements. Socony Mobil Oil Company, Inc. 150 East 42 Street, N. Y. (at Lexington)

PERFORMANCE ENGINEER [[173029]] Aircraft &Space Vehicle Systems Evaluation Diversified projects include the evaluation of advanced propulsion concepts for subsonic, hypersonic and space vehicles in terms of system performance capabilities. Sustained program with excellent support from services from the largest industrial computing efforts by experienced component specialists. Minimum qualifications for these positions include a M.S. degree in aeronautical engineering plus 3 related experience.
UNITED AIRCRAFT CORPORATION 400 Main Street . East Hartford, Conn. Please write to Mr. W. M. Walsh RESEARCH LABORATORIES

Notes: We identify four ads from the unprocessed text in Figure 1. The job titles that we have identified, located at the beginning of each ad, are written in bold. Using Spitz-Oener's (2006) lists of task categories, we highlight nonroutine analytic tasks: "creating" and "evaluation" refer to nonroutine analytic tasks. We place in rectangles words that refer to nonroutine interactive tasks: "advertising," "media," and "sales." We also search for nonroutine manual, routine cognitive, and routine manual tasks. There are no mentions of these tasks within these ads. Using Deming and Kahn's (2018) lists, we place in ovals words that refer to Financial skills: "accounting," "auditing," and "cost." We place in dashed trapezoids words that refer to Project Management: "construction," "projects," and "engineering." In addition, "Computing" in the Performance Engineer ad refers to Deming and Kahn's (2018) Computer skill; "sales" in the Transportation Advertising Supervisor Ad refers to the Customer Service skill; and "staff" and "personnel" in the Accountant ad refer to the People Management skill. There were no mentions of other Deming and Kahn (2018) skills in these four ads. The six-digit code in square brackets refers to the SOC code we have identified: 132011 is the code for Accountants and Auditors; 172141 is the code for Mechanical Engineers; 531031 is the code for First-Line Supervisors of Transportation and Material-Moving Machine and Vehicle Operators; and 173029 is the code for Engineering Technicians.

Table 1: Common Occupations

Job Title		6-Digit SOC Occupations		4-Digit SOC Occupations	
Description	Count	Description	Count	Description	Count
Secretary	165.0	439022: Typist	363.3	4360: Secretary	638.8
Typist	103.5	436012: Legal Secretary	266.4	4390: Other Admin.	564.1
Clerk	97.9	414012: Sales Rep.	239.2	4330: Financial Clerks	363.2
Assistant	89.4	412031: Retail Sales	234.6	1320: Accountant	344.5
Sales	86.5	132011: Accountant	217.3	4140: Sales Rep.	286.0
Salesperson	83.9	436014: Secretary	199.8	4120: Retail Sales	278.1
Bookkeeper	69.6	436011: Exec. Secretary	149.7	4340: Record Clerks	227.3
Accounting	69.5	433031: Bill Collectors	148.6	1511: Computer Sci.	202.6
Clerk Typist	68.5	434031: Credit Authorizers	145.1	1720: Engineers	199.5
Engineer	62.8	433021: Bookkeeper	138.0	1730: Drafters	178.6

Notes: This table lists the top 10 job titles (columns 1-2), the top 10 6-digit SOC codes (columns 3-4), and the top 10 4-digit SOC codes (columns 5-6) in the *Boston Globe*, *New York Times*, and *Wall Street Journal* data. Counts are given in thousands of newspaper job ads.

education requirements.[18]

Table 2 presents, for each task in Spitz-Oener's (2006) classification, the most task-intensive occupations. For each job title-year combination, we first compute the number of mentions of task h per 1,000 job ad words, $\widetilde{T}^h_{j,t}$, and the fraction of year t ads that have j as the job title, $S_{j,t}$. Then, for each of the 200 most commonly appearing job titles, we compute the average of $\widetilde{T}^h_{j,t}$ (and also $S_{j,t}$) across the years in our sample. We find that engineering jobs are among the occupations most intensive in nonroutine analytic tasks. Sales occupations mention nonroutine interactive tasks most frequently, while mechanical and electrical occupations rank highest in their intensity of nonroutine manual tasks. Clerical and production-related positions mention routine cognitive and routine manual task-related words most frequently.

2.6 Comparison to Existing Data Sets, Selection, and Time-varying Measurement Error

Thus far we have shown that our data contain valuable information about job tasks. Before our main analysis, we compare our new data set to existing data sources. We then discuss the robustness checks we perform on the data, to test for changing patterns of selection or measurement error over the sample period.

First, we compare occupation-specific measurements in our data set to those in existing data sources. In Appendix B.2, we compare occupations' O*NET importance scores—for various O*NET work styles, skill requirements, knowledge requirements, and work activities—to the frequency of words corresponding to these job attributes in our new data set. We find that cross-sectional correlations, looking across occupations, between O*NET's measures and

[18]We also consider the distribution of vacancies across occupations in our data, compared to employment shares in Boston and New York in the decennial census. Not surprisingly, our vacancy data more closely track the occupational shares in Boston and New York than the U.S. as a whole, but they track U.S. employment shares notably well.

Table 2: Top Job Titles by Spitz-Oener (2006) Task Category

Nonroutine Analytic			Nonroutine Interactive		
Design Engineer	0.0005	20.06	Sales Manager	0.0018	18.50
Mechanical Engineer	0.0010	19.28	Account Executive	0.0010	17.53
Systems Engineer	0.0004	18.81	Sales Executive	0.0006	16.92
Electrical Engineer	0.0007	17.92	Sales Representative	0.0017	15.88
Project Engineer	0.0006	16.87	Sales Engineer	0.0012	15.61
Nonroutine Manual			**Routine Cognitive**		
Mechanic	0.0014	6.58	Payroll Clerk	0.0008	15.90
Auto Mechanic	0.0006	4.97	Billing Clerk	0.0005	13.74
Electronic Technician	0.0007	4.37	Bookkeeper Full Charge	0.0015	12.09
Electrician	0.0006	4.33	Assistant Bookkeeper	0.0022	11.37
Superintendent	0.0016	3.75	Bookkeeper	0.0083	9.76
Routine Manual					
Machinist	0.0012	5.29			
Mechanic	0.0014	2.45			
Mechanical Engineer	0.0010	1.77			
Foremen	0.0016	1.64			
Design Engineer	0.0005	1.35			

Notes: This table lists the top five job titles according to the frequency with which different activity-related words are mentioned. Within each panel, the first column gives the job title; the second column gives $1/51 \cdot \sum_{t=1950}^{2000} S_{j,t}$—i.e., the average share of ads belonging to the job title; and the final column gives the average frequency of task h words among job title j's ads, per 1,000 ad words.

measures from our newspaper data fall for the most part within the 0.40 to 0.65 range. In Appendix B.3, we compare our new data set with the DOT. We show that, across occupations, tasks are positively correlated with those measured in the DOT. We then consider the DOT's usefulness for time-series analysis and argue that, while carefully constructed in the cross-section, these measures miss much of the evolution of occupational characteristics over time.

Second, in Appendix C.1, we document that there is no more than a weak, marginally significant trend in average ad length, and that there are no meaningful trends in the share of ad words that do not appear in an English dictionary. Such trends, if they were present and important in the data, would be suggestive of trends in measurement error within our sample period (due, for example, to changing typographical conventions or improvements in image quality). Based on these exercises, we do not find evidence of time-varying measurement error. We also emphasize that because we use the CBOW model, our analysis is less sensitive to changing diction over time, since word substitutions of synonyms would be measured uniformly as task words.

In Appendix C.2, we consider the possibility of trends in selection of posting vacancies in newspapers over time. While we do not observe the firm's decision directly, we are able to use the Current Population Survey to study the worker side, and the decision to search using alternative methods. Specifically, we check whether workers exhibit trends in their propensity to search using jobs ads; we also investigate whether there are differential trends by the task intensity of their prior occupation. If, for example, workers in occupations that are high in nonroutine tasks are more likely to search in newspapers over time, compared to workers in occupations low in nonroutine tasks, we would be concerned that selection is causing us to overstate the upward trend in nonroutine tasks. The analysis in Appendix C.2 shows that there are no differential trends in selection over time on the worker search side, which provides some suggestive evidence that selection into newspaper posting has been stable over our period of analysis.

There is still the possibility of geographic selection *within* occupations over time. Without an available data set to measure within-occupation tasks over the sample period, we cannot directly test for this source of bias. However, we can perform a direct test over a more recent, out-of-sample period, which we do in Appendix C.3. Using a five percent sample of ads that were posted online and collected by EMSI (totaling 7.6 million ads), we compare the task content of ads that were posted for jobs in the New York City and Boston metro areas to jobs based elsewhere. In particular, we examine whether, within occupations, the task content is systematically different in Boston and New York City compared to the rest of the U.S., and whether there have been differential trends in occupational tasks. We find that job ads in the New York City and Boston metro areas are indeed statistically different, but only slightly so; the difference amounts to at most 0.05 standard deviations of each of these task measures. We find that these differences are even smaller within occupations. Overall, geographic selection by task intensity appears to be minor when compared to the overall dispersion in task measures across all online job ads.

3 Trends in Tasks

In this section, we document trends in occupational tasks from 1950 to 2000. We show first that the labor market has experienced dramatic shifts toward nonroutine tasks and away from routine ones. Second, we show that a large part of this change reflects an evolution of occupations themselves, with a smaller fraction accounted for by shifts in employment across occupations. We emphasize that this finding holds regardless of how finely we define occupations or whether we use the Spitz-Oener or the Deming and Kahn classification. Finally, we argue that these findings, while demonstrating that the transformation of the U.S. workplace has been larger than previously thought, are entirely consistent with previous findings in the literature, and in particular with those of Autor, Levy, and Murnane (2003).

3.1 Overall Trends

Table 3 presents changes in task mentions, grouped according to the definitions introduced in Spitz-Oener (2006). In each of the five panels within this table, the first row presents the mean task frequency per 1,000 words at the beginning of the sample, in 1950. We call this $\overline{T}_{1950}$. In 1950, the economy-wide average was 2.77 mentions of nonroutine analytic tasks, 5.06 mentions of nonroutine interactive tasks, 0.91 mentions of nonroutine manual tasks, 1.89 mentions of routine cognitive tasks, and 0.97 mentions of routine manual tasks. In the remaining rows of each panel, we display changes in the task mentions. The measure in the first column of each panel, which we interpret as the aggregate task content in the economy, presents changes in task mentions across occupations. According to this measure, the frequency of nonroutine analytic tasks increased by 75 log points between 1950 and 2000. Over the same period, the frequency of nonroutine interactive tasks increased by 38 log points. Conversely, routine manual task mentions substantially declined, decreasing from 0.97 to 0.06 mentions per 1,000 job ad words. The decline of routine cognitive tasks is also considerable, going from 1.89 to 0.85 mentions per 1,000 job ad words.

These changes reflect both between-occupation and within-occupation changes in tasks. To assess the relative importance of between- versus within-occupation forces in shaping these trends, we decompose changes in the aggregate content of each task according to the following equation:

$$\overline{T}_t = \overline{T}_{1950} + \sum_j \vartheta_{j,1950} \left(\widetilde{T}_{j,t} - \widetilde{T}_{j,1950} \right) + \sum_j \left(\vartheta_{j,t} - \vartheta_{j,1950} \right) \widetilde{T}_{j,t}. \tag{1}$$

In this equation, $\widetilde{T}_{j,t}$ measures the frequency of task-related words for occupation j in year t.[19] The $\vartheta_{j,t}$ terms measure the share of workers in occupation j at time t according to the decennial census, while $\overline{T}_t$ denotes the average frequency of the task-related word at time t.[20] On the right-hand side of Equation 1, the first sum captures shifts in the overall mentions due to within-occupation changes in task-related word mentions. The second sum captures shifts in the share of workers across occupations. We use a 6-digit SOC classification to perform this decomposition separately for each of the five tasks introduced by Spitz-Oener (2006). The second and third columns of Table 3 list changes in $\overline{T}_t$ due to the within- and between-components of Equation 1. The final column gives the proportion of the overall changes in the task due to the "Within" components.

This table shows that a substantial portion of the changes in task content have occurred within rather than between 6-digit SOC occupations: 87 percent of the increase in nonroutine analytic tasks and 74 percent of the increase in nonroutine interactive tasks are due to within-occupation rather than between-occupation shifts in tasks. Similarly, all of the decline in routine cognitive tasks and 85 percent of the decline in routine manual tasks are

[19]In Table 3 and in subsequent decomposition tables, each decade t contains surrounding years to reduce the effect of sampling error: "1950" contains ads from 1950 to 1953; "1960" contains ads from 1958 to 1962; "1970" contains ads from 1968 to 1972; "1980" contains ads from 1978 to 1982; "1990" contains ads from 1988 to 1992; and "2000" contains ads from 1997 to 2000.

[20]Throughout this section, we draw from the sample of full-time workers—workers who were are between the age of 16 and 65, who work for wages, who worked at least 40 weeks in the preceding year, and who have non-imputed gender, age, occupation, and education data. We construct our own mapping between 4-digit SOC codes and Census occ1990 codes by taking the modal SOC code for each occ1990 code (drawing on a sample of all workers in the 2000 census public use sample, and the 2007 and 2013 American Community Survey for which both variables are measured). From our full-time worker sample, we compute the share of workers who work in 4-digit SOC occupation o in decennial census years; call this number $\vartheta_{o^4,t}$. Then, to compute weights for 6-digit SOC code occupations, we multiply $\vartheta_{o^4,t}$ by the fraction of year-t ads for the 6-digit SOC code (within j' s 4-digit SOC). Below, when we use j to refer to a job title, to compute $\vartheta_{j,t}$ we multiply $\vartheta_{o^4,t}$ by the fraction of year-t ads (within j's 4-digit SOC code) that correspond to job title j.

Table 3: Trends in Keyword Frequencies: 6-digit SOCs

	Total	Within	Between	Within Share	Total	Within	Between	Within Share
	A. Nonroutine Analytic				B. Nonroutine Interactive			
1950 Level	2.77				5.06			
	(0.03)				(0.07)			
1950-1960	0.59	0.31	0.28	0.53	-0.11	-0.17	0.06	1.50
	(0.06)	(0.06)	(0.01)	(0.05)	(0.07)	(0.07)	(0.02)	(0.92)
1960-1970	-0.07	-0.17	0.10	2.40	-0.44	-0.60	0.16	1.37
	(0.07)	(0.06)	(0.02)	(15.32)	(0.05)	(0.06)	(0.02)	(0.07)
1970-1980	0.96	0.67	0.29	0.70	1.12	0.84	0.28	0.75
	(0.08)	(0.07)	(0.04)	(0.03)	(0.06)	(0.07)	(0.04)	(0.04)
1980-1990	0.28	0.20	0.08	0.72	0.98	0.99	-0.00	1.01
	(0.10)	(0.10)	(0.07)	(0.27)	(0.08)	(0.12)	(0.08)	(0.09)
1990-2000	1.35	1.69	-0.34	1.25	0.79	0.66	0.13	0.84
	(0.10)	(0.18)	(0.14)	(0.11)	(0.10)	(0.17)	(0.14)	(0.19)
1950-2000	3.11	2.70	0.40	0.87	2.33	1.72	0.62	0.74
	(0.07)	(0.16)	(0.13)	(0.04)	(0.11)	(0.17)	(0.09)	(0.05)
	C. Nonroutine Manual				D. Routine Cognitive			
1950 Level	0.91				1.89			
	(0.03)				(0.03)			
1950-1960	-0.09	-0.09	0.00	1.03	-0.69	-0.63	-0.07	0.90
	(0.05)	(0.05)	(0.01)	(0.40)	(0.03)	(0.03)	(0.01)	(0.01)
1960-1970	-0.06	-0.09	0.03	1.57	-0.25	-0.32	0.07	1.29
	(0.03)	(0.03)	(0.01)	(1.70)	(0.03)	(0.03)	(0.01)	(0.05)
1970-1980	0.32	0.41	-0.09	1.29	-0.11	-0.11	-0.00	0.97
	(0.02)	(0.03)	(0.01)	(0.04)	(0.02)	(0.02)	(0.01)	(0.11)
1980-1990	-0.33	-0.37	0.04	1.14	0.03	0.01	0.02	0.30
	(0.03)	(0.03)	(0.02)	(0.06)	(0.03)	(0.03)	(0.02)	(1.99)
1990-2000	-0.01	-0.02	0.01	3.29	-0.02	-0.02	-0.00	0.98
	(0.04)	(0.04)	(0.03)	(2.95)	(0.04)	(0.04)	(0.03)	(3.20)
1950-2000	-0.16	-0.17	0.00	1.03	-1.04	-1.06	0.02	1.02
	(0.04)	(0.04)	(0.02)	(0.15)	(0.03)	(0.04)	(0.03)	(0.03)
	E. Routine Manual							
1950 Level	0.97							
	(0.03)							
1950-1960	-0.25	-0.21	-0.05	0.81				
	(0.03)	(0.04)	(0.01)	(0.05)				
1960-1970	-0.28	-0.29	0.01	1.03				
	(0.02)	(0.03)	(0.01)	(0.04)				
1970-1980	-0.03	0.12	-0.15	-3.70				
	(0.01)	(0.02)	(0.01)	(3.71)				
1980-1990	-0.27	-0.39	0.12	1.42				
	(0.01)	(0.03)	(0.02)	(0.05)				
1990-2000	-0.08	-0.01	-0.06	0.18				
	(0.01)	(0.05)	(0.05)	(0.67)				
1950-2000	-0.91	-0.78	-0.14	0.85				
	(0.03)	(0.06)	(0.05)	(0.05)				

Notes: Occupations are defined using the 6-digit SOC classification. Within each panel, we compute keyword frequencies per 1,000 ad words at the beginning of the sample (first row), decade-by-decade changes (second through sixth rows), and cumulative changes over the 50-year period (seventh row). In these averages, occupation shares for each 4-digit SOC are given by the number of full-time workers in the decennial census. Terms within parentheses give bootstrapped standard errors, based on resampling ads from our newspaper text 40 times.

due to within-occupation task shifts. Moreover, the within-occupation shifts are the primary source of task changes not only when looking over the 50-year period, but also when looking within each decade. Note that the "Within Share" need not be bounded between 0 and 1 if within-occupation and between-occupation shifts in task content move in opposite directions.[21] Summing across the five task groups, 88 percent of the overall task changes occurred within 6-digit SOC codes.[22]

The extent to which between-occupation changes are responsible for overall changes in tasks is potentially sensitive to the coarseness of occupation definitions. If occupations are coarsely defined, one would tend to estimate that between-occupation changes are relatively unimportant. To gauge the sensitivity of our results to our definition of occupation, Table 4 performs the same decomposition, now using job titles instead of 6-digit SOC codes as the occupational unit. This is the finest classification one could possibly apply when decomposing trends in keyword frequencies into between-occupation and within-occupation components. As in Table 3, there has been a substantial shift away from routine manual and nonroutine analytic tasks. Also similar to the previous decomposition, within-occupation shifts account for a large majority—83 percent for nonroutine analytic tasks and 91 percent for routine manual tasks—of the overall changes. Overall, summing across the five task groups, 88 percent of the economy-wide task changes have occurred within job titles.

In Table 5, we use Deming and Kahn's categorization of skills. Among these skills Computer, Customer Service, and Social skills have increased most starkly. For seven of the nine skills, with Financial and Problem Solving skills as the two exceptions, within-job title changes are the primary source of growth in mentions of skill-related words.

3.2 Sensitivity Analysis

In Appendix E we consider the sensitivity of the results given in Section 3.1 to different normalizations and weighting methods, to different subsamples, and to alternative mappings of words to tasks.

In our benchmark decompositions above, we use the frequency of task mentions per 1,000 job ad words as our task measure. While this measure has the advantage of being simple and easy to describe, a potential disadvantage is that different task measures are not directly comparable with one another: The fact that the frequency of nonroutine interactive tasks is 10 times greater than that of nonroutine manual tasks (6.2 nonroutine interactive mentions versus 0.6 nonroutine manual task mentions per 1,000 job ad words) does not necessarily imply

[21]The "Within Shares" reported in the final columns of Table 3 are largely consistent with Table 5 of Spitz-Oener (2006). There, Spitz-Oener (2006) calculates that nearly all of the changes in West German task content, between 1979 and 1999, occurred within rather than between occupations.

[22]We first compute the overall changes between 1950 and 2000 summing across the five task categories: $4.91 = \left|\log\left(\frac{3.11+2.77}{2.77}\right)\right| + \left|\log\left(\frac{2.33+5.06}{5.06}\right)\right| + \left|\log\left(\frac{0.91-0.17}{0.91}\right)\right| + \left|\log\left(\frac{1.89-1.04}{1.89}\right)\right| + \left|\log\left(\frac{0.97-0.91}{0.97}\right)\right|$. Second, we compute the portion of those changes that arise from the within-occupation component: $4.31 = 0.87 \cdot \left|\log\left(\frac{3.11+2.77}{2.77}\right)\right| + 0.74 \cdot \left|\log\left(\frac{2.33+5.06}{5.06}\right)\right| + 1.03 \cdot \left|\log\left(\frac{0.91-0.17}{0.91}\right)\right| + 1.02 \cdot \left|\log\left(\frac{1.89-1.04}{1.89}\right)\right| + 0.85 \cdot \left|\log\left(\frac{0.97-0.91}{0.97}\right)\right|$. Taking the ratio of the two sums yields our 88 percent figure. Below, we use this as our summary statistic as the contribution of the within-occupation margin to overall task changes.

Table 4: Trends in Keyword Frequencies: Job Titles

	Total	Within	Between	Within Share	Total	Within	Between	Within Share
	A. Nonroutine Analytic				B. Nonroutine Interactive			
1950 Level	2.86 (0.03)				5.03 (0.07)			
1950-1960	0.54 (0.07)	-0.04 (0.05)	0.58 (0.04)	-0.08 (0.11)	-0.04 (0.08)	-0.23 (0.08)	0.20 (0.05)	6.60 (27.23)
1960-1970	-0.15 (0.07)	-0.06 (0.07)	-0.09 (0.06)	0.41 (0.56)	-0.53 (0.06)	-0.57 (0.11)	0.04 (0.09)	1.07 (0.18)
1970-1980	0.67 (0.07)	0.30 (0.07)	0.37 (0.08)	0.45 (0.10)	1.08 (0.06)	0.63 (0.12)	0.44 (0.10)	0.59 (0.10)
1980-1990	0.30 (0.08)	0.38 (0.13)	-0.08 (0.12)	1.28 (0.51)	0.99 (0.09)	1.03 (0.20)	-0.04 (0.21)	1.04 (0.21)
1990-2000	1.26 (0.10)	1.58 (0.29)	-0.32 (0.28)	1.25 (0.22)	0.61 (0.10)	0.91 (0.31)	-0.30 (0.34)	1.49 (0.73)
1950-2000	2.62 (0.06)	2.16 (0.28)	0.46 (0.26)	0.83 (0.10)	2.11 (0.12)	1.77 (0.29)	0.34 (0.30)	0.84 (0.14)
	C. Nonroutine Manual				D. Routine Cognitive			
1950 Level	0.97 (0.03)				1.99 (0.03)			
1950-1960	-0.10 (0.05)	-0.15 (0.05)	0.06 (0.02)	1.56 (4.23)	-0.72 (0.03)	-0.49 (0.04)	-0.22 (0.02)	0.69 (0.04)
1960-1970	-0.07 (0.04)	-0.07 (0.03)	-0.00 (0.02)	0.96 (0.38)	-0.26 (0.03)	-0.32 (0.04)	0.06 (0.04)	1.21 (0.15)
1970-1980	0.33 (0.02)	0.30 (0.04)	0.03 (0.03)	0.92 (0.10)	-0.13 (0.02)	-0.12 (0.04)	-0.01 (0.04)	0.93 (0.35)
1980-1990	-0.34 (0.03)	-0.26 (0.05)	-0.09 (0.05)	0.75 (0.16)	0.05 (0.03)	0.14 (0.06)	-0.08 (0.05)	2.53 (6.24)
1990-2000	-0.03 (0.04)	-0.01 (0.08)	-0.02 (0.07)	0.28 (9.81)	-0.04 (0.04)	-0.14 (0.09)	0.10 (0.08)	3.41 (35.48)
1950-2000	-0.21 (0.04)	-0.19 (0.06)	-0.03 (0.05)	0.88 (0.26)	-1.10 (0.03)	-0.94 (0.07)	-0.16 (0.07)	0.86 (0.06)
	E. Routine Manual							
1950 Level	0.91 (0.04)							
1950-1960	-0.26 (0.04)	-0.20 (0.04)	-0.06 (0.02)	0.78 (0.08)				
1960-1970	-0.24 (0.02)	-0.25 (0.03)	0.02 (0.02)	1.07 (0.09)				
1970-1980	-0.02 (0.01)	0.11 (0.03)	-0.13 (0.03)	-5.88 (31.45)				
1980-1990	-0.27 (0.01)	-0.36 (0.03)	0.09 (0.03)	1.35 (0.10)				
1990-2000	-0.07 (0.01)	-0.07 (0.03)	0.00 (0.03)	1.02 (0.40)				
1950-2000	-0.85 (0.04)	-0.77 (0.04)	-0.08 (0.02)	0.91 (0.03)				

Notes: See the notes for Table 3. In comparison, we here apply an occupation classification scheme based on job titles, as opposed to 6-digit SOC codes.

Table 5: Trends in Keyword Frequencies: Deming and Kahn (2018) Task Measures

	Total	Within	Between	Within Share	Total	Within	Between	Within Share
	A. Character				B. Computer			
1950 Level	4.48				0.41			
	(0.07)				(0.01)			
1950-1960	-0.08	-0.01	-0.07	0.11	0.73	0.38	0.35	0.52
	(0.08)	(0.10)	(0.05)	(16.01)	(0.03)	(0.03)	(0.03)	(0.03)
1960-1970	0.80	0.53	0.27	0.66	0.19	0.24	-0.04	1.22
	(0.06)	(0.09)	(0.08)	(0.10)	(0.03)	(0.04)	(0.04)	(0.25)
1970-1980	1.60	1.77	-0.18	1.11	0.89	0.71	0.17	0.80
	(0.10)	(0.13)	(0.11)	(0.07)	(0.04)	(0.06)	(0.07)	(0.07)
1980-1990	0.60	0.51	0.09	0.84	1.29	1.75	-0.47	1.36
	(0.15)	(0.24)	(0.20)	(0.36)	(0.07)	(0.14)	(0.15)	(0.12)
1990-2000	-1.18	-1.26	0.08	1.07	1.37	1.11	0.26	0.81
	(0.10)	(0.26)	(0.24)	(0.20)	(0.09)	(0.17)	(0.17)	(0.12)
1950-2000	1.74	1.55	0.19	0.89	4.46	4.19	0.27	0.94
	(0.09)	(0.22)	(0.22)	(0.13)	(0.07)	(0.13)	(0.12)	(0.03)
	C. Customer Service				D. Financial			
1950 Level	2.86				2.45			
	(0.05)				(0.03)			
1950-1960	0.18	0.04	0.15	0.19	-0.26	-0.31	0.05	1.18
	(0.05)	(0.06)	(0.03)	(0.40)	(0.05)	(0.06)	(0.03)	(0.14)
1960-1970	-0.11	-0.11	-0.01	0.95	0.01	-0.27	0.28	-26.72
	(0.05)	(0.06)	(0.06)	(1.11)	(0.05)	(0.06)	(0.05)	(17.17)
1970-1980	0.82	0.82	-0.00	1.00	-0.03	-0.30	0.26	8.68
	(0.05)	(0.09)	(0.07)	(0.09)	(0.04)	(0.05)	(0.05)	(32.32)
1980-1990	1.65	1.45	0.20	0.88	0.35	0.31	0.04	0.89
	(0.07)	(0.15)	(0.13)	(0.08)	(0.04)	(0.04)	(0.05)	(0.14)
1990-2000	0.22	0.71	-0.49	3.21	0.29	0.29	0.00	0.98
	(0.08)	(0.26)	(0.26)	(2.83)	(0.05)	(0.11)	(0.12)	(0.44)
1950-2000	2.76	2.91	-0.15	1.05	0.35	-0.28	0.64	-0.80
	(0.09)	(0.27)	(0.25)	(0.09)	(0.05)	(0.12)	(0.10)	(0.42)
	E. People Management				F. Problem Solving			
1950 Level	1.78				0.97			
	(0.02)				(0.02)			
1950-1960	0.59	0.30	0.29	0.51	0.35	0.11	0.24	0.33
	(0.04)	(0.04)	(0.04)	(0.07)	(0.04)	(0.04)	(0.03)	(0.10)
1960-1970	0.61	0.57	0.04	0.94	-0.31	-0.22	-0.09	0.71
	(0.04)	(0.06)	(0.06)	(0.10)	(0.03)	(0.03)	(0.03)	(0.10)
1970-1980	0.41	-0.03	0.44	-0.07	0.12	0.07	0.05	0.62
	(0.05)	(0.07)	(0.06)	(0.18)	(0.02)	(0.04)	(0.04)	(0.29)
1980-1990	0.09	0.20	-0.11	2.29	0.19	0.11	0.08	0.58
	(0.05)	(0.15)	(0.16)	(15.09)	(0.03)	(0.06)	(0.06)	(0.30)
1990-2000	-0.61	-0.36	-0.25	0.59	0.19	0.12	0.07	0.63
	(0.07)	(0.19)	(0.22)	(0.38)	(0.04)	(0.06)	(0.06)	(0.33)
1950-2000	1.09	0.68	0.41	0.63	0.55	0.20	0.34	0.37
	(0.05)	(0.11)	(0.12)	(0.10)	(0.03)	(0.06)	(0.04)	(0.09)

Notes: Continued on the following page.

Table 5 (Continued): Trends in Keyword Frequencies: Deming and Kahn (2018) Task Measures

	Total	Within	Between	Within Share	Total	Within	Between	Within Share
	G. Project Management				H. Social			
1950 Level	2.56 (0.03)				0.29 (0.01)			
1950-1960	0.82 (0.07)	0.01 (0.06)	0.80 (0.05)	0.02 (0.07)	0.07 (0.02)	-0.02 (0.01)	0.08 (0.01)	-0.24 (0.30)
1960-1970	-0.21 (0.09)	-0.10 (0.07)	-0.11 (0.07)	0.47 (0.38)	0.03 (0.01)	0.04 (0.02)	-0.01 (0.01)	1.42 (1.14)
1970-1980	0.87 (0.10)	0.38 (0.08)	0.50 (0.09)	0.43 (0.08)	0.39 (0.01)	0.27 (0.03)	0.12 (0.03)	0.69 (0.07)
1980-1990	0.06 (0.10)	0.34 (0.12)	-0.28 (0.11)	6.16 (19.64)	0.70 (0.03)	0.64 (0.05)	0.06 (0.05)	0.91 (0.07)
1990-2000	0.75 (0.09)	1.40 (0.21)	-0.65 (0.19)	1.87 (0.28)	0.41 (0.03)	0.46 (0.12)	-0.05 (0.12)	1.13 (0.32)
1950-2000	2.28 (0.07)	2.03 (0.17)	0.25 (0.15)	0.89 (0.07)	1.59 (0.03)	1.38 (0.12)	0.21 (0.12)	0.87 (0.07)
	I. Writing							
1950 Level	0.43 (0.01)							
1950-1960	0.02 (0.01)	-0.01 (0.01)	0.02 (0.01)	-0.30 (25.19)				
1960-1970	-0.13 (0.01)	-0.15 (0.02)	0.03 (0.01)	1.22 (0.11)				
1970-1980	0.11 (0.01)	0.12 (0.03)	-0.02 (0.03)	1.15 (0.26)				
1980-1990	0.29 (0.01)	0.17 (0.04)	0.12 (0.04)	0.60 (0.13)				
1990-2000	0.10 (0.02)	0.21 (0.06)	-0.10 (0.06)	1.99 (0.69)				
1950-2000	0.39 (0.02)	0.35 (0.05)	0.05 (0.05)	0.88 (0.13)				

Notes: See the notes for Table 3. In comparison, we here apply an occupation classification scheme based on job titles, as opposed to 6-digit SOC codes.

that nonroutine interactive tasks are more "important" than nonroutine manual tasks. These differences in magnitudes could instead reflect the breadth of the task word lists. In our first robustness check we apply a set of normalizations to place task measures on a comparable scale. Specifically, for each job title and year, we normalize its task-related mentions of each individual task by the sum of all mentions across tasks. In other words, we present task content as shares. With these normalizations, as in our benchmark decompositions, we document a substantial shift away from routine tasks and toward nonroutine interactive and analytic tasks. Further, the predominant share of the overall changes in occupational characteristics occurs within rather than between job titles. These results are presented in Tables 19 and 20.

In Equation 1 we compute our ϑ weights to match the share of workers across 4-digit SOC codes. In our second robustness check, our ϑ weights instead reflect job titles' share of vacancies in our data set. The results are unchanged with this alternate weighting scheme.

Third, throughout our decompositions we have pooled display ads and classified ads, and we have pooled ads from the *Boston Globe*, *New York Times*, and *Wall Street Journal*. Ads from different regions or in different formats may differ in their task mentions (e.g., display ads tend to mention nonroutine analytic tasks more frequently). Potentially, the changes we report in Section 3.1 may reflect the changing composition across formats and newspapers. In our third check, we recompute our decompositions separately using two of the main subsamples: *New York Times* classified ads and *New York Times* display ads. While display ads tend to contain a greater frequency of nonroutine analytic and interactive tasks and classified ads contain a greater frequency of nonroutine manual and routine cognitive tasks, there has been a shift toward nonroutine analytic and interactive tasks and away from routine tasks in both sets of ads. Moreover, in both sets of ads, most of the task changes occur within job titles.

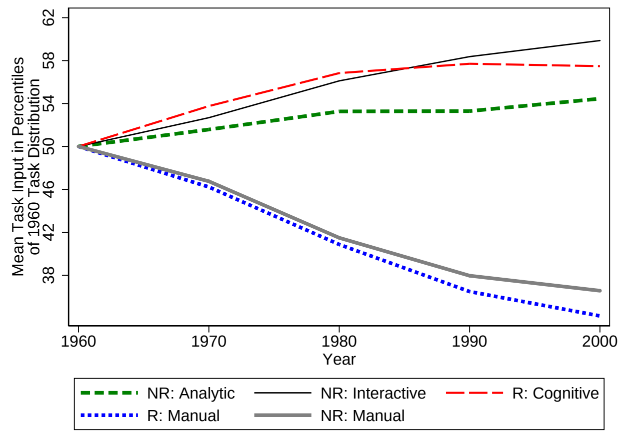
Fourth, we recompute Table 4 with Spitz-Oener's (2006) original mapping between tasks and words (i.e., excluding the words we appended from our CBOW model). Again, our conclusions on the shifts in jobs' task contents are unchanged: Instead of the 88 percent figure corresponding to Table 4, in this robustness check 96 percent of the task changes have occurred within job titles.

Fifth, in the same appendix, we investigate a potential limitation of our approach, namely that we are using job ads (which characterize newly formed jobs) to measure the entire stock of jobs existing at that point in time. Using a perpetual inventory type method, we construct a measure of the stock of each task in each occupation, then recompute the overall and within-occupation shifts in task content. As in our benchmark calculations, the within job-title margin accounts for more than four-fifths of the overall shift in jobs' task content.

3.3 Revisiting Autor, Levy, and Murnane (2003)

We close this section by relating these findings to well-established results in the literature. The decompositions we have performed on our new data set suggest that a large share of changes in the workplace have taken place within narrowly defined job groupings (either job titles or occupations). A previous literature, however, has established large changes in aggregate task demand coming from shifts in employment shares between occupations.

Figure 3: Comparison to Autor, Levy, and Murnane (2003), Figure 1



Notes: Industry-gender-education groups are ranked by their task content, as of 1960. Plotted task percentiles in the succeeding years are employment weighted averages. There are 2,440 cells, representing the combination of two genders, five education groups (<HS, HS, Some College, College, Post-graduate) and 244 industries (defined by the census ind1990 variable).

To show that these two views are consistent, we examine whether our newspaper-based task measures give a portrayal of between-occupation shifts similar to that in the preceding literature. In particular, we replicate Figure 1 of Autor, Levy, and Murnane (2003), which reports a key finding in the task literature. In this exercise, industry-gender-education groups are ranked according to the task scores of the occupations in which these groups work.[23] Then, taking the 1960 distribution of employment as the baseline year, Autor, Levy, and Murnane (2003) compute (for each of the five tasks, individually) the employment-weighted mean of the percentiles of the task distribution at different points in time from 1960 to 1998. According to Figure 1 of Autor, Levy, and Murnane (2003), nonroutine analytic and interactive task content increases by 8.7 and 12.2 percentiles, respectively, over this period. Aggregate nonroutine manual, routine cognitive, and routine manual task content decreases by 8.7, 5.6, and 0.8 percentiles. Their figure demonstrates that there has been substantial between-occupation shifts away from routine task-intensive occupations.

In Figure 3, we perform the same exercise, now using our newspaper-based nonroutine and routine task measures. Like Autor, Levy, and Murnane (2003), we compute percentiles of demographic groups' task averages based on their 1977 task content. We then compute the mean employment-weighted percentile for each year between 1960 and 2000, taking 1960 employment shares as the baseline. Nonroutine analytic, nonroutine interactive, and routine cognitive task content increases by 4.5, 9.9, and 7.5 percentiles, respectively. Moreover, the ag-

[23] These task scores come from specific questions within the DOT. According to Autor, Levy, and Murnane (2003), GED math scores are a measure of nonroutine analytic tasks; the direction, planning, and control measure corresponds to nonroutine interactive tasks; setting limits, tolerances, and standards is a measure of routine cognitive tasks; finger dexterity is a measure of routine manual tasks; and eye, hand, and foot coordination is a measure of nonroutine manual tasks.

gregate nonroutine manual and routine manual task measures decrease by 13.4 percentiles and 15.8 percentiles, respectively. Overall, the growth rates are similar when using our newspaper data or the DOT: Across the five task measures, the correlation between the two sets of growth rates equals 0.55. Pooling across the five task measures and four decades, the correlation in the two sets of decade-by-decade growth rates equals 0.46. The main difference between the data sources is that the estimated 1960s and 1970s change in routine manual tasks is -9.2 percentiles in our newspaper data versus 5.6 percentiles according to the DOT.

This exercise indicates that while our decompositions point to within-occupation shifts as an important source of changes in the economy's task content, it is also consistent with one of the foundational results of the task literature: There are substantial between-occupation shifts from routine to nonroutine tasks.

4 Narratives of the Changing Nature of Work

In the previous section, we documented two broad trends: First, a substantial share of the shifts in the tasks that workers perform has occurred within rather than across conventionally defined (6-digit SOC) occupations. Second, using a job-title-based categorization—the finest categorization possible—the contribution of within-occupation shifts is equally substantial. Complementing this analysis, in this section we zoom in, giving concrete examples of the evolution of specific job titles and their associated tasks (Section 4.1). We then discuss the emergence and disappearance of individual job titles (Section 4.2). We intentionally choose a mix of white- and blue-collar jobs to highlight the possible uses of the data and to provide a portrait of the changing nature of work.

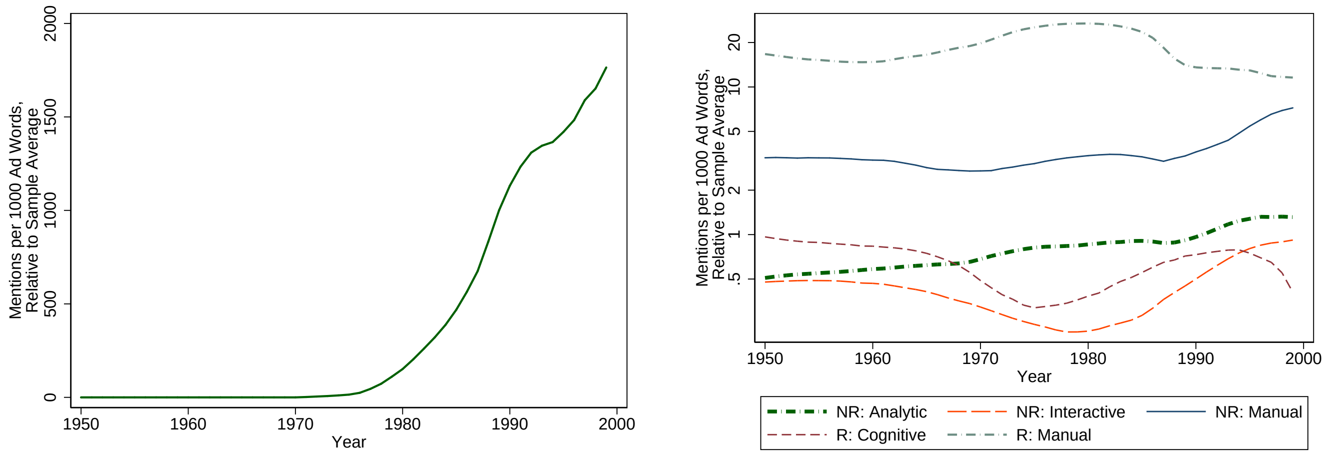
4.1 Narratives of Task Changes within Jobs

This section discusses four vignettes, showing that our new data source supports the findings of prior case studies. We depict within-job-title task shifts by comparing individual job titles at different points of time.

Our first vignette is motivated by Bartel, Ichniowski, and Shaw's (2007) study of the effect of Computer Numerical Control (CNC) technologies in steel valve manufacturers. According to Bartel, Ichniowski, and Shaw (2007), the introduction of CNC technologies led to a reduction in the demand for worker-performed routine manual tasks. In the left panel of Figure 4, we first plot the frequency of mentions of CNC technologies in Machinist job ads.[24] To facilitate comparability across job title characteristics, the plots in this subsection divide each task frequency by the average in our data set. CNC technologies were rarely, if ever, mentioned up to 1980, then mentioned 0.8 times per 1,000 job ad words in the 1980s, and 1.7 times per 1,000 job ad words in the 1990s. These frequencies are 604 and 1,351 times the sample average frequency of CNC technologies. In the right panel, we plot the prevalence of task mentions for Machinist workers. Mentions of routine manual tasks were roughly constant for the first

[24] We search for one of the following four strings: "cnc lath*," "cnc mach*," "cnc mill*," or "cnc prog*."

Figure 4: Machinist CNC and Task Measures



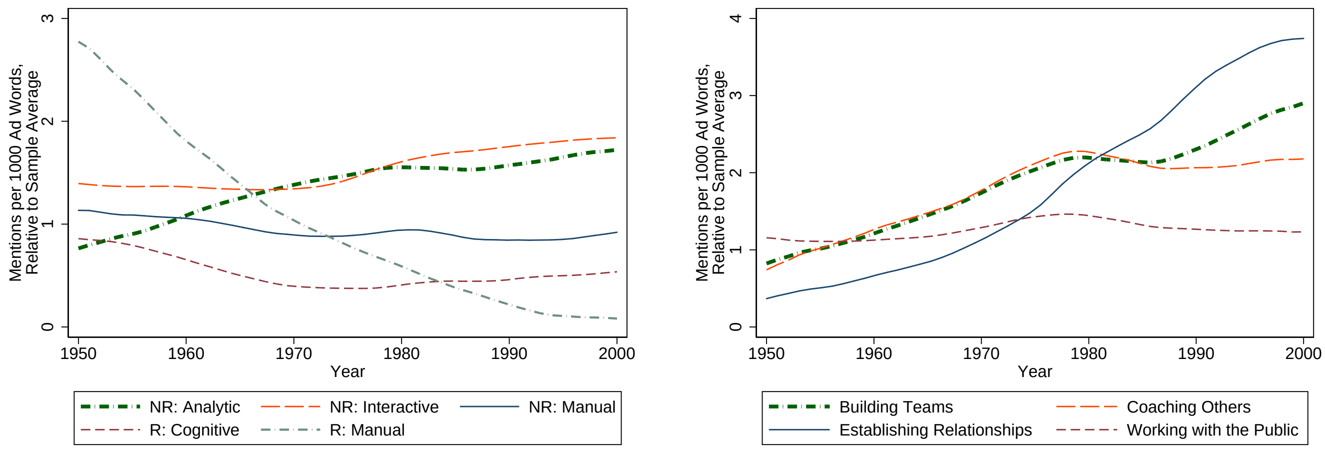
Notes: The left panel presents the frequency of mentions of Computer Numerical Control in Machinist job ads. The right panel presents the frequency of mentions of Spitz-Oener (2006) tasks among Machinist job ads. In both panels, measures are divided by the average frequency, averaging over all job titles and all years. Both panels apply a local polynomial smoother, using a bandwidth of 4 years. The right panel is plotted on a log scale.

few decades of our sample, then fell between the 1980s and 1990s from 5.5 mentions (20 times the sample average) to 3.4 mentions (12 times the sample average) per 1,000 job ad words. On the other hand, nonroutine manual and nonroutine analytic tasks increased in importance beginning in the 1980s: The frequency of nonroutine analytic tasks nearly doubled between the 1980s and 1990s, from 3.8 mentions to 6.6 mentions per 1,000 job ad words. In sum, coincident with the diffusion of CNC technologies, Machinist jobs shifted away from routine manual tasks toward nonroutine tasks.

The left panel of Figure 5 explores changes in the task content of ads with Manager as the job title. Between 1950 and 2000, the frequency of words related to nonroutine interactive tasks in managerial occupations increased modestly. This trend reflects a small increase in the number of words related to selling and a large increase in words the National Research Council (1999) has emphasized in their characterization of the changing nature of managerial work. Summarizing the contemporaneous literature, the National Research Council (1999) writes that trends in managerial work involve "the growing importance of skills in dealing with organizations and people external to the firm, ... the requirement that [managers] 'coach'... and facilitate relations between workers" (pp. 137-138).

Motivated by this characterization, we plot, in the right panel of Figure 5, trends in the mentions of four O*NET work activities: Working with the Public (O*NET Element 4.A.4.a.3), Establishing and Maintaining Relationships (4.A.4.a.4), Building Teams (4.A.4.b.2), and Coaching (4.A.4.b.5). Between the early 1950s and late 1990s, mentions of these four work activities respectively increased by 9 log points (from 9.8 to 10.7 mentions per 1,000 words of Working with the Public), 241 log points (from 0.27 to 3.01 mentions per 1,000 words of Establishing

Figure 5: Manager Task Measures



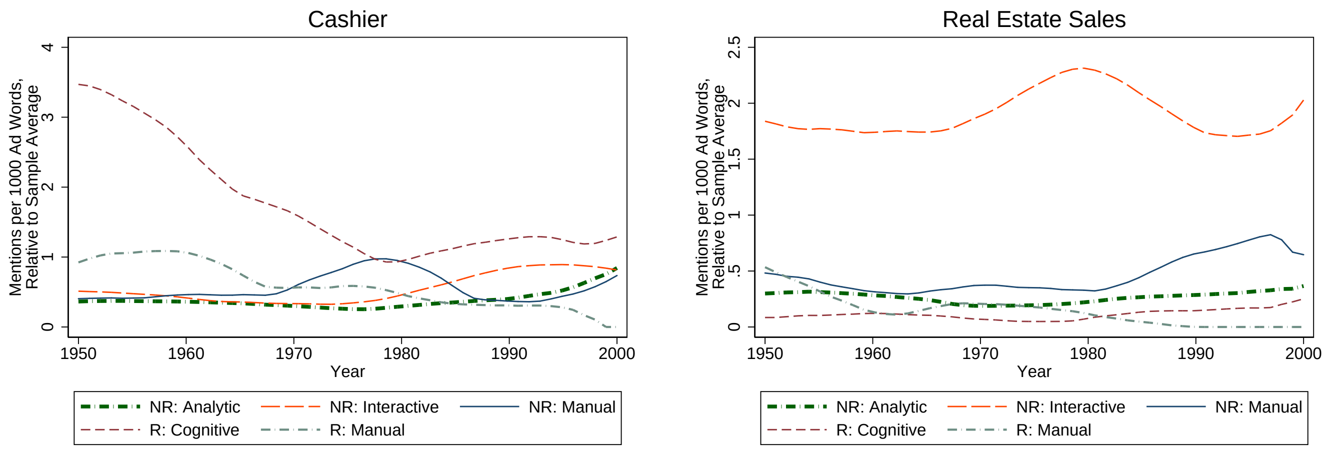
Notes: The left panel presents the frequency of mentions of Spitz-Oener (2006) tasks among ads carrying the Manager job title. The right panel presents the frequency of mentions of different O*NET Activity measures for Manager jobs. In both panels, measures are divided by the average frequency, averaging over all job titles and all years. Both panels apply a local polynomial smoother, using a bandwidth of 4 years.

and Maintaining Relationships), 137 log points (from 1.00 to 3.95 mentions per 1,000 ad words of Building Teams), and 119 log points (from 0.56 to 1.86 mentions per 1,000 ad words of Coaching). In sum, while tasks associated with building and maintaining interpersonal relationships have always been central to managerial occupations, the importance of such tasks has escalated since 1950.

Our third vignette explores changes in the task content of Cashier jobs. Over the second half of the 20th century, organizational and technological shifts altered the environment in which Cashiers work. In their study of the retail sector, Basker, Klimek, and Van (2012) chronicle an increase in the prevalence of chains, of general merchandise formats, and of establishment size. These increases in retailer size and scope complemented new technologies—bar-code scanners and electronic data interchanges—that reduced the demand for worker-performed routine cognitive tasks. The left panel of Figure 6 confirms this narrative: The frequency of routine cognitive tasks in Cashier jobs decreased from 4.3 mentions per 1,000 words in the 1950s (3.4 times the average across all ads and years) to 1.4 mentions per 1,000 words (1.1 times the sample average) in the 1990s. Conversely, the frequency of nonroutine interactive tasks nearly doubled over the sample period.

Our final example discusses a job title for which the task composition is relatively constant: Real Estate Sales. Over the five decades of the sample, the frequency of nonroutine interactive words—the task most central to Real Estate Sales jobs—exhibits no clear trend, increasing from 11.2 mentions per 1,000 job ad words in the 1950s to 13.2 mentions in the 1970s, before decreasing to 11.1 mentions in the 1990s. While it is inherently difficult to find prior research that narrates stagnation in an occupation group, we note that Hendel, Nevo, and Ortalo-

Figure 6: Cashier and Real Estate Sales Task Measures



Notes: In both panels, measures are divided by the average frequency, averaging over all job titles and all years. Both panels apply a local polynomial smoother, using a bandwidth of 4 years.

Magne (2009) recently described the job of a Real Estate Agent as someone who gives "the homeowner access to a number of services. The National Association of Realtors (NAR) argues that realtors provide valuable help with setting the listing price, preparing the house, checking potential buyers' qualifications, showing the house, bargaining the terms of a deal, and handling the paperwork. Another advantage of working with a realtor is access to the MLS [Multiple Listing Service]" (p. 1881). This job description mirrors the 1965 Dictionary of Occupational Titles' definition of a Real Estate Agent as someone who "accompanies prospects to property sites, quotes purchase price, describes features, and discusses conditions of sale or terms of lease. Draws up real estate contracts." Moreover, the Multiple Listing Service mentioned in Hendel, Nevo, and Ortalo-Magne's (2009) quote dates to the late 19th century.

To close this section, Table 6 presents a second, complementary illustration of the ways in which job titles have changed over time. We begin by computing the decade-by-decade average task content of each of the job titles discussed in Figures 4 through 6. For instance, in the 1950s, we compute that Manager jobs contained 4.2 mentions (per 1,000 words) of nonroutine analytic tasks, 8.6 mentions of nonroutine interactive tasks, 1.0 mentions of nonroutine manual tasks, and 0.7 mentions each of routine cognitive tasks and routine manual tasks. For this decade-by-job-title combination, we search for the job title whose task content, averaged over the entire half-century sample period, is closest to this five-dimensional vector.[25] Managerial jobs

[25]The candidate similar job titles are the 200 most frequently mentioned job titles. We apply a Euclidean distance metric. The distance between job title i in decade d and job title j in the 1950-2000 sample is

$$\sum_{h \in \{\text{Spitz-Oener Tasks}\}} \frac{1}{\left(\overline{T}^h\right)^2} \left(\widetilde{T}^h_{i,d} - \widetilde{T}^h_j\right)^2 .$$

In this expression, $\overline{T}^h$ equals the average frequency (in mentions per 1,000 job ad words) of task h across all of the in the 1950s closely mirrored—according to this five-dimensional representation—Production Manager jobs. Averaging over all ads in our sample period, ads with Production Manager as the job title contained 5.4 mentions of nonroutine analytic tasks, 8.3 mentions of nonroutine interactive tasks, 0.4 mentions of nonroutine manual tasks, 0.4 mentions of routine cognitive tasks, and 0.9 mentions of routine manual tasks. Over time, the nonroutine analytic and interactive task content of "Manager" jobs increased. Correspondingly, we find that 1960s Manager job ads were similar to Supervisor ads, while 1970s Manager ads were similar to the 1950-2000 average of Manager ads. By the end of the sample, Manager job ads more closely resembled ads for Coordinators.

The remaining three panels of Table 6 characterize the evolution of Machinist, Cashier, and Real Estate Sales job ads. Machinist job ads only meaningfully shifted between the 1980s and 1990s. In the last decade of our sample, Machinist ads began to resemble 1950-2000 Electrician job ads. Cashier job ads from the 1950s and 1960s contained similar task combinations to Office Assistant and Cashier ads. By the 1990s, Cashier job ads more closely resembled ads for Accountants.[26]

4.2 Emerging and Disappearing Job Titles

An exceptional feature of our data set is its ability to characterize the emergence and disappearance of job titles over the second half of the 20th century.[27] In exploring the evolution of work in the U.S., a natural question is whether new job titles differ in their content from older job titles. To the extent that shifts in job-title mix occur within conventionally defined occupation codes, existing data sets will understate variation in jobs' task content. In this section, therefore, we explore shifts in the mix of job titles present over our sample period, within 6-digit SOCs.

Figure 7 provides four illustrative examples of job-title turnover within 6-digit SOCs. These examples draw on blue-collar, low-skilled white-collar, and high-skilled white-collar occupations. In the top left panel, we plot two job titles within the Printing Press Operator SOC occupation (where the SOC code is 515112). Over the sample period, the share of ads corresponding to the Pressman job title declined from 0.23 percent (in the 1950s) to 0.04 percent (in the 1990s). The prevalence of the Offset Stripper job title increased over the first few decades of the sample, peaking around 1980.[28] Moreover, these job titles were not only placed at dif-

ads in our data set, $\widetilde{T}^h_{i,d}$ equals the frequency of task h in ads in decade d and job title i, and $\widetilde{T}^h_j$ equals the frequency of task h in ads in job title j. Dividing by $\left(\overline{T}^h\right)^2$ places all of the tasks on a comparable scale.

[26]In Appendix F, Table 21 presents this same exercise, this time measuring task content as shares. We show that our selected job titles display equally remarkable transitions in this task space, even though the nearest job titles are not identical to those in Table 6.

[27]Lin (2011) compares vintages of the DOT and the U.S. Census Classified Indexes to classify new job titles, as they appear over long horizons. Relative to Lin (2011), we are able to characterize the task and skill content of new job titles. Beyond identifying emerging job titles, we are also able to identify disappearing jobs, both of them at higher frequencies than Lin's approach allows.

[28]Version 4.0 of O*NET contains a separate 8-digit SOC code, 515022.06, associated with Strippers. According to this version of O*NET, Strippers are workers who "Cut and arrange film into flats (layout sheets resembling a

Table 6: Near Job Titles

	Frequencies	Similar Job Title	Frequencies of Similar Job Title
Panel A: Manager			
1950-1959	(4.19, 8.58, 0.70, 1.05, 0.74)	Production Manager	(5.43, 8.29, 0.44, 0.36, 0.87)
1960-1969	(5.94, 8.42, 0.61, 0.70, 0.40)	Supervisor	(4.91, 6.63, 0.81, 1.12, 0.37)
1970-1979	(7.08, 8.89, 0.54, 0.44, 0.22)	Manager	(6.95, 10.00, 0.57, 0.64, 0.22)
1980-1989	(7.29, 10.64, 0.57, 0.59, 0.12)	Coordinator	(7.70, 10.16, 0.61, 0.88, 0.05)
1990-2000	(8.10, 11.46, 0.53, 0.64, 0.03)	Coordinator	(7.70, 10.16, 0.61, 0.88, 0.05)
Panel B: Machinist			
1950-1959	(2.64, 3.12, 2.10, 1.14, 4.36)	Machinist	(3.23, 2.52, 2.00, 0.90, 5.29)
1960-1969	(2.87, 2.63, 1.77, 1.07, 4.78)	Machinist	(3.23, 2.52, 2.00, 0.90, 5.29)
1970-1979	(4.00, 1.36, 1.87, 0.40, 7.44)	Machinist	(3.23, 2.52, 2.00, 0.90, 5.29)
1980-1989	(3.78, 1.95, 2.10, 0.57, 5.53)	Machinist	(3.23, 2.52, 2.00, 0.90, 5.29)
1990-2000	(6.61, 5.40, 3.78, 1.22, 3.45)	Electrician	(4.29, 2.63, 4.33, 0.43, 0.76)
Panel C: Cashier			
1950-1959	(1.84, 3.09, 0.25, 4.33, 0.31)	Office Assistant	(2.52, 4.23, 0.18, 4.70, 0.29)
1960-1969	(1.55, 2.22, 0.31, 2.26, 0.19)	Cashier	(1.75, 3.14, 0.33, 2.68, 0.20)
1970-1979	(1.16, 1.94, 0.61, 1.50, 0.18)	Computer Operator	(2.37, 2.01, 0.62, 1.46, 0.19)
1980-1989	(1.72, 4.13, 0.32, 1.58, 0.07)	Secretary Assistant	(2.21, 4.63, 0.17, 1.62, 0.07)
1990-2000	(2.95, 5.58, 0.26, 1.40, 0.10)	Accountant	(2.99, 4.04, 0.27, 1.50, 0.09)
Panel D: Real Estate Sales			
1950-1959	(1.53, 11.23, 0.28, 0.11, 0.11)	Real Estate Sales	(1.27, 12.25, 0.28, 0.15, 0.04)
1960-1969	(1.17, 11.14, 0.20, 0.18, 0.05)	Real Estate Sales	(1.27, 12.25, 0.28, 0.15, 0.04)
1970-1979	(0.90, 13.15, 0.20, 0.06, 0.05)	Real Estate Sales	(1.27, 12.25, 0.28, 0.15, 0.04)
1980-1989	(1.24, 13.35, 0.20, 0.19, 0.01)	Real Estate Sales	(1.27, 12.25, 0.28, 0.15, 0.04)
1990-2000	(1.66, 11.09, 0.62, 0.22, 0.00)	Furniture Salesperson	(2.65, 9.88, 0.48, 0.31, 0.14)

Notes: The first column gives the five task measures of the job title-decade combination. The five coordinates are: nonroutine analytic, nonroutine interactive, nonroutine manual, routine cognitive, and routine manual. The second column gives the job title—among the 200 most frequently mentioned job titles— that has a task mix (averaged over the whole sample period) that is most similar. The final column gives the task mix for this similar job title.

ferent points in time, but also correspond to jobs of different task intensities. The frequency of routine manual tasks is five times higher (0.50 mentions per 1,000 job ad words) in Pressman job ads than in Offset Stripper jobs (0.09 mentions per 1,000 job ad words).

In the top right panel, we plot the frequency of Data Processing and Teletype Operator job titles, both which map to the 439021 SOC code. The latter job title comprised 0.05 percent of the job titles in our data set in the 1950s.[29] Partially as a result of the introduction of the fax machine, low-cost personal computers, and other, newer forms of information and communication technologies, Teletype Operator jobs have essentially disappeared by the 1980s. Within the same 6-digit SOC code, the Data Processing job title emerged in the 1960s. This job title's frequency increased in the 1960s and 1970s, peaking at around 0.09 percent in the

film negative of text in its final form) which are used to make plates. Prepare separate flats for each color." The introduction of digital prepress technologies has largely replaced the tasks performed by Offset Strippers.

[29] A teletype machine is "a printing device resembling a typewriter that is used to send and receive telephonic signals—formerly a U.S. registered trademark." Merriam-Webster Dictionary (2019)

early-to-middle 1980s, then declining over the remainder of the sample period. As with job ads corresponding to the Printing Press Operator occupation code, the older vintage Teletype Operator job ads mention routine tasks more frequently compared to the newer vintage Data Processing job ads.

Our third set of job titles relates to Secretarial and Administrative Assistant occupations. With the introduction of word processing equipment and software, job titles specifically relating to typing have declined in frequency over the sample period. In their place, job titles denoting interaction with visitors or clients have increased in frequency. While both Assistant Typist and Secretary Receptionist jobs are heavily centered on routine cognitive tasks, Secretary Receptionist jobs contain a greater frequency of nonroutine interactive tasks and fewer routine cognitive tasks.

Our final example compares two occupations that fall within the Accountants and Auditors SOC occupation code: Auditor and Staff Accountant. Between the 1950s and 1990s, the share of ads referring to Staff Accountant positions increased sixfold, from 0.01 percent to 0.06 percent. Over the same period, the share of Auditor ads fell from 0.33 percent to 0.09 percent. While both Staff Accountants and Auditors work with firms' financial statements, Auditors' work centers more on verification rather than preparation. Moreover, these differences are reflected in our Spitz-Oener-based task measures. Averaging over the ads within our newspaper text, Auditor positions include 3.3 mentions of nonroutine analytic tasks per 1,000 job ad words, which is half of that for Staff Accountant jobs.

The key takeaway from this analysis is that even within 6-digit SOC codes, there has been a substantial transformation in the composition of ads' job titles. This transformation holds more broadly: Of the job titles that were the most common within their 6-digit SOC in the 1950s, nearly 40 percent had completely disappeared by the 1990s.[30] Similarly, of the job titles that were the most common within their 6-digit SOC in the 1990s, more than 45 percent were not in existence in the 1950s.[31]

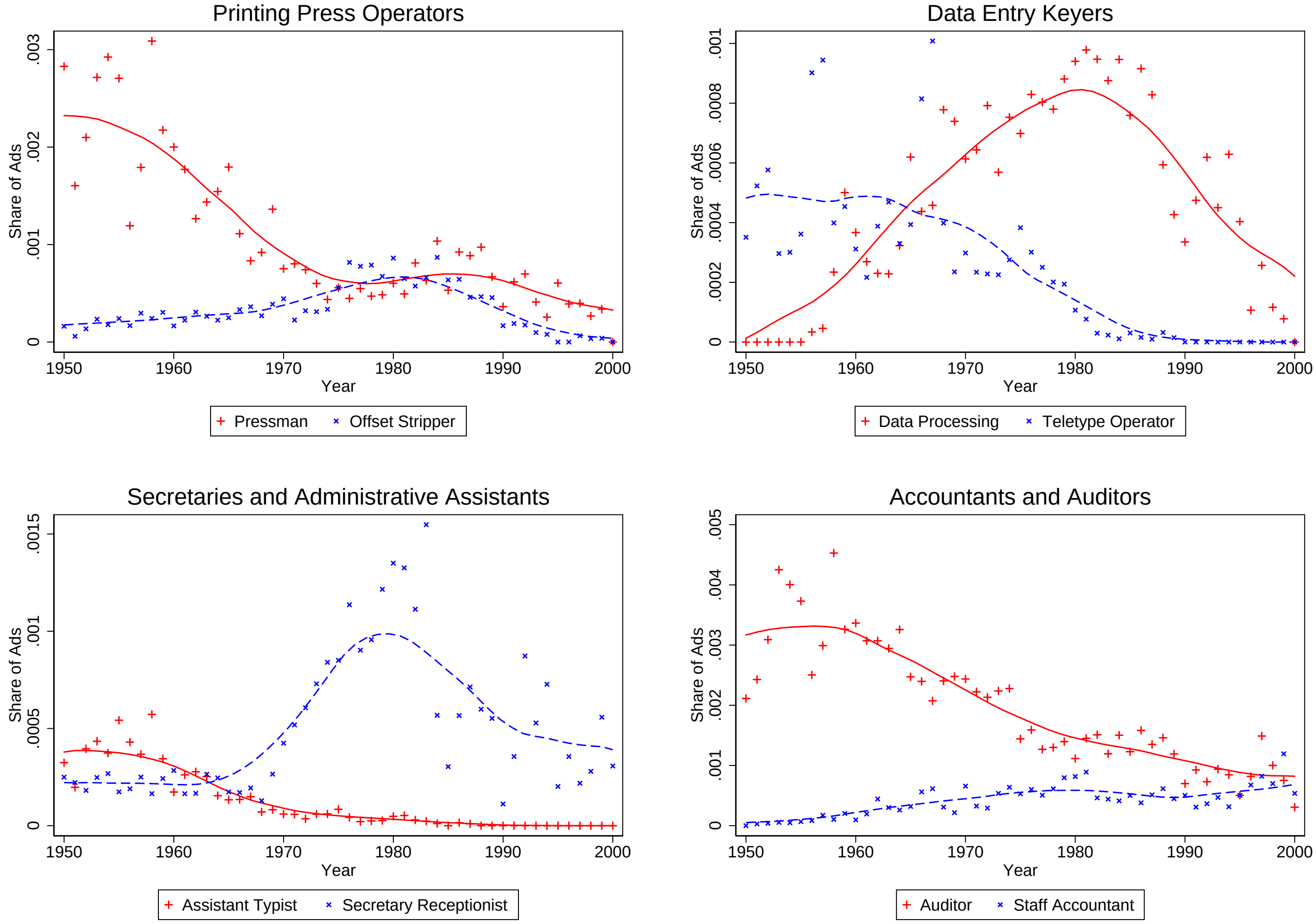
A second takeaway from these vignettes is that compositional changes in job titles are not merely cosmetic, but instead represent real changes in occupational tasks. In particular, ads corresponding to newer vintage job titles contain a greater share of nonroutine tasks and a lesser share of routine tasks.

We next explore the extent to which this second takeaway is a more systematic feature of occupational change. We first define v_j^p, *vintages* of job title *j*, as the p^{th} quantile of the distribution of years in which the job title appears in our data; in computing these quantiles for each job title, we weight according to the job title's share of ads (S_{jt}) in each year. For p close to 0, v_j^p compares different job titles based on when they first emerged in our data

[30] Linotype Operators, Nurse Governess, and Office Boy were the most common job titles within their 6-digit SOCs—515111, 311011, and 35021, respectively—in the 1950s. None of these job titles were present in any job ads in the 1990s. Among the set of disappearing job titles, these three were the most common job titles in the 1950s (as a share of all 1950s job ads).

[31] Nurse Practitioners, Medical Billers, and Telemarketers were the most common job titles within their SOC codes—291171, 292071, and 419041, respectively—in the 1990s. There were no ads corresponding to these job titles in the 1950s.

Figure 7: Job Titles' Vacancy Shares



Notes: Within each panel, we plot the raw share (in a "+" or "×") and smoothed frequency of two job titles within the same 6-digit SOC. In the four panels, we plot job titles from Printing Press Operators (SOC 515112), Data Entry Keyers (SOC 439021), Secretaries and Administrative Assistants (SOC 436014), and Accountants and Auditors (SOC 132011). Within each panel, we apply a local polynomial smoother, with a bandwidth of 4 years.

set. In contrast, v_j^p for p close to 1 compares job titles based on their disappearance from our data set. For instance, while Secretary Receptionist and Offset Stripper were both increasing in frequency between the 1950s and the 1980s, the Offset Stripper job title disappeared before Secretary Receptionist jobs. Correspondingly, $v_j^{0.05} = 1955$ for both job titles. But $v_j^{0.95} = 1989$ for Offset Stripper jobs, lower than the value for Secretary Receptionist jobs, 1997. On the other hand, since Offset Stripper jobs both emerged and disappeared before Staff Accountant jobs, v_j^p is greater for j=Staff Accountant than for j=Offset Stripper for both $p = 0.05$ and $p = 0.95$.

With these definitions in hand, we regress our task measures against our job-title vintage measures:

$$task_j^h = \beta_o + \beta_1 v_j^p + \varepsilon_{j,h}. \tag{2}$$

In Equation 2, $task_j^h$ measures the average number of mentions of task h per 1,000 job ad words in job title j's ads over the sample period, and β_o are SOC fixed effects. Table 7 reports the results of this regression. New job titles are associated with a greater frequency of nonroutine analytic and interactive tasks and a lower frequency of routine cognitive and routine manual tasks.[32] These patterns hold both within and across occupations (Panels A, C, and E versus Panels B, D, and F), and for our three job-title vintage measures (Panels A and B versus Panels C and D versus Panels E and F). In the final column of Table 7, we demonstrate that ads with newer vintage job titles contain a greater frequency of computer-related words.[33]

The changing composition of job titles also illustrates the different phases of the digital revolution. In Figure 8, we plot four job titles that refer to different aspects of the development of information and communication technologies. Job ads for Software Engineers first appeared around 1970, became increasingly common in the 1970s, and had no clear increase thereafter. Appearing in the 1970s and 1980s, Developer and Database Administrator jobs grew rapidly in the 1990s. Finally, mirroring the diffusion of network technologies in the 1980s and 1990s, Network Engineer positions only emerged in the late 1980s.[34] The rapid diffusion of new job titles in computer occupations accords with Deming and Noray's (2018) characterization of 1983-92 as a period of transformation within STEM occupations.[35]

[32] Using the coefficient estimates from Panel D, a one-decade increase in the entry vintage is associated with a 0.12 standard deviation reduction in mentions (per 1,000 job ad words) of routine cognitive tasks, a 0.28 standard deviation reduction in the frequency of routine manual tasks, and a 0.17 standard deviation increase in mentions of Deming and Kahn's computer skills.

[33] Appendix F replicates this exercise with job title-year pairs as the unit of observation, and with year fixed effects included in our regression specification. The directional results are for the most part unchanged, though with smaller magnitudes than in Table 7. A reason for these differences is that the specification we explore in Appendix F requires that the job titles being compared be observed within the same year, thus removing all information coming from non-overlapping job titles.

[34] Unplotted, and appearing even more recently than Network Engineer jobs, are job titles specifically referring to the world wide web. A majority of the ads corresponding to Web Developer, Web Designer, and Web Master jobs were placed after 1998.

[35] Deming and Noray (2018) use our data set to construct measures of change within occupations over time. STEM occupations include not only computer related occupations but also occupations within SOC codes beginning with 17 or 19. Moreover, their measures of occupational change will encapsulate not only within-job-title changes in skills and tasks but also shifts in job title composition, similar to those depicted in Figure 8.

Table 7: Relationship Between Task Measures and Job-title Vintages

Dependent	Nonroutine			Routine		Deming and Kahn
Variable	Analytic	Interactive	Manual	Cognitive	Manual	Computer
Panel A: No SOC Fixed Effects, $p = 0.05$						
Coefficient	0.032	0.046	0.001	-0.029	-0.008	0.076
Standard Error	0.007	0.008	0.001	0.006	0.001	0.003
Panel B: 6-Digit SOC Fixed Effects, $p = 0.05$						
Coefficient	0.011	0.024	-0.001	-0.015	-0.007	0.054
Standard Error	0.002	0.002	0.000	0.001	0.000	0.001
Panel C: No Fixed Effects, $p = 0.50$						
Coefficient	0.050	0.081	0.001	-0.041	-0.013	0.101
Standard Error	0.007	0.008	0.001	0.005	0.001	0.003
Panel D: 6-Digit SOC Fixed Effects, $p = 0.50$						
Coefficient	0.036	0.049	-0.001	-0.020	-0.010	0.090
Standard Error	0.001	0.002	0.000	0.001	0.000	0.001
Panel E: No Fixed Effects, $p = 0.95$						
Coefficient	0.027	0.047	-0.001	-0.013	-0.008	0.058
Standard Error	0.006	0.007	0.001	0.005	0.000	0.004
Panel F: 6-Digit SOC Fixed Effects, $p = 0.95$						
Coefficient	0.025	0.028	0.000	-0.003	-0.005	0.052
Standard Error	0.001	0.002	0.000	0.002	0.000	0.001

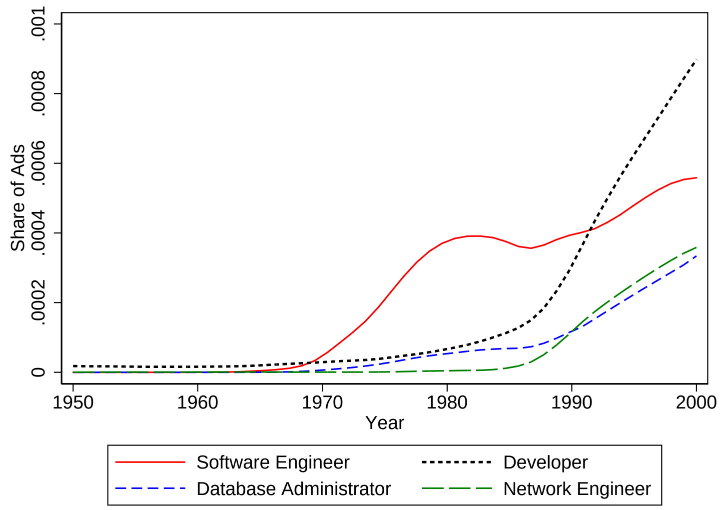
Notes: Within each panel and column, we present coefficient estimates and standard errors corresponding to estimates of Equation 2.

5 Conclusion

In this paper, we introduce a new data set and use it to chronicle changes in U.S. occupations and job tasks between 1950 and 2000. We document that a predominant share of changes in the task composition of the workforce has occurred within rather than between occupations. Beyond the decline that occupations intensive in routine tasks have experienced as a share of the workforce—a central pattern of the existing task literature—individual occupations' routine task content has declined as well. We also show that while our findings resonate with previous findings for individual case studies, our new data set readily lends itself to a more exhaustive analysis of the evolution of the labor market than is possible based on standard data sources.

Beyond this project, our newspaper data have the potential to address other economic questions related to the labor market. For example, in related work we use the text to measure the adoption of new computer technologies in order to study how these technologies interact with the task content of jobs (Atalay, Phongthiengtham, Sotelo, and Tannenbaum, 2018). More generally, we view our newspaper-based job vacancy text as offering an opportunity to study, over a longer time horizon, questions that have been examined using online job vacancies.

Figure 8: Computer Job Titles' Vacancy Shares



Notes: We plot the share of ads corresponding to each job title. We apply a local polynomial smoother, with a bandwidth of 4 years.

References

Abraham, K. G. (1987): "Help-Wanted Advertising, Job Vacancies, and Unemployment," *Brookings Papers on Economic Activity*, 1987(1), 207–248.

Acemoglu, D., and D. Autor (2011): "Skills, Tasks and Technologies: Implications for Employment and Earnings," *Handbook of Labor Economics*, 4, 1043–1171.

Anastasopoulos, J., G. J. Borjas, G. G. Cook, and M. Lachanski (2018): "Job Vacancies and Immigration: Evidence from Pre-and Post-Mariel Miami," Discussion paper.

Atalay, E., P. Phongthiengtham, S. Sotelo, and D. Tannenbaum (2018): "New Technologies and the Labor Market," *Journal of Monetary Economics*, 97, 48–67.

Autor, D. H. (2013): "The "Task Approach" to Labor Markets: An Overview," *Journal of Labor Market Research*, 46(3), 185–199.

——— (2015): "Why Are There Still So Many Jobs? The History and Future of Workplace Automation," *Journal of Economic Perspectives*, 29(3), 3–30.

Autor, D. H., and D. Dorn (2013): "The Growth of Low-Skill Service Jobs and the Polarization of the US Labor Market," *American Economic Review*, 103(5), 1553–1597.

Autor, D. H., L. Katz, and M. Kearney (2005): "The Polarization of the U.S. Labor Market," *American Economic Review*, 96(2), 189–194.

Autor, D. H., F. Levy, and R. J. Murnane (2003): "The Skill Content of Recent Technological Change: An Empirical Exploration," *Quarterly Journal of Economics*, 118(4), 1279–1333.

Bartel, A., C. Ichniowski, and K. Shaw (2007): "How Does Information Technology Affect Productivity? Plant-Level Comparisons of Product Innovation, Process Improvement, and Worker Skills," *Quarterly Journal of Economics*, 122(4), 1721–1758.

Basker, E., S. Klimek, and P. H. Van (2012): "Supersize It: The Growth of Retail Chains and the Rise of the "Big-Box" Store," *Journal of Economics & Management Strategy*, 21(3), 541–582.

Brynjolfsson, E., and A. McAfee (2014): *The Second Machine Age: Work, Progress, and Prosperity in a Time of Brilliant Technologies*. W. W. Norton & Company, 1st edn.

Cortes, G. M., N. Jaimovich, and H. E. Siu (2018): "The "End of Men" and Rise of Women in the High-Skilled Labor Market," Working Paper 24274, National Bureau of Economic Research.

Deming, D. (2017): "The Growing Importance of Social Skills in the Labor Market," *Quarterly Journal of Economics*, 132(4), 1593–1640.

Deming, D., and L. B. Kahn (2018): "Skill Requirements across Firms and Labor Markets: Evidence from Job Postings for Professionals," *Journal of Labor Economics*, 36(S1), 337–369.

Deming, D., and K. L. Noray (2018): "STEM Careers and Technological Change," Working Paper 25065, National Bureau of Economic Research.

DeVaro, J., and O. Gurtler (2018): "Advertising and Labor Market Matching: A Tour Through the Times," *Journal of Labor Economics*, 36(1), 253–307.

Firpo, S., N. M. Fortin, and T. Lemieux (2014): "Occupational Tasks and Changes in the Wage Structure," IZA Discussion Papers 5542, Institute for the Study of Labor (IZA).

Gentzkow, M., B. T. Kelly, and M. Taddy (2018): "Text as Data," *Journal of Economic Literature*, forthcoming.

Hendel, I., A. Nevo, and F. Ortalo-Magne (2009): "The Relative Performance of Real Estate Marketing Platforms: MLS versus FSBOMadison.com," *American Economic Review*, 99(5), 1878–1898.

Hershbein, B. J., and L. B. Kahn (2018): "Do Recessions Accelerate Routine-Biased Technological Change? Evidence from Vacancy Postings," *American Economic Review*, 108(7), 1737–1772.

John, O. P., L. P. Naumann, and C. J. Soto (2008): "Paradigm Shift to the Integrative Big Five Trait Taxonomy: History, Measurement, and Conceptual Issues," in *Handbook of Personality: Theory and Research*, ed. by O. P. John, R. W. Robins, and L. A. Pervin, pp. 114–158. The Guilford Press.

Lin, J. (2011): "Technological Adaptation, Cities, and New Work," *The Review of Economics and Statistics*, 93(2), 554–574.

Marinescu, I., and R. Wolthoff (2019): "Opening the Black Box of the Matching Function: the Power of Words," *Journal of Labor Economics*, forthcoming.

Merriam-Webster Dictionary (2019): *teletype*. Merriam-Webster Inc.

Michaels, G., F. Rauch, and S. J. Redding (2019): "Task Specialization in U.S. Cities from 1880 to 2000," *Journal of the European Economic Association*, forthcoming.

Miller, A. R., D. J. Treiman, P. S. Cain, and P. A. Roose (1980): *Work, Jobs and Occupations: A Critical Review of the Dictionary of Occupational Titles*. National Academy Press.

Modestino, A. S., D. Shoag, and J. Ballance (2019): "Upskilling: Do Employers Demand Greater Skill When Skilled Workers are Plentiful?," *Review of Economics and Statistics*, forthcoming.

National Research Council (1999): *The Changing Nature of Work: Implications for Occupational Analysis*. National Academy Press.

——— (2010): *A Database for a Changing Economy: Review of the Occupational Information Network (O*NET)*. National Academy Press.

Ross, M. (2017): "Routine-Biased Technical Change: Panel Evidence of Task Orientation and Wage Effects," *Labour Economics*, 48, 198–214.

Ruggles, S., K. Genadek, R. Goeken, J. Grover, and M. Sobek (2015): "Integrated Public Use Microdata Series: Version 6.0," Minneapolis, MN: Historical Census Projects, University of Minnesota.

Spitz-Oener, A. (2006): "Technical Change, Job Tasks, and Rising Educational Demands: Looking Outside the Wage Structure," *Journal of Labor Economics*, 24(2), 235–270.

Print Appendix

A Data Users' Guide

This is a guide to the data set introduced in "The Evolution of Work in the United States."

Site and Contents The site `https://occupationdata.github.io` contains all materials related to the data set:

- Details on the procedure by which we (i) process the digitized text, (ii) classify ads as job ads versus other types of advertisements, (iii) determine the boundaries of each individual ad, (iv) identify the job title within each job ad, (v) map words to job characteristics, and (vi) map job titles to occupational codes.
- Python notebooks that implement the six-step procedure.
- The file apst_mapping.xls, which details the mapping between raw text and job characteristics.
- The final analysis data sets.

Data set vintages The site currently hosts the third version of our data set, uploaded on May 15, 2019. The site also archives the two previous versions we have released: the first version, which was made available on July 1, 2017, and the second version, which was made available on April 7, 2018. While we do not anticipate major changes in the future, we may add additional variables over time. We will continue to archive older versions of our data set.

Data set contents The data page contains eight downloadable data sets, in which the data are aggregated to the following levels: (i) job title, (ii) job title × year pair, (iii) SOC code occupation, (iv) SOC code × year pair, (v) OCC code occupation, (vi) OCC code × year pair; (vii) job title × source pair; and (viii) job title × year × source triple.[36] While the sample period in the published article is 1950 to 2000, the data sets contain information from ads that date to 1940.

The list below explains the variables in our data set. For each variable that measures job characteristics, we provide the number of word mentions per ad that correspond to a particular job characteristic. Each of the eight data downloadable data sets contains the following sets of variables:

- activity_*, requirement_*, skill_*, style_*: These variables correspond to different O*NET Work Elements. Variables that end with a *_C in their name include words taken from our continuous bag of words model.
- big5_*: These variables correspond to "Big 5" traits. We use the categorization of words to Big 5 traits described by John, Naumann, and Soto (2008).
- deming_*: These variables correspond to the skill measures discussed in Deming and Kahn (2018). Variables that end with a *_C in their name include words taken from our continuous bag of words model.
- degree_*: These variables correspond to seven potential degrees: associate's; bachelor of arts; bachelor of science; master's; MBA; PhD; and CPA.
- experience_*: These variables correspond to experience requirements—whether employers ask for 1 year, 2 years, 3 years, 4 years, or 5+ years of experience.
- oth_* : These variables correspond to various job characteristics, including: the hours of the job (both the total number and the actual schedule), whether the applicant is asked for a salary history, and whether the employer offers tuition reimbursement.

[36] Users of our data set should be able to reproduce the third, fourth, fifth, or sixth data sets from the first two data sets. To do so, users can merge the job-title-based data sets with the mapping between job titles, SOC codes, and OCC codes that we provide. Here, "source" refers to whether the job ad appears as a *Boston Globe* classified ad, a *Boston Globe* display ad, a *New York Times* classified ad, a *New York Times* display ad, or a *Wall Street Journal* classified ad. Users of our data set should be able to reproduce the first or second data sets from the last two data sets.

- spitz_* : These variables correspond to nonroutine (analytic, interactive, or manual) or routine (cognitive or manual) tasks. Variables that end with a *_C in their name include words taken from our continuous bag of words model.

- technology_*: These variables count the number of mentions of different pieces of technology. The 48 technologies are listed in Atalay, Phongthiengtham, Sotelo, and Tannenbaum (2018).

- length; words: The first of these variables counts the number of correctly spelled words, incorrectly spelled words, and non-word tokens per ad. The second of these variables counts the number of correctly spelled words per ad. In work that uses our data set, we suggest normalizing per-ad job measures by the number of correctly spelled words per ad.

- ct2: This variable gives the number of ads corresponding to the given observation.

Online Appendix

B Additional Calculations Related to Section 2

This appendix presents comparisons of measures from our new data set to measures from the decennial census (Appendix B.1), from O*NET (Appendix B.2), and from the DOT (Appendix B.3). Then, we compute the top occupations for each Deming and Kahn (2018) skill measure (Appendix B.4).

B.1 Comparison to the Decennial Census

Certain variables are present in both our new newspaper data and in the census. With the aim of demonstrating the overall reliability of our newspaper data, we compare the frequency of different occupations, as well as educational characteristics for each occupation, across the two data sources.

First, Figures 9 and 10 depict the share of workers (in the decennial census) in different occupational groups, along with the frequency of job ads in the same groups. Figure 9 presents this relationship at the 2-digit level. In the six decades depicted within the figure, the correlations between census job frequencies and frequencies in our newspaper job ads range between 0.59 (in 1950) to 0.81 (in 1990). Our newspaper data set over-represents the Sales, Health Practitioner, and Architecture/Engineering occupational groups, and conversely under-represents the Transportation, Production, and Installation and Maintenance occupational groups. (Hershbein and Kahn, 2018's data set of online job postings also exhibited a similar under-representation of blue-collar occupations.)[37] Figure 10 presents the same set of relationships, now using a 4-digit SOC classification. Here, the correlations among the two measures of occupational size are weaker, ranging between 0.31 in 1960 to 0.48 in 1980. Figure 11 reproduces Figure 10 with occupations' census employment shares computed using only counts of workers from the Boston and New York MSAs.[38] The average correlation in the six panels of Figure 11 is 0.55, approximately 14 percentage points higher than in Figure 10.

Second, we compare measured educational attainment of occupations' workers in the decennial census to our vacancy postings' stated education requirements. In the newspaper text, we search among a list of acronyms and words to identify an undergraduate degree as a requirement, and a second list of acronyms and words to identify a professional degree requirement.[39] In Figure 12, we compare the undergraduate requirements across 4-digit SOC codes. Within

[37]While blue-collar workers are under-represented in our newspaper data relative to their employment shares, we emphasize that our analysis of changes in occupations' task content (or of economy-wide task content) is not affected by this under-representation, since we weight occupations by their employment shares.

[38]To ensure that the boundaries of the MSAs are fixed through time, we remove individuals who reside in counties which were added to the New York MSA definitions part of the way through our sample period: Hunterdon County, Middlesex County, Somerset County, Sussex County, and Warren County. All five of these counties are in New Jersey.

[39]These two lists are (i) "bachelors," "bachelor," "ba," "bsme," "bs," "bsche," "bsce," "bscs," and "bsee" and (ii) "cpa," "masters," "ma," "mba," and "phd."

Figure 9: Occupation Shares: Newspaper Vacancies versus U.S. Employment

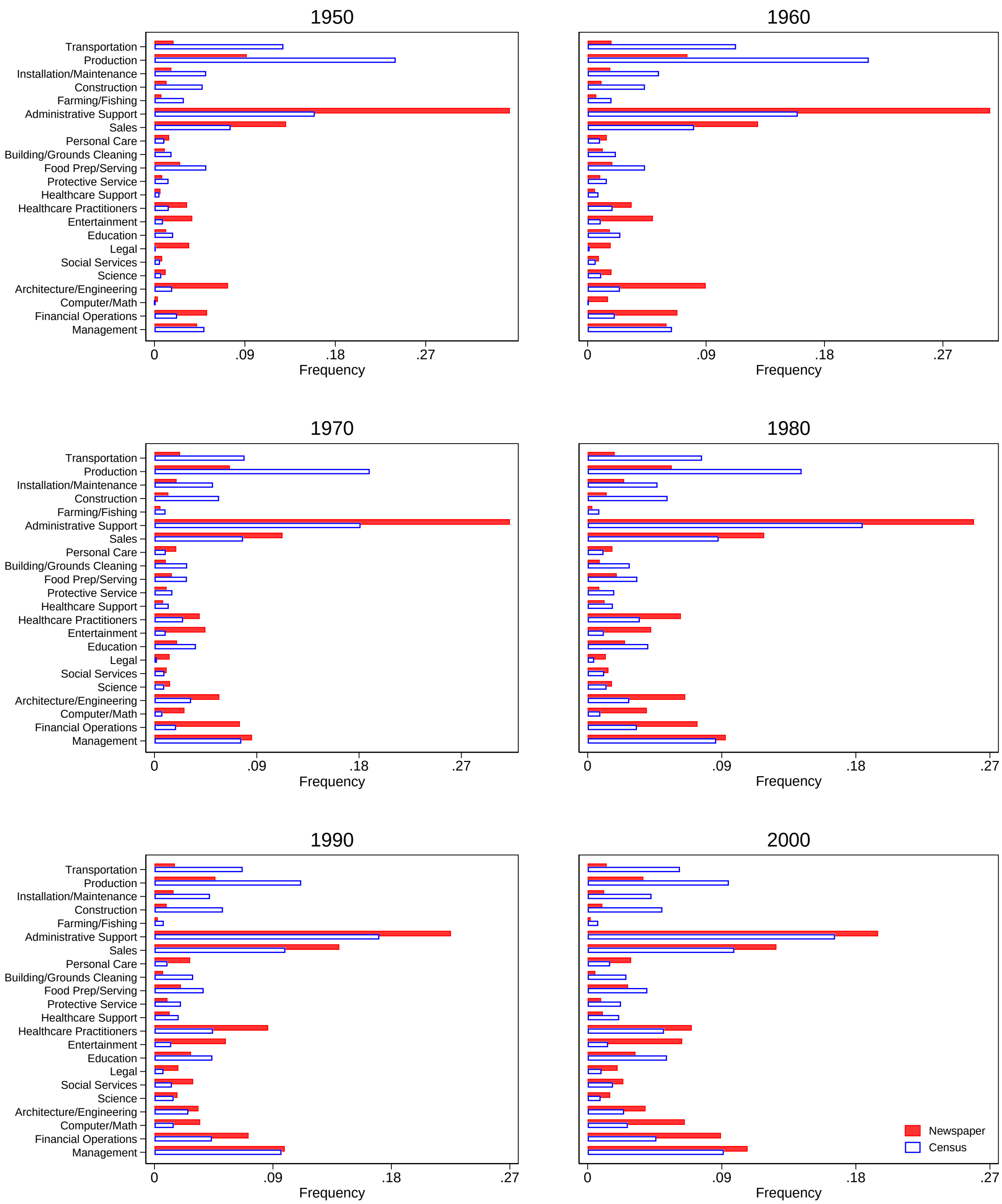
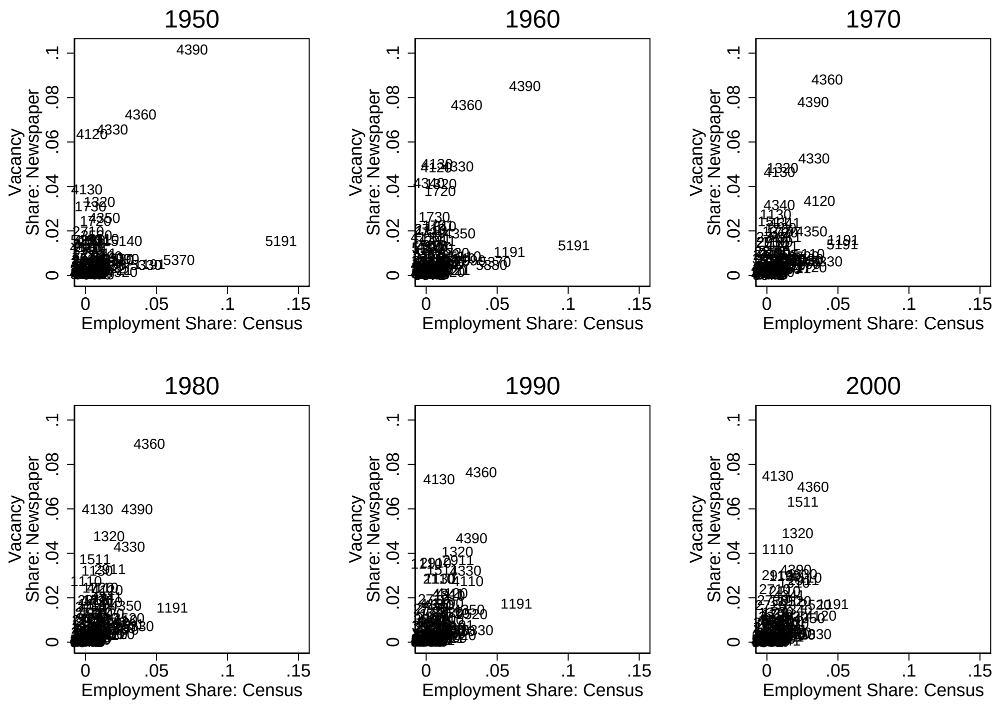


Figure 10: Occupation Shares: Newspaper Vacancies versus U.S. Employment



the individual years that are plotted, the correlations between the two measures are 0.46, 0.70, 0.66, 0.64, 0.63, and 0.62.

In Figure 13, we perform the same exercise for professional and post-graduate degrees. Here, the extent to which our data align with educational attainment in the decennial census is substantially weaker. The correlation in the pooled sample of years and occupations is 0.26. For the individual years in our sample, the correlations across SOC codes are 0.16, 0.18, 0.22, 0.32, 0.32, and 0.20. Overall, we conclude that the undergraduate degree requirement data which we extract from our newspaper data are correlated with the more cleanly measured census data on workers' educational attainment, but only weakly so for professional and graduate degrees.

B.2 Comparison to O*NET

With the aim of validating our data set, we map our text to O*NET's work styles, skills, knowledge requirements, and work activities (corresponding to O*NET Elements 1C, 2A and 2B, 2C, and 4A, respectively). For each O*NET Element, we begin by looking for words and phrases related to the O*NET Title and words within the O*NET Element Description. We then append to our initial lists of words and phrases synonyms from our continuous bag of words model.

Figure 14 relates the O*NET Importance measure to newspaper keyword frequencies. Each panel 14 presents a comparison for a different O*NET Element: one work style (Cooperation),

Figure 11: Occupation Shares: Newspaper Vacancies versus Boston and New York MSA Employment

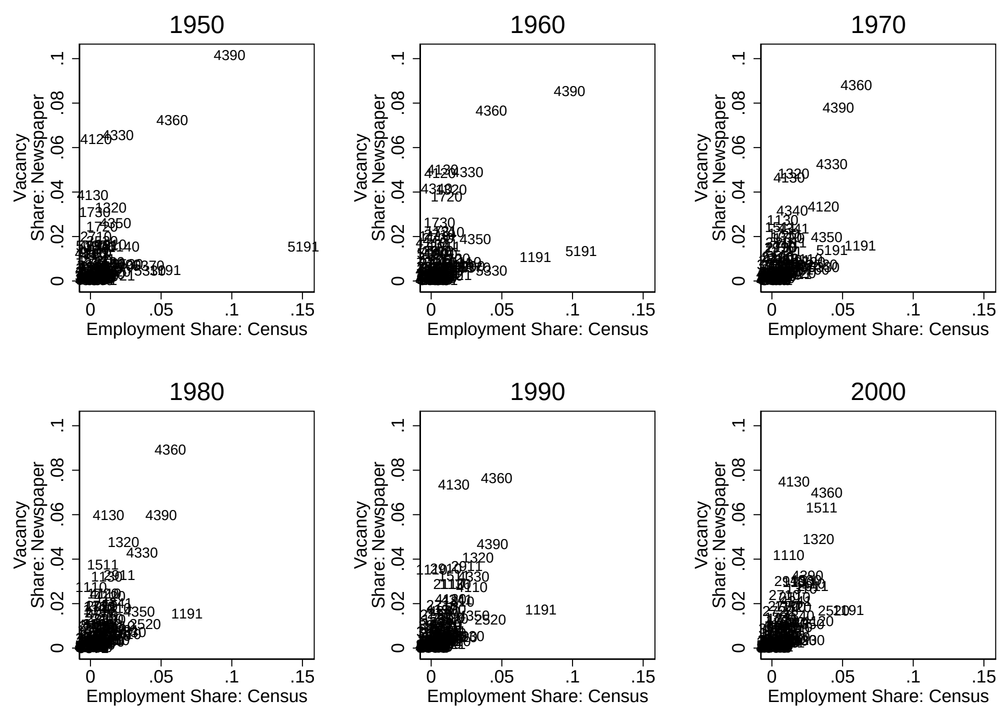
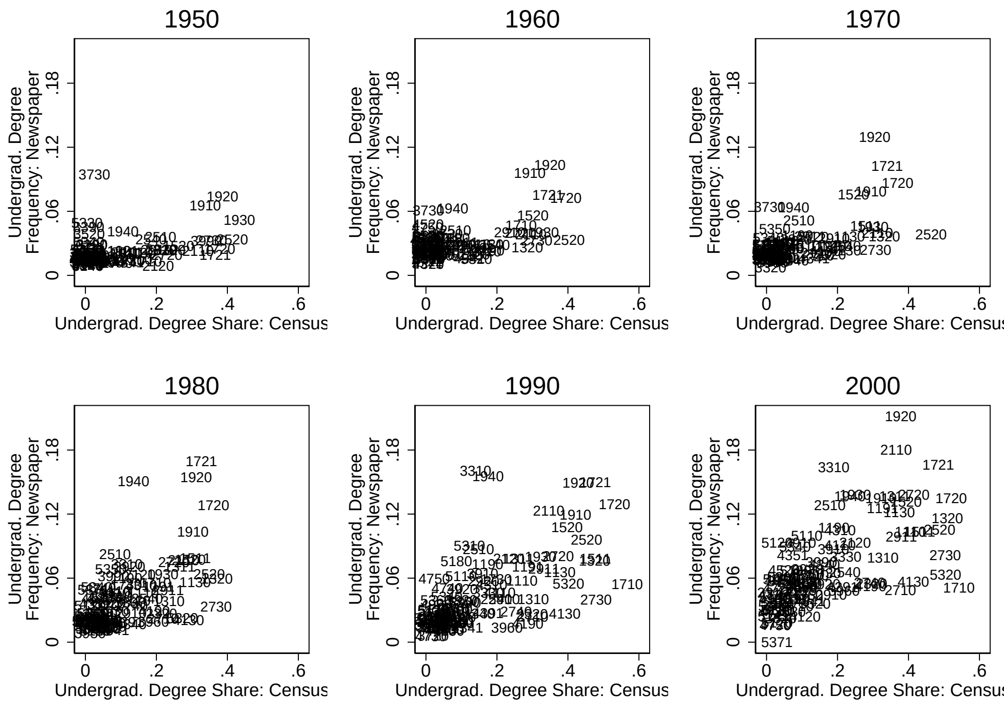


Figure 12: Educational Characteristics by Occupation



Notes: Each panel describes the relationship between the share of workers in each occupation with an undergraduate degree (according to the decennial census) on the x-axis; the fraction of newspaper ads which mention an undergraduate degree is on the y-axis.

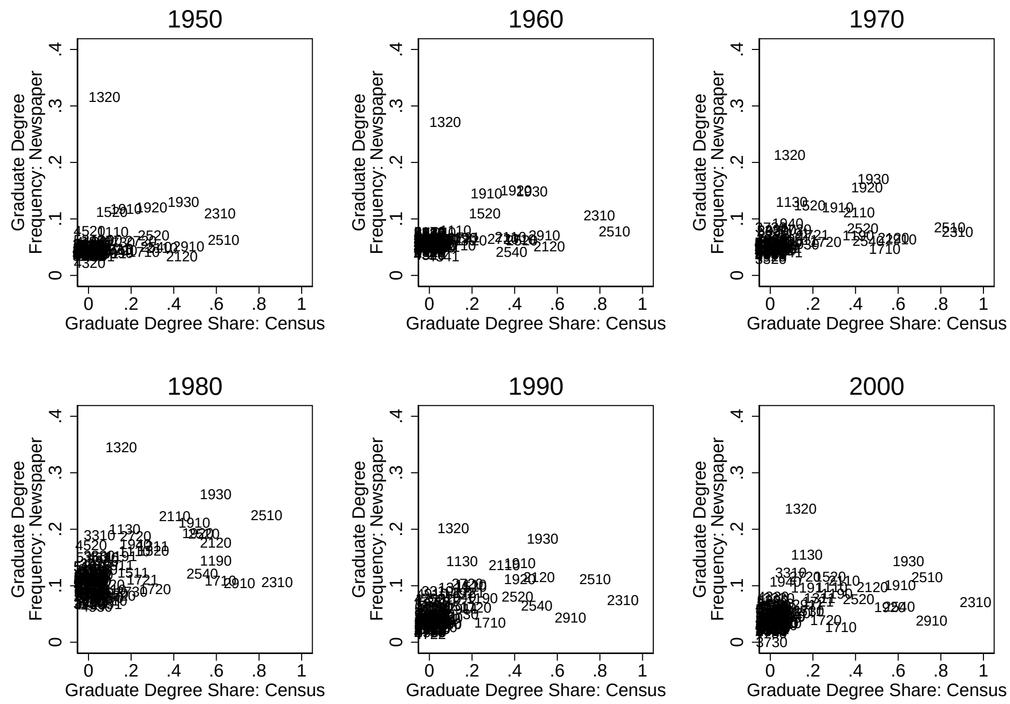
one skill (Active Listening), one knowledge requirement (Personnel and Human Resources), and one work activity (Operating Vehicles, Mechanized Devices, or Equipment). Within each panel, each data point represents a single 4-digit SOC occupation: For example, the "2310" (the code for Lawyers, Judges, and Related Workers) in the top right panel indicates that the O*NET Importance of the skill of "Active Listening" is 4.5 (on a scale from 1 to 5), while in the newspaper data, we detect 0.15 Management of Material Resources related keywords per 1000 (correctly spelled) job ad words. The correlations (weighted by the number of vacancy postings in our newspaper data) in these four plots are 0.27, 0.54, 0.54, and 0.37, respectively.[40]

The four relationships depicted in Figure 14 are broadly representative of the concordance between O*NET Importance measures and our vacancy postings' keyword frequencies: The correlation between our measures and existing O*NET measures of occupational work styles, skill, knowledge requirement, and activity measures are, for the most part, in the 0.40 to 0.65 range, and are somewhat higher for knowledge requirements, skills, and activities (where the mean correlations are 0.57, 0.54, and 0.49, respectively) than for work styles (where the mean correlation is 0.32).[41]

[40] Across all 125 O*NET Elements, the unweighted correlations are lower by 3 percentage points on average.

[41] As we discuss in footnote 19, the O*NET database may not be the ideal benchmark for comparison, given its

Figure 13: Educational Characteristics by Occupation



Notes: Each panel describes the relationship between the share of workers in each occupation with a graduate degree (according to the decennial census) on the x-axis; the fraction of newspaper ads which mention a graduate degree is on the y-axis.

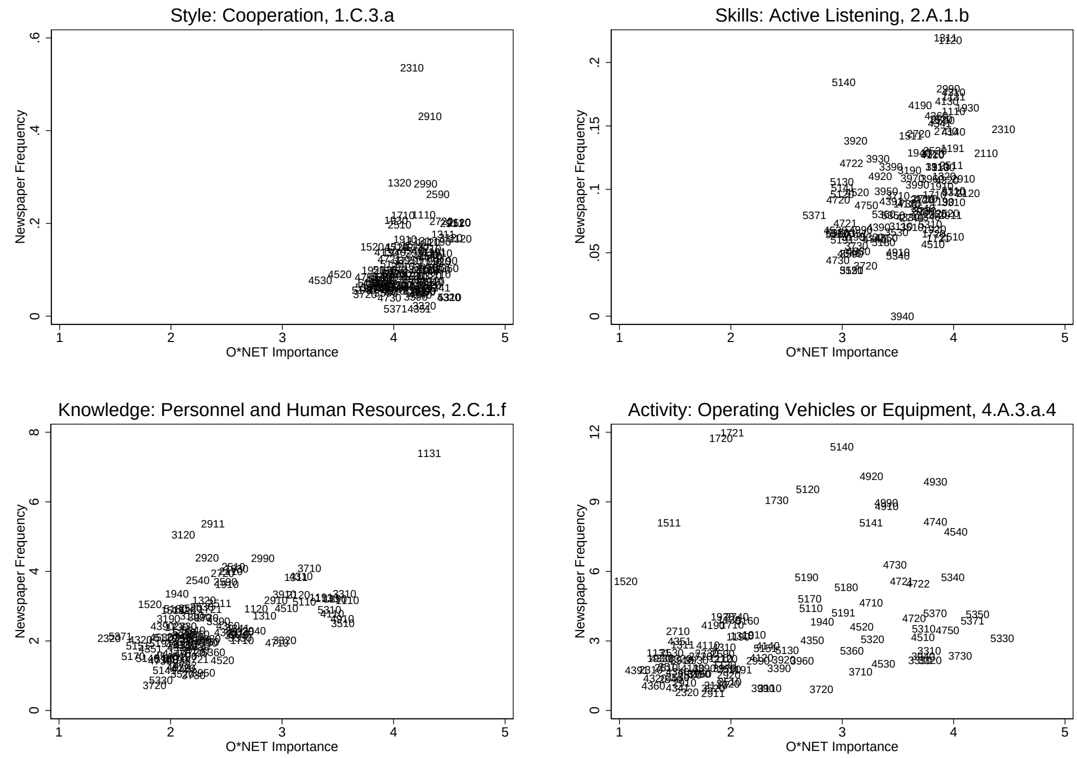
B.3 Comparison to the DOT

In Section 3.3, we replicated Figure 1 of Autor, Levy, and Murnane (2003), one of the key empirical findings in the task literature. We showed that our new data set aligns with the Dictionary of Occupational Titles in its depiction of between-occupation shifts in task content. In this appendix, we provide an additional set of comparisons between our new data set and the Dictionary of Occupational Titles.

We first directly compare our newspaper measures to the analogous measures in a single vintage of the DOT. In the left panel of Figure 15, we plot the relationship between the Dictionary of Occupational Titles GED math measure, Autor, Levy, and Murnane (2003)'s benchmark measure of nonroutine analytic task intensity, and our newspaper-based nonroutine analytic task measure. From both data sets, we take values from 1977. The correlation between the two measures is 0.79. According to both data sets, engineering and computer-related occupations are those that have the highest nonroutine analytic task content. In the right panel of Figure 15, we present the analogous relationship for nonroutine interactive task measures. Here, the correlation is 0.16. The correlations for the other three measures are

well-known limitations for measuring occupational tasks (Autor, 2013). Nevertheless, we interpret these correlations as evidence that the newspaper text has valuable information about occupational tasks.

Figure 14: O*NET Importance Measures and Newspaper Keyword Frequencies



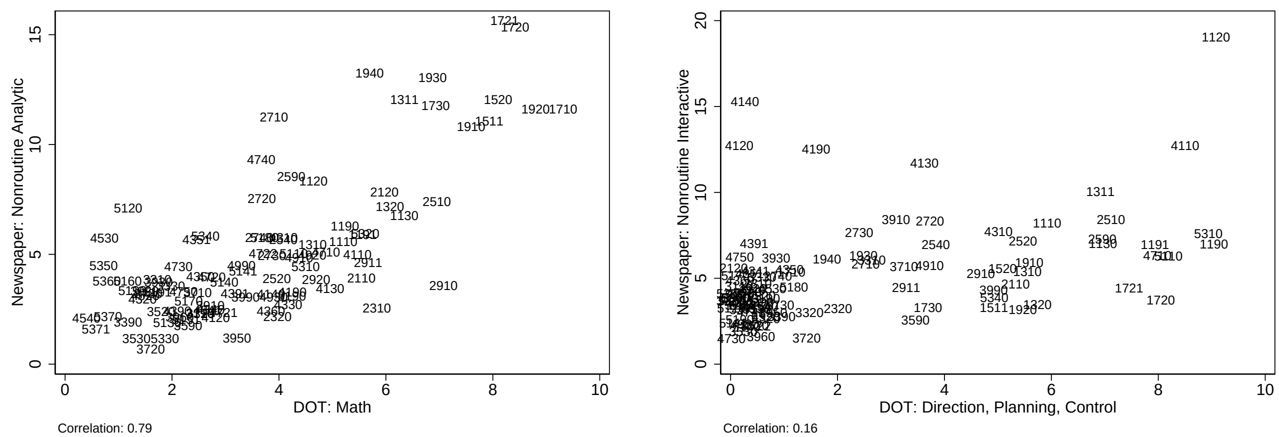
Notes: Each panel corresponds to one O*NET element. In each panel, each point represents a SOC code. The value of the x-axis represents the O*NET Importance measure (from version 22.1 of the O*NET database). The y-axis measures the number of keyword appearances per 1000 job ad words, using data from the *Boston Globe*, *New York Times*, and *Wall Street Journal*.

0.39 for nonroutine manual tasks, 0.34 for routine cognitive tasks, and 0.02 for routine manual tasks. So, for four out the five task groups, our newspaper-based task measures align at least moderately with those in the DOT.[42]

As far as we are aware, the 1977 and 1991 Dictionary of Occupational Titles (DOT) — which are the underlying source of the Autor, Levy, and Murnane measures — are the sole data set from which one could potentially measure within-occupation changes in U.S. task content over our sample period. We now present evidence that the DOT is ill-suited to measurement of within-occupation changes in tasks, corroborating the characterization made by Autor, Levy, and Murnane (2003), who note the "limited sampling of occupations (particularly in the service

[42]While we view DOT and O*NET as useful benchmarks, they too have issues, which extend beyond their limited ability to track within-occupation changes in job characteristics over time. In their review of the design of the O*NET data collection program, the National Research Council (2010) identifies several aspects of O*NET which may limit its usefulness as a research tool. Summarizing these issues, Autor (2013) writes that in both the DOT and O*NET, "job content measures are often vague, repetitive, and constructed using ambiguous and value-laden scales that are likely to confuse respondents" (p. 191). We should neither expect nor hope that our measures exactly align with DOT or O*NET measures, but we interpret the correlations as reassuring evidence that the newspaper text is a valuable source of task data.

Figure 15: Comparison of DOT and Newspaper Task Measures: 1977 Levels



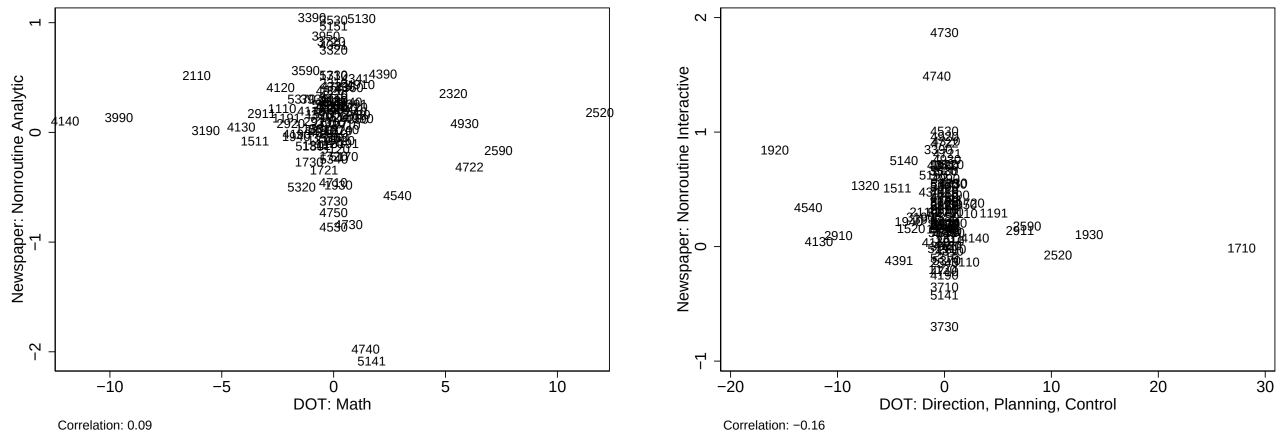
Notes: The left panel gives the relationship between the DOT GED math variable with our newspaper-based nonroutine analytic task measure (stated as number of mentions per 1000 job ad words). The right panel presents the same relationship for the DOT direction, planning, and control measure and our newspaper-based nonroutine interactive task measure. The numbers within the scatter plot characterize the SOC code. The stated correlation is computed with weights given by the newspaper number of job ads per occupation as of 1977.

sector), imprecise definitions of measured constructs, and omission of important job skills" (p. 1292-1293) limit the usefulness of the DOT for time series analysis.

While there is a substantial correlation in levels between our newspaper-based task measures and the DOT measures, no such correlation exists when looking at task growth rates. According to the DOT, from 1977 to 1991 there was a decline in nonroutine analytic tasks within occupations; routine manual tasks increased within occupations (see the bottom row of Table 6 of Autor, Levy, and Murnane, 2003). This is the opposite of what we find. Moreover, the correlation in occupations' changes in task intensity, from 1977 to 1991, is much weaker when comparing the two data sets. Figure 16 plots the correspondence for nonroutine analytic (left panel) and nonroutine interactive (right panel) tasks. For the five task measures, the correlations in growth rates in task intensities are: 0.09 (for nonroutine analytic tasks), -0.16 (nonroutine interactive), -0.11 (nonroutine manual), -0.04 (routine cognitive), and 0.14 (routine manual). Overall, there is essentially no relationship between the growth rates of DOT task measures and the growth rates of our newspaper-based task measures.

For many occupations, the DOT's measures were not updated between the 1977 and 1991 vintages. Suggestive of this, the correlation across occupations in the GED math scores across the 1977 and 1991 vintages of the DOT equals 0.98. To highlight this serial correlation and illustrate the limited nature of the time series that is available with the DOT, we plot the task measures in the 1977 and 1991 editions, in Figure 17. This figure indicates that, for a large fraction of occupations, the GED math measure (left panel) and the direction, planning, and control measure (right panel) are essentially the same across DOT editions. The correlations for the three un-plotted tasks are 0.95 for finger dexterity; 0.95 for eye, hand, and foot co-

Figure 16: Comparison of DOT and Newspaper Task Measures: 1977 to 1991 Growth Rates



Notes: The left panel gives the relationship between the DOT GED math variable with our newspaper-based nonroutine analytic task measure (stated as a growth rate between 1977 and 1991). The right panel presents the same relationship for the DOT direction, planning, and control measure and our newspaper-based nonroutine interactive task measure. The numbers within the scatter plot depict the SOC Code. The stated correlation is computed with weights given by the number of newspaper job ads per occupation as of 1977 and 1991.

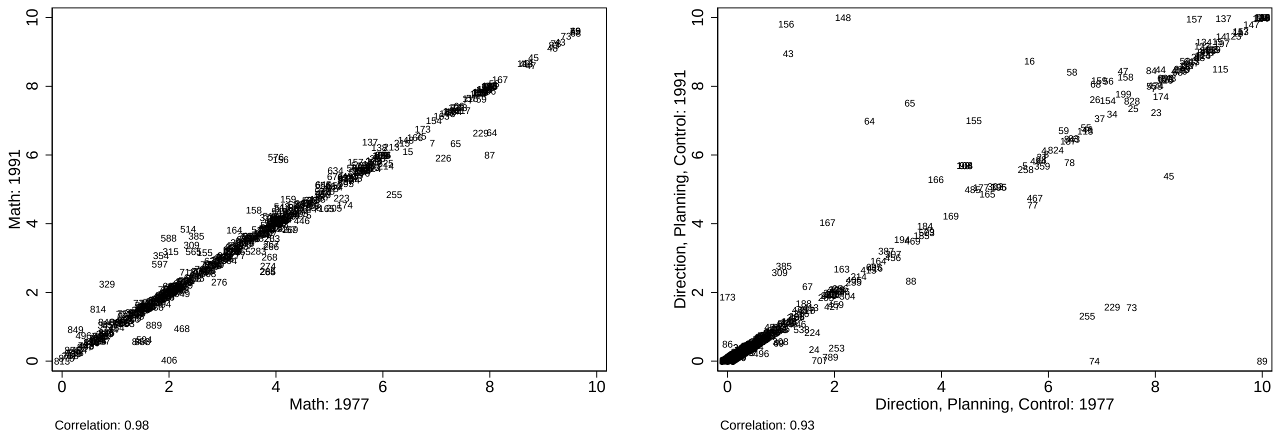
ordination; and 0.87 for setting tolerances.[43] These correlations, especially those for the GED math variable, are suggestive of irregular and incomplete updating of occupations' task content measures between 1977 and 1991.

It is hypothetically possible that there were actually no task changes, within occupations, for a large number of occupations. This point of view, however, is inconsistent National Research Council (1999) and Spitz-Oener (2006). To be clear, for the main empirical exercise that Autor, Levy, and Murnane (2003) perform—measuring the relationship between occupations' task content changes and changes in computer adoption rates—the fact that many task measures were not updated by DOT examiners does not pose a problem. However, these plots do indicate that the DOT is ill-suited in measuring within-occupation changes in task content for a broad swath of occupations.

In summary, across occupations, our task measures broadly align with those in the Dictionary of Occupational Titles. However, the portrayals of within-occupation task trends — comparing our newspaper data with the DOT—are starkly different. In contrast to what our newspaper data indicate, the DOT data set indicates that there has been a shift within occupations away from nonroutine analytic tasks towards routine manual tasks.

[43] The unweighted correlations are higher than the weighted correlations by 0.02, on average.

Figure 17: Comparison of 1977 and 1991 DOT



Notes: The left panel gives the relationship, according to the 1977 and 1991 editions of the DOT, of occupations' GED math variable. The right panel presents the same relationship for the DOT direction, planning, and control measure. The numbers within the scatter plot are the 1980-90 occupation code, as defined by Autor, Levy, and Murnane. The stated correlation is computed with employment weights, given by summing across individuals working in each occupation as sampled in the 1984 CPS.

B.4 Top Occupations

In addition to the measures developed by Spitz-Oener (2006), we apply the mapping between keywords and skills that Deming and Kahn (2018) use in their study of the relationship between firms' characteristics and the skill requirements in their vacancy postings. For each skill group, we append words that are similar to those mentioned in footnote 16, using the continuous bag of words model to identify words and phrases that are similar to one another.

Table 8 lists the top occupations according to the skill groups in Deming and Kahn (2018). As one would expect, ads for sales representatives and sales managers have the highest frequency of words related to customer service skills; ads for financial specialists and accountants have the highest frequency of words related to financial skills; ads for health diagnosticians have the highest frequency of words related to people management; and ads for engineers have the highest frequency of words related to project management.

C Selection and Measurement Error

C.1 Trends in Ad Length and Spelling Accuracy

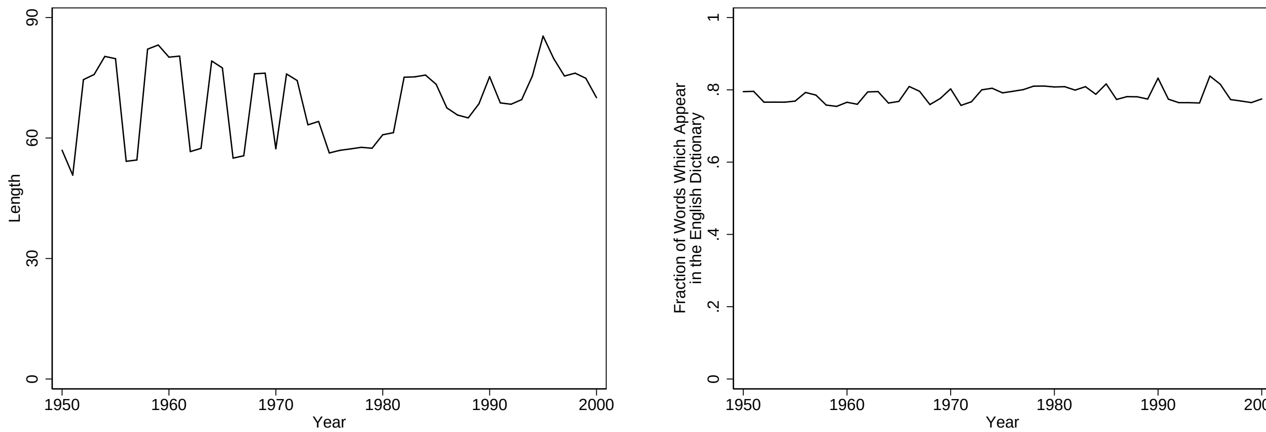
In Figure 18, we plot the average length of each ad, and the fraction of correctly spelled words for each ad. These plots indicate that there is a weak upward trend in ad length over our sample period — the average number of words per ad in our data set is 69.2 in the 1950s, 69.3 in the 1960s, 62.0 in the 1970s, 68.8 in the 1980s, and 74.5 from 1990 to 2000 — and that there is no trend in the fraction of words that are correctly spelled (i.e., words that are in our English dictionary). The motivation for these plots is that any time-varying measurement

Table 8: Top Occupations According to the Deming and Kahn (2018) Classification of Skills

Character			Computer		
Retail Sales	0.0004	13.23	Systems Analyst	0.0010	18.41
Dental Assistant	0.0007	12.27	Systems Engineer	0.0004	17.50
Management Trainee	0.0012	11.58	Programmer Analyst	0.0014	15.35
Real Estate Sales	0.0007	11.34	Computer Operator	0.0005	13.41
Secretary Administrative Assistant	0.0005	10.73	Programmer	0.0035	13.02
Customer Service			**Financial**		
Retail Sales	0.0004	17.41	Financial Analyst	0.0009	26.00
Sales Representative	0.0017	15.07	Staff Accountant	0.0004	24.87
Sales Manager	0.0018	14.71	Assistant Controller	0.0007	22.73
Sales Engineer	0.0012	14.12	Accountant Junior	0.0009	22.26
Sales Trainee	0.0011	13.95	Accountant	0.0010	22.06
People Management			**Problem Solving**		
Executive Director	0.0007	9.67	Physicist	0.0004	7.34
Management Trainee	0.0012	7.58	Chemist	0.0017	7.04
RN	0.0070	7.34	Statistical Typist	0.0009	6.72
Physical Therapist	0.0007	7.05	Chemical Engineer	0.0003	4.90
Director	0.0033	6.87	Systems Engineer	0.0004	4.34
Project Management			**Social**		
Project Engineer	0.0006	28.96	Social Worker	0.0015	6.97
Project Manager	0.0008	24.59	Executive Director	0.0007	4.10
Mechanical Engineer	0.0010	24.05	Worker	0.0005	4.03
Design Engineer	0.0005	22.48	Systems Engineer	0.0004	3.91
Electrical Engineer	0.0007	21.85	Account Executive	0.0010	3.19
Writing					
Editorial Assistant	0.0005	8.45			
Editor	0.0022	8.27			
Technical Writer	0.0007	7.97			
Writer	0.0010	6.83			
Proofreader	0.0009	3.19			

Notes: This table lists the top five occupations according to the frequency with which different activity-related words are mentioned. Within each panel, the first column gives the SOC code and title; the second column gives $1/51 \cdot \sum_{t=1950}^{2000} S_{jt}$ — the average share of ads belonging to the job title; and the final column gives the frequency of task h words among job title j's ads, per 1000 ad words. Footnote 16 contains the words and phrases corresponding to each skill that were used in Deming and Kahn (2018). To these lists, we append similar words, using the continuous bag of words model introduced in Section 2.3.

Figure 18: Trends in Ad Length, Fraction of Correctly Spelled Words



Notes: The left panel plots the average length (including both words that appear in the English dictionary and those that do not). The right panel plots the fraction of words within each ad that are English-dictionary words. The correlation between year and ad length is 0.27 (with a p-value of 0.088), and between year and the fraction of words which are correctly spelled is 0.09.

error in our newspaper text would manifest as trends in the share of correctly spelled words. Reassuringly, no such trend is apparent.

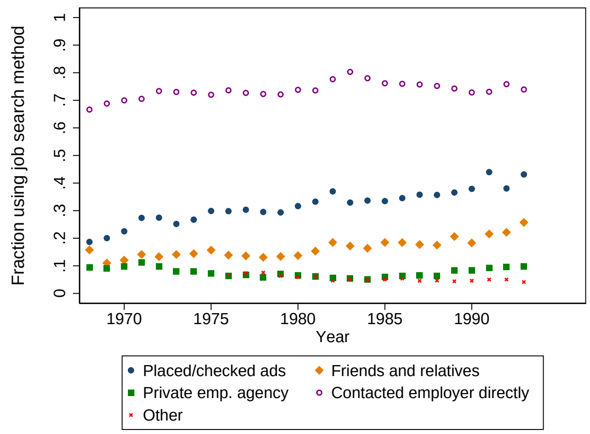
C.2 Methods of Job Search

In this section we consider the possibility that the ads which appear in our data set represent a selected sample of all job search methods. In our main analysis, we observe a dramatic increase in words related to nonroutine tasks, which we interpret as reflecting the increasing importance of nonroutine tasks in the economy. But it is also plausible that employers posting vacancies for jobs requiring nonroutine tasks are increasingly likely to post in newspaper ads over time. This section provides empirical evidence that the representativeness of our data set (among the set of all channels of job search) has not changed within the sample period.

Here, we measure the methods that unemployed workers use to search for jobs. We can do this using the IPUMS CPS-ASEC (Ruggles, Genadek, Goeken, Grover, and Sobek, 2015). Unemployed workers are asked whether they have used particular job search methods, and are allowed to report as many methods as they like. The population analyzed here includes unemployed civilian workers, who are looking for a job, and who are between the ages of 16 and 64. Figure 19 reports the fraction of these workers who use alternative methods for finding a job. The variable of interest for our study is whether the unemployed worker "placed or answered ads" as a method of job search.

Figure 19 shows trends in the method of job search over time. Two methods, placing or answering ads and searching through friends and relatives, increase steadily from 1968 to 1993. Note that by themselves these upward trends are not necessarily problematic; what could pose a problem, however, is the presence of differential trends by occupation, educational background,

Figure 19: Methods of Job Search Among Unemployed



Notes: The figure above reports the fraction of unemployed workers who use alternative methods for finding a job. Respondents are allowed to report as many methods as they deem appropriate; therefore the fraction using each method need not sum to 1.

or other demographic characteristics.

In what follows we consider whether there is selection into job search by task intensity of the worker's prior occupation. If, for example, workers in occupations that are high in nonroutine tasks are more likely to search in newspapers over time, compared to workers in occupations low in nonroutine tasks, we would be concerned that selection is causing us to overstate the upward trend in nonroutine tasks.

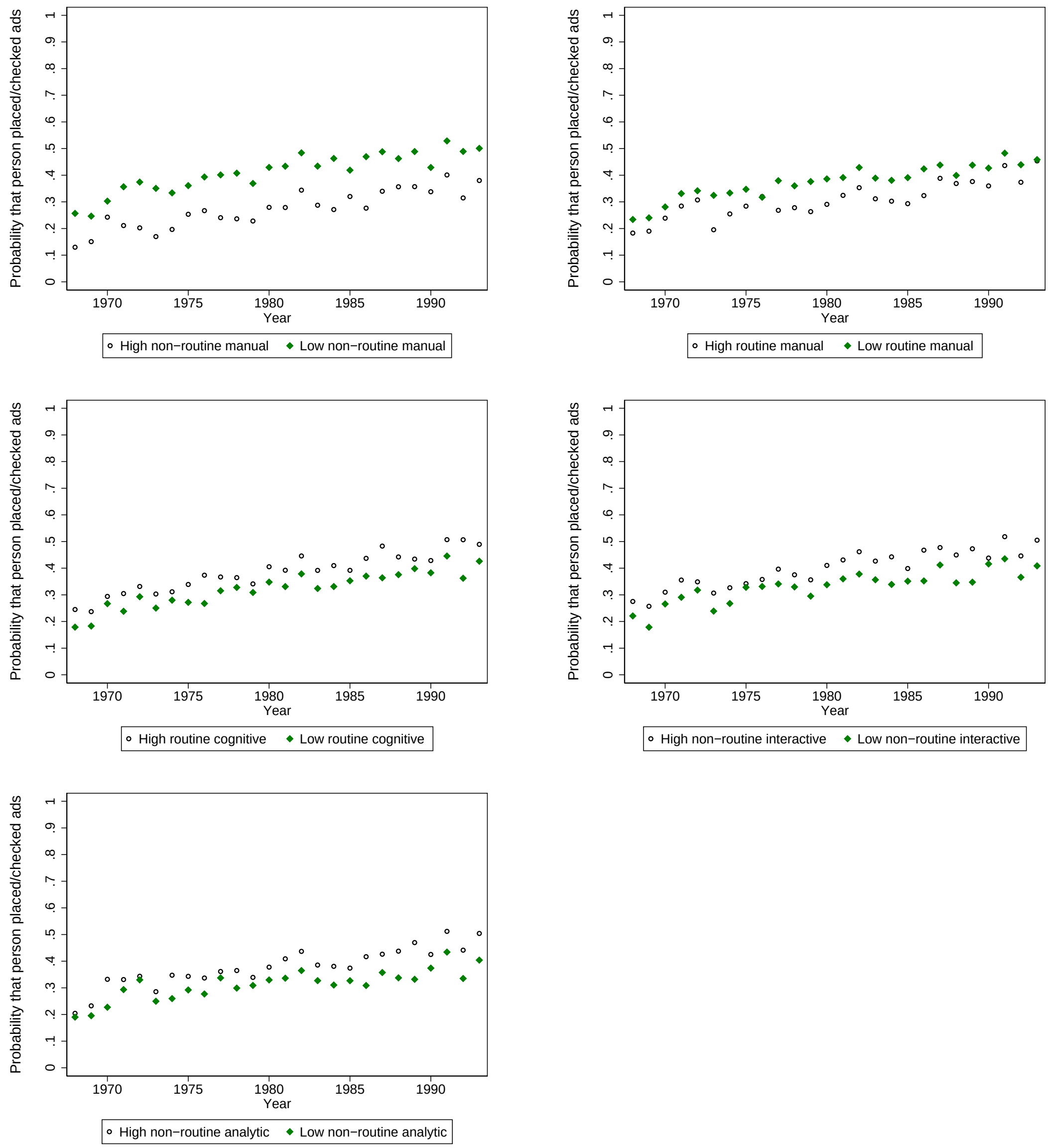
To test this hypothesis, we first compute the mean task content in each occupation over the entire sample period. We then plot the fraction of workers searching for jobs through ads whose last occupation was highly intensive in, say, nonroutine interactive tasks (75th percentile or higher) and the same for workers in occupations that have a low intensity in the same task (25th percentile or lower).[44]

Figure 20 plots the yearly averages for high versus low task intensity occupations. The main takeaway is that while the overall trend is increasing, there does not appear to be a differential trend by the task intensity of the worker's prior occupation. This is reassuring for the main results of the paper because if, for example, the observed rise in interactive tasks were driven by selection of highly interactive job vacancies into newspapers, we would expect workers who work in highly interactive jobs to search more in newspapers over time, relative to workers in low interactive jobs.[45]

[44]The analysis that follows is not sensitive to this choice of threshold for high and low intensity occupations.

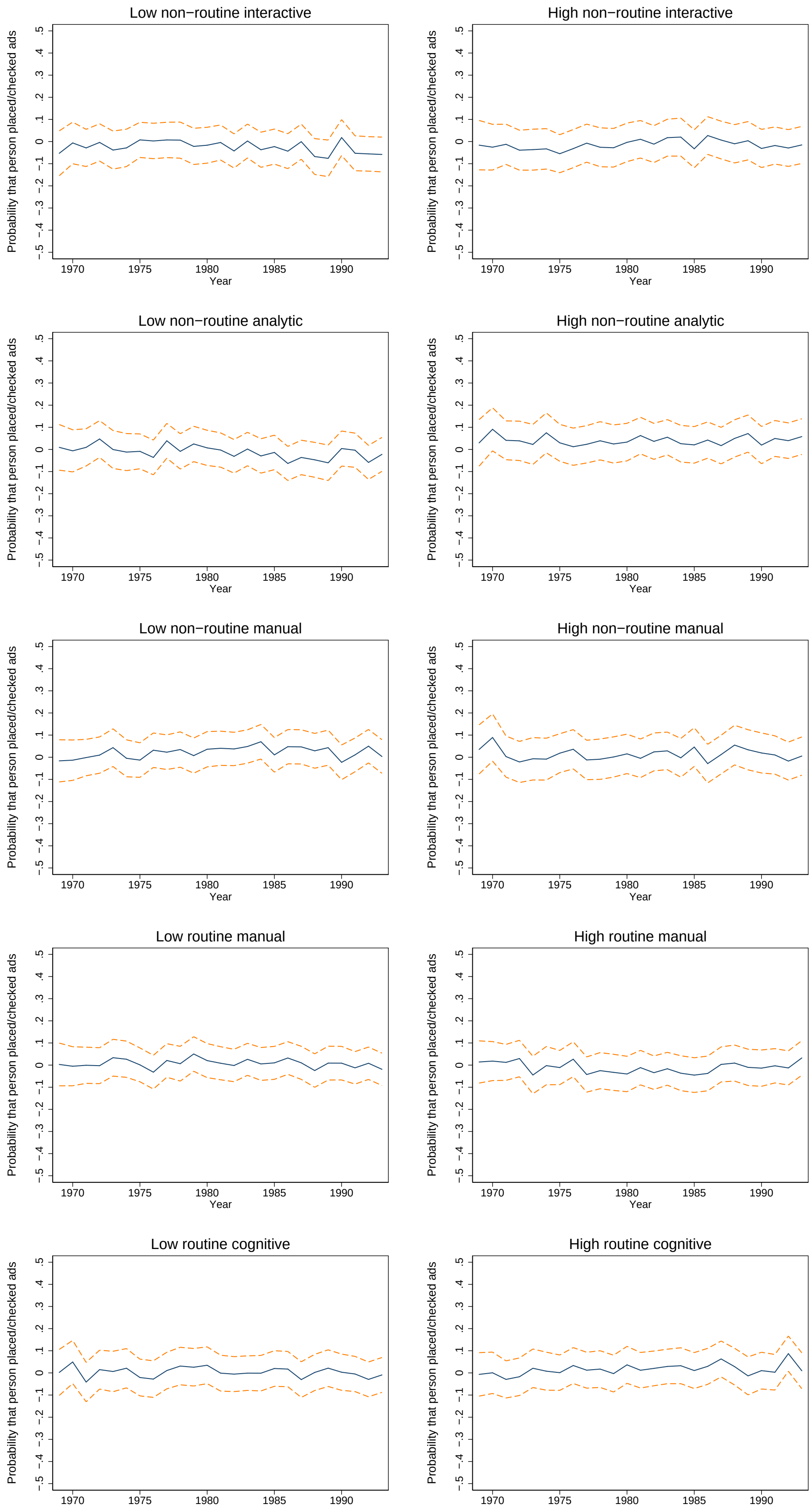
[45]While trends in job search do not appear to differ by occupation, there are *level* differences in job search: For example, workers in high routine cognitive occupations are more likely to use job ads as a search method compared with workers in low routine cognitive occupations. This pattern is consistent with our finding in Appendix B that job vacancies in administrative support occupations are more likely to appear in newspapers when compared to overall employment. That (i) occupations with high routine cognitive task content are more likely to appear in newspapers, and (ii) workers from these occupations are more likely to search in newspapers is reassuring for this validation exercise, since it demonstrates that demand-side differences in vacancy posting behavior are also reflected in supply

Figure 20: Trends in Job Search Method by Task Intensity of Occupation



Notes: The figure above plots the fraction of job seekers using job ads as a search method, by task intensity of prior occupation. "High" refers to being in an occupation in the 75th percentile or higher in a given task, while "low" refers to being in the 25th or lower percentile in a given task.

Figure 21: Trends in Job Search Method by Task Intensity of Occupation



Notes: The figure above plots the estimates for β_t in Equation 3 for each of the five tasks, along with the 95 percent confidence intervals. Each panel represents the results of a separate regression.

We test this hypothesis formally using the following regression:

$$y_i = \beta_0 + \beta_t \widetilde{T}_h^{\tau} + x_i^{'}\gamma + \iota_t + \epsilon_i, \quad (3)$$

where $\widetilde{T}_h^{\tau}$ is an indicator for being in the τth percentile of the task h distribution (and h indicates one of the five Spitz-Oener task measures). The vector x_i are controls including gender, marital status, experience dummies (<10 years, 10-19 years, 20-29 years, and 30+ years), a non-white race dummy, and dummy variables over our five educational groups. Figure 21 plots the estimates for β_t. The omitted year is 1968, so coefficients β_t are interpreted as relative to 1968. Overall, Figure 21 suggests no detectable trends in job search behavior through ads.

C.3 Representativeness of Boston and New York Job Ads

Our newspaper data contain information almost exclusively about vacancies in the New York City and Boston metro areas. We used this information about New York City and Boston ads to characterize the skill and task content of jobs throughout the United States. This discrepancy could potentially be problematic, especially since workers in New York City and Boston are not representative of U.S. workers more generally. Workers in these metro areas tend to have higher education, are paid higher wages, and are over-represented in certain types of occupations (e.g., in financial management, in tertiary education, etc.) and under-represented in others. What is more, this non-representativeness may be growing over time (for example, the college graduate share in New York City and Boston has increased faster than in other parts of the country.)

Unfortunately, we cannot examine — based on our newspaper data — whether our occupations' task measures are substantially different in Boston and New York compared to the rest of the United States. However, we have a sample of text from vacancy postings from a more recent period, from October 2011 to March 2017, from which we can examine the representativeness of Boston and New York. Our sample is drawn from a 5 percent sample of ads, 7.6 million ads, which were collected by EMSI.[46]

To do so, we begin by computing our nonroutine and routine task measures, using the same mapping between words and task groups that we use in the rest of the paper. We then perform a set of regressions characterized by the following equation:

$$\text{task}_{ajt}^{h} \quad = \quad \beta_h \cdot 1_{a \in \{\text{Boston, New York}\}} + \iota_{jh} + \iota_{th} + \iota_{sh} + \epsilon_{ahjt}. \quad (4)$$

In Equation 4, h refers to one of five routine and nonroutine task categories; task_{ajt}^{h} equals the number of mentions of task h (relative to the number of words in the ad) in a, published

side search behavior.

[46] For this exercise, we drop the first three months — October 2011 to December 2011 — as the number of ads collected per month is rapidly expanding over the very beginning of the EMSI sample period (suggesting that, relative to the rest of the sample period, the samples in the first few months may not be representative.)

Table 9: Estimates from Equation 4

Fixed Effect	Nonroutine Analytic	Nonroutine Interactive	Nonroutine Manual	Routine Cognitive	Routine Manual
None	0.341	0.319	-0.125	-0.012	0.046
	(0.011)	(0.011)	(0.004)	(0.003)	(0.003)
4-digit SOC	0.142	0.168	-0.085	-0.019	0.061
	(0.010)	(0.010)	(0.004)	(0.003)	(0.003)
6-digit SOC	0.074	0.177	-0.083	-0.025	0.052
	(0.010)	(0.010)	(0.004)	(0.003)	(0.003)
Job Title	-0.023	0.078	-0.062	-0.014	0.024
	(0.009)	(0.009)	(0.004)	(0.003)	(0.002)
Mean of h	5.246	5.028	1.019	0.596	0.250
Std. Dev. of h	6.330	6.236	2.401	1.929	1.547

Notes: Each column presents the coefficient estimates, standard errors, and sample statistics of one of our five Spitz-Oener task measures. The first four set of rows present coefficient estimates and standard errors of β_h, with each set of rows applying a different occupation fixed effect. The sample in these regressions includes the job ads for which we could retrieve an SOC code based on the ad's job title, 5.5 million job ads. The final two rows present the average and standard deviation of the task measure in our sample of 5.5 million ads.

in year t, for an occupation j; ι_{jh}, ι_{th}, and ι_{sh} respectively refer to occupation fixed effects, year fixed effects, and fixed effects for the job message board from which EMSI procured the data.[47] The coefficient of interest is β_h, characterizing the relative frequency of task h in the Boston and New York metro areas, relative to the rest of the U.S. We conduct regressions with increasingly detailed occupation fixed effects. These regressions will allow us to assess the extent to which, for example, Engineers in New York and Boston differ from those in the rest of the U.S. (using a 4-digit SOC fixed effect), Electrical Engineers in New York and Boston are unique (using a 6-digit SOC fixed effects), or Wire Design Installation Engineers in New York and Boston are unique (using job title fixed effects.)

The results from this exercise are given in Table 9. We find substantial differences in the overall task content of Boston and New York jobs, relative to the rest of the country. Per 1000 job ad words, there are 0.34 additional nonroutine analytic task words (0.054= 0.34/6.33 standard deviations) and 0.32 nonroutine interactive task words (0.051 standard deviations) in Boston and New York. However, much of the differences are due to the fact that the occupational mix of Boston and New York are different from that of the country as a whole (as opposed to individual occupations differing in their task content). Using 4-digit SOC fixed effects, the nonroutine analytic and interactive task content of jobs in New York and Boston are higher by 0.022 and 0.027 standard deviations, respectively. Using more detailed fixed effects, at the level of 6-digit SOC codes or job titles, leads to even smaller discrepancies between our two metro areas and the rest of the U.S.

We are not only specifically interested in the level of non-representativeness of our New

[47] As the sample period has progressed, EMSI has collected job ad text from an increasingly wide variety of job posting websites. We include website-specific fixed effects to account for the changing composition over the period.

York and Boston newspaper text, but also in trends in non-representativeness over our 1950 to 2000 sample period. In fact, since our contribution relates to within-occupation trends in task content, trends in non-representativeness of New York and Boston would be especially problematic. For the short (five-year) period from which we have online job ad text, we can examine whether there are any trends in the task content of New York and Boston jobs relative to jobs in other portions of the U.S. To this end, we examine regressions characterized by the following equation:

$$\text{task}^{h}_{ajt} \quad = \quad [\beta_h + \gamma_h \cdot (t - 2012)] \cdot 1_{a \in \{\text{Boston, New York}\}} + \iota_{jh} + \iota_{th} + \iota_{sh} + \epsilon_{ahjt} \tag{5}$$

The parameter of interest in Equation 5 is γ_h; it characterizes the growth rate in task h mentions over the sample period in Boston and New York compared to the rest of the U.S. As before, inclusion of occupation fixed effects tends to reduce the magnitude of the γ_h coefficients. The one coefficient estimate of γ_h that is most indicative of substantial trends in the non-representativeness of New York and Boston jobs is that of routine manual tasks with job title, 4-digit SOC, or 6- digit SOC fixed effects. Using job title fixed effects, ads from Boston and New York (relative to the rest of the United States) mentioned an additional 0.04 (=0.007·5) routine manual task words (per 1000 job ad words) in 2017 relative to 2012. This difference represents 0.023 standard deviations of the routine manual task measure. For the other four task measures, the trend in the difference between Boston and New York task mentions and task mentions in the rest of the country is at most 0.020 standard deviations of the task measure.

Overall, while there are statistically significant differences in ads posted in Boston and New York, relative to the U.S., these differences largely exist between occupations rather than within occupations. Moreover, the differences between New York and Boston and the rest of the U.S. are modest, when compared to the overall dispersion in task measures, across all online job ads.

D Details on the Construction of the Database

This section provides further details that, due to space constraints, we could not include in Section 2. As discussed in that section, constructing the database entails transforming raw, unstructured text into a set of job ads for which we identify job titles and task contents. This requires four steps: (i) identifying pages of job ads from the broader sample of advertisements, (ii) processing the newspaper text files, (iii) grouping occupations according to useful classifications, and (iv) eliciting task and skill related information. We turn to each next. Note that some of the language in this appendix is taken directly from Section 2.

Table 10: Estimates from Equation 5

Fixed Effect		Nonroutine Analytic	Nonroutine Interactive	Nonroutine Manual	Routine Cognitive	Routine Manual
None	β_h	0.375	0.275	-0.172	-0.027	-0.026
		(0.025)	(0.025)	(0.010)	(0.008)	(0.006)
	γ_h	0.034	0.032	-0.018	-0.005	0.001
		(0.005)	(0.005)	(0.002)	(0.002)	(0.001)
4-digit SOC	β_h	0.084	0.143	-0.088	-0.030	-0.001
		(0.022)	(0.023)	(0.009)	(0.007)	(0.006)
	γ_h	-0.006	0.001	-0.009	-0.001	0.001
		(0.004)	(0.004)	(0.002)	(0.001)	(0.001)
6-digit SOC	β_h	-0.059	0.079	0.083	0.026	0.128
		(0.039)	(0.039)	(0.015)	(0.012)	(0.010)
	γ_h	-0.009	0.003	0.002	0.001	0.020
		(0.007)	(0.007)	(0.003)	(0.002)	(0.002)
Job Title	β_h	-0.017	0.061	0.010	0.009	0.092
		(0.035)	(0.036)	(0.014)	(0.012)	(0.009)
	γ_h	0.002	0.025	-0.005	-0.003	0.007
		(0.006)	(0.006)	(0.002)	(0.002)	(0.002)
Mean of h		5.246	5.029	1.020	0.596	0.250
Std. Dev. of h		6.330	6.236	2.401	1.929	1.547

Notes: Each column presents the coefficient estimates, standard errors, and sample statistics of one of our five Spitz-Oener task measures. The first four sets of rows present coefficient estimates and standard errors of β_h and γ_h, with each set of rows applying a different occupation fixed effect. The final two rows present the average and standard deviation of the task measure in our sample of 5.5 million ads.

D.1 Details on the Latent Dirichlet Allocation Procedure, Used to Distinguish Vacancy Postings from Other Ads

Given the massive amount of newspaper text, it is practically impossible for us to manually distinguish job vacancy postings from other types of advertisements. A simple solution would be to remove newspaper pages where no job vacancy related words can be found. This solution, however, could be problematic as, for example, the word "sales" appears in vacancy postings for "sales representatives" and to advertise retail sales. Nevertheless, it is reasonable to assume that job vacancy postings would have different features (distributions of words, to be more precise) compared to other types of advertisements.

In our context, the Latent Dirichlet Allocation (LDA) model is used to distinguish pages of job ads (one of the model's topics) from other groups of ads. Estimation of the LDA model denotes estimation of the probability that different sets of words (e.g., "experience," "sale," "price") appear in different pages of advertisements, conditional on the topic of the ad. Since each page of advertisements contains a collection of words, the model will allow us to compute the probability that any one page of advertisements is comprised of job ads. Roughly put, the model identifies sets of words that frequently appear together in the same documents within a text corpus. For example, if there were only two types of ads in our newspaper data, job ads or sales ads, one set of ads would be characterized by containing the words "experience," "years," or "opportunity." A second set of ads would be characterized by containing the words "store," "save," or "price." Using this intuition, we apply LDA, an algorithm that categorizes documents within a corpus on the basis of their words. It is an "unsupervised learning algorithm," in the sense that a training data set is not required. The exposition in this section draws heavily from Blei et al. (2003, pp. 996-998).

Notation and Terminology

1. A *vocabulary, V,* is a set of all possible words.
2. A *word* w is a vector of length $|V|$. If w takes on the ith element of the vocabulary, then $w_i = 1$. Otherwise, $w_i = 0$.
3. A *document* is a sequence of N words denoted by $\mathbf{d} = (w_1, w_2 ... w_N)$.
4. A *corpus* is a collection of M documents denoted by $\boldsymbol{D} = (\mathbf{d}_1, \mathbf{d}_2 ..., \mathbf{d}_M)$.
5. A *topic* $z \in \{z_1, z_2, ..., z_K\}$ denotes a "hidden label" across documents in a corpus. The dimensionality K is assumed to be known and fixed.

Data Generating Process

The model assumes the following process.

1. First, choose a vector $\alpha = (\alpha_1, \alpha_2, ..., \alpha_K)$ and a K by V matrix β. Hold these α and β fixed throughout the corpus.
2. Next, for each document $\mathbf{d_m}$ in the corpus, choose a K-dimensional topic weight vector θ_m drawn from a Dirichlet distribution with parameter vector α. That is,

$$\Pr\left(\theta_{m1}, \theta_{m2}, ..., \theta_{mK} | \alpha_1, \alpha_2, ..., \alpha_K\right) = \frac{\Gamma\left(\sum_{k=1}^{K} \alpha_k\right)}{\prod_{k=1}^{K} \Gamma\left(\alpha_k\right)} \cdot \prod_{k=1}^{K} \left(\theta_{mk}\right)^{\alpha_k - 1},$$

   where each $\alpha_k > 0$ and $\Gamma(\cdot)$ refers to the Gamma function.

3. Finally, each word in a document $\mathbf{d}_m$ is determined by first choosing a topic $z \in \{z_1, z_2, ..., z_K\}$ where the probability of choosing a particular topic k is equal to $\Pr(z = z_k | \theta_{m1}, \theta_{m2}, ..., \theta_{mK}) = \theta_{mk}$. Then, choose a word w_n from a word-topic probability matrix β where the n, k element of β=$\Pr\left(w_n = 1 | z_k = 1\right)$.

Conditional on α and β, the joint distribution of a topic mixture θ, a set of topics $\mathbf{z}$, and a document $\mathbf{d}_m$ (which contains words w_n) is given by:

$$\Pr\left(\theta, \mathbf{z}, \mathbf{d}_m | \alpha, \beta\right) = p\left(\theta | \alpha\right) \prod_{n=1}^{N} p\left(z_k | \theta\right) p\left(w_n | z_k, \beta\right).$$

The marginal distribution, or likelihood, of a document $\mathbf{d}_m$ which contains words w_n is given by integrating over θ and summing over potential topics z_k:

$$\begin{aligned}
\Pr\left(\mathbf{d}_m|\alpha,\beta\right) &= \int p\left(\theta|\alpha\right)\left(\prod_{n=1}^{N}\sum_{k=1}^{K} p\left(z_k|\theta\right)p\left(w_n|z_k,\beta\right)\right)d\theta \\
&= \frac{\Gamma\left(\sum_{k=1}^{K}\alpha_k\right)}{\prod_{k=1}^{K}\Gamma\left(\alpha_k\right)}\cdot\int\prod_{k=1}^{K}\left(\theta_{mk}\right)^{\alpha_k-1}\prod_{n=1}^{N}\sum_{k=1}^{K}\prod_{v=1}^{V}\left(\theta_{mk}\beta_{kv}\right)^{w_n}d\theta.
\end{aligned}$$

Estimation

The main purpose of LDA is to determine the distribution of the latent topics conditional on the observed words in each document. The distribution is as follows:

$$\Pr\left(\theta,\mathbf{z}|\mathbf{d}_m\alpha,\beta\right) = \frac{\Pr\left(\theta,\mathbf{z},\mathbf{d}_m|\alpha,\beta\right)}{\Pr\left(\mathbf{d}_m\alpha,\beta\right)}.$$

The estimated values, $\widehat{\alpha}$ and $\widehat{\beta}$, are values of α and β which maximize the log likelihood of the documents:

$$\left(\widehat{\alpha},\widehat{\beta}\right) = \arg\max\left\{\sum_{m=1}^{M}\log\left[\Pr\left(\mathbf{d}_m|,\alpha,\beta\right)\right]\right\}.$$

The posterior distribution cannot be computed directly. As a feasible approximation, we use Hoffman et al. (2010)'s Expectation Maximization algorithm. The python code for this algorithm is part of the *gensim* module; see Rehurek and Sojka (2010).

Details on Our Implementation

To construct our LDA model, we take samples of 100 thousand pages of advertisements from each of our newspapers, separately: display ads in the *Boston Globe*, spanning 1960 to 1983; display ads in the *New York Times*, 1940 to 2000; classified ads in the *Boston Globe*, 1960 to 1983; classified ads in the *New York Times*, 1940 to 2000; and classified ads in the *Wall Street Journal*, 1940 to 1998. Since the text in display ads is larger, our code more easily identifies and processes the text in these ads. For this reason, we apply our processing code separately for these different types of ads.

For each of our five subsamples, we first restrict attention to pages of advertisements which are at least 200 words. From these pages of ads, we remove *stop words* (e.g., common words like "a," "the," and "and"), numerals, and words that are not contained in the English dictionary. We then *stem* words; that is, we remove word affixes so that words in different forms—singular nouns, plural nouns, verbs, adjectives, and adverbs—are grouped as one. To emphasize, the removal of certain types of words and the stemming of words pertains to the construction of our LDA model. Once we have estimated this model, we will restore our original text.

After estimating the model, each page in each subsample is defined by a probability distribution over K topics. We pick the pages for which the probability of belonging to the topic with words common in vacancy postings is greater than 0.40. The choice of the cutoff balances a trade-off between throwing out too many vacancy postings (particularly job ads in sales-related occupations) and including too many non-job ads in our data set. Choosing a low cutoff will lead us to include pages of non-job-related ads at this stage. However, since succeeding stages will discard ads without job titles, these pages of non-job ads will be excluded.[48]

LDA Results

In Table 11, we present partial results from our LDA procedure, listing the ten words which are most predictive of each topic for each of the subsamples in our sample: the *Boston Globe* classified ads, the *Boston Globe* display ads, the *New York Times* classified and display ads, and the *Wall Street Journal* classified ads. We chose the number of topics, K, so that (i) there is a clear, identifiable topic associated with job ads, but (ii) if we were to add a $K + 1^{\text{st}}$ topic, then there would be multiple job-related topics resulting from the LDA model. The words presented in these tables are those with the highest values of β_{nk}.

D.2 Processing the Newspaper Text Files

The goal of this step is to parse the raw text files to produce a set of separate ads, complete with job titles and word content.

Discerning the Boundaries between Vacancy Postings In the ProQuest data set, the advertisements on a single page are all grouped in a single text field. Our next task is to identify when one vacancy posting ends and a second posting begins. Here, certain phrases at the beginning or end of individual help wanted ads allow us to identify the boundaries between ads. We use the following three-step rule to demarcate individual ads:

- Addresses: Most job vacancy posts have the employers' addresses at the end. The first step of our algorithm marks the end of an advertisement. We are able to match zip codes, cities, and address fragments, such as such as "150 East 42 Street, N. Y."

- Ending phrases: Some phrases indicate that a job vacancy post is ending, for example: "send [...] resume," "submit [...] resume," "in confidence to," "affirmative action employer," "equal opportunity;" or "equal opportunities." The algorithm marks the end of an advertisement if any of these patterns is detected and starts a new one after the following line.

- Beginning of the posts: A job vacancy post usually starts with a job title, which stands alone within a few lines and is uppercase. If we detect consecutive short lines of uppercase

[48] Within economics, we are aware of one application of LDA, which classifies Federal Open Market Committee statements by topic. See Fligstein et al. (2014) and Hansen et al. (2018).

Table 11: Predictive Word Stems in the LDA Model

Panel A: *Boston Globe* Classified Ads	
1	opportun experi work call salari year employ posit manag resum
2	offic new day avail want free inc busi servic mass
3	auto new car call ford low stereo rte price motor
4	bdrm bath kit mod new bay condo home area back
5	bdrm bay mod back avail kit bath studio call build
Panel B: *Boston Globe* Display Ads	
1	system experi comput opportun year manag engin program requir design
2	reg save store size price color style set regular charg
3	car price new auto power tire stereo air door stock
4	day free new one call coupon travel per offer week
5	street open inc ave mass call rte rout new home
Panel C: *New York Times* Classified Ads	
1	resum seek call must work exp excel new salari send
2	new home owner acr call car hous den area ask
3	build ave new park call studio east avail fee fir
Panel D: *New York Times* Display Ads	
1	experi manag system comput new opportun program requir year salari
2	school sat sun new call music ticket program wed art
3	day hotel travel free night includ new call per beach
4	one get make new year help take like time busi
5	new room call home ave avail park build floor offic
6	new white size avenu black store fifth floor wool open
7	free call new order phone charg card pleas send mail
8	rate new fund bank invest offer inc may compani interest
9	ave new street avenu park plaza unit east mall twin
10	car new call auto leas drive mile dealer power price
11	new book time world art film one magazin page news
12	price reg save design color set furnitur store select rug
Panel E: *Wall Street Journal* Classified Ads	
1	experi resum salari opportun posit year market requir send develop
2	acr home call room new view beach pool bath hous
3	estat real properti offic leas locat unit call build new
4	busi street journal box wall call compani servic new avail
5	new call air owner price interior avail number ad car

letters, we group those lines together. We then test whether the lines are a job title (see below). If so, the algorithm assigns the beginning of an advertisement here.

Identifying the Advertisement's Job Title Finally, since one of the main goals of the project is to identify how individual occupations' task contents have changed over time, it will be necessary to assign each vacancy posting to its corresponding occupation. On their website, O*NET publishes, for each occupation, a "Sample of Reported Job Titles." We retrieve these titles, a list of more than eight thousand, from the O*NET website. From this list of titles, we construct a list of one-word personal nouns. For instance, "Billing, Cost, and Rate Clerks" is a potential job title according to O*NET; see `http://www.onetonline.org/link/summary/43-3021.02`. Since it is exceedingly unlikely that this exact phrase appears in any of our ads, we identify a potential job title to appear when the word "Clerk" is mentioned.

Then, in each line in which either (i) words are all-capitalized or (ii) only one or two words appear, we search among the words in that line of advertisement text for a personal-noun job title. According to our example in Figure 1, in the body of the paper, this would occur in the lines containing "ACCOUNTANTS," "MECHANICAL ENGINEER "METHODS ENGR," "RESUMES PRINTED," "Needs A," "TRANSPORTATION ADVERTISING SUPERVISOR," "With ...," "PERFORMANCE ENGINEERS", and "RESEARCH LABORATORIES UNITED AIRCRAFT CORPORATION." The lines with "ACCOUNTANTS," "MECHANICAL ENGINEER," "TRANSPORTATION ADVERTISING SUPERVISOR," and "PERFORMANCE ENGINEER" also contain a personal-noun job title. As a result, the contents of these lines are reported as the ads' job titles. Our algorithm correctly recognizes that "RESUMES PRINTED" and "Needs A" do not refer to job titles, but also erroneously omits "METHODS ENGR" from the list of job titles.

D.3 Details on the Continuous Bag of Words Model

The goal of the continuous bag of words (CBOW) model is to compute the similarity among words or phrases in our corpus. The first three subsections of this appendix provide a basic set up of such a model, drawing from Section 2 of Bengio et al. (2003). After this, we describe how we use our estimated continuous bag of words model to link job titles to SOC codes and job ad text to categories of occupational characteristics.

Notation and Terminology

1. A *word,* w_i, is a unit of text.

2. A *vocabulary, V,* is a set of all possible words.

3. A *corpus* is a sequence of words denoted by $\{w_1, w_2 ... w_T\}$.

4. A *context* of a word is a set of adjacent words of predetermined distance. For our model, a context of a word w_i is $\mathcal{H} = \{w_{i-1}, w_{i-2}, ... w_{i-n}, w_{i+1}, ..., w_{i+n}\}$, a set of $2n - 1$ words which appear within a n-word window of w_i .

Model Setup and Estimation

The underlying assumption in the continuous bag of word model is that words in similar contexts share semantic meaning in the population of text data. In the CBOW model, similar context refers to a set adjacent words, typically a fixed number of n words surrounding the word.[49]

The objective, which we will try to maximize via maximum likelihood, is given by the probability of observing a word w_i conditional on the features of the words in its context $C(\mathcal{H})$. Below, we will use $\hat{P}\left(w_i|C(\mathcal{H})\right)$ to denote this probability (which is our MLE objective). The model estimation can be divided into two parts:

1. A mapping C from each word w_i in V to a real vector of predetermined length N. Here N will be parameter we are free to choose, describing how many features to include in our model to describe each individual word. In practice, C is a |V| by N dimensional matrix.

2. A function g which maps a sequence of C words in the context to a conditional probability distribution over words. $\hat{P}\left(w_i|C(\mathcal{H})\right) = g\left(w_i, C\left(w_{j1}\right), C\left(w_{j2}\right), ...\right)$, where all of the j belong to $\mathcal{H}$. In practice, g can be represented as a N by |V| matrix for each possible context $\mathcal{H}$.

In these two steps, we are predicting the likelihood of observing a particular word w_i based on the features of the words that surround it. Our model will yield a good representation of the words in our vocabulary if they accurately and parsimoniously describe the attributes of these words. The maximum likelihood procedure chooses C and g to match conditional probabilities observed in the corpus. Though the idea is relatively simple, the dimensionality of the model requires additional adjustments to reduce the computational burden. To this end, we follow the procedure as mentioned in Mikolov et al. (2013a; 2013b). We choose the dimension of C to be 300, and the context of word w_i to include the five words succeeding and preceding each w_i. In writing out the MLE objective function, we omit words w_i which appear fewer than five times in our corpus.[50]

Construction of the CBOW Model

As part of a separate ongoing project, EMSI has provided us a wide sample of job ads posted online between October 2011 and March 2017. As with our newspaper data, these text contain a job title for each vacancy posting. Using our sample of text from the *Boston Globe*, *New York Times*, and *Wall Street Journal* and the entries from sample of 4.2 million job ads that were posted in January 2012 or January 2016, we construct a continuous bag of words model, applying the procedure outlined in the previous subsection. The output of this model is a

[49] However, given the same set of adjacent words, the order does not matter. For example, if the window size is 1, then, the context [..., w_1, $\overline{w}$, w_2, ...] is the same as [..., w_2, $\overline{w}$, w_1, ...] for any word $\overline{w}$.

[50] Mikolov et al. (2013a) estimated a model using text from a Google News corpus, and found that increasing the dimensionality of the model's vector representation from 300 to 600 led to only small improvements in performance.

vector representation, C, for each word. A phrase, too, can be represented as a vector, as the sum of the vectors of the phrase's constituent words. For example, we will find it useful to construct a vector representation of a phrase like "construction manager." To do so, we would simply sum the vectors for "construction" and "manager."

With our estimate of C we use a cosine similarity score: $\frac{C(w_i)\cdot C(w_j)}{|C(w_i)||C(w_j)|}$ to compute similarity between two words (or phrases) w_i and w_j. We use this similarity score for two purposes: to link job titles to SOC codes, and to link the words used in the body of job ads to categories of work characteristics. In the following two subsections, we detail these two applications of our CBOW model.

Grouping Occupations and Mapping Them to SOC Codes

In the newspaper data, postings for the same occupation appear via multiple distinct job titles. For example, vacancy postings for registered nurses will be advertised using job titles which include "rn," "registered nurse," or "staff nurse." These job titles all map to the same occupation: 291141 using the BLS Standard Occupational Classification (SOC) system, or 3130 according to the 2000 to 2009 vintage of the Census Occupation Code. To group job titles to occupation codes, we apply the BLS SOC code. We first lightly edit job titles to reduce the number of unique titles: We combine titles which are very similar to one another (e.g., replacing "host/hostesses" with "host," and "accounting" with "accountant," etc.); replace plural person nouns with their singular form (e.g., replacing "nurses" with "nurse," "foremen" with "foreman," etc.); and remove abbreviations (e.g., replacing "sr" with "senior," "asst" with "assistant," and "customer service rep" with "customer service representative").

From this shorter list, we apply a *continuous bag of words* model in combination with an ancillary data set provided to us by EMSI (see Bengio et al., 2003, and Mikolov et al., 2013a; 2013b). Generally speaking, a continuous bag of words model is based on the idea that words or phrases are similar if they themselves appear (in text corpora) near similar words. For example, to the extent that "nurse" and "rn" both tend to appear next to words like "patient," "medical," or "acute" one would conclude that "nurse" and "rn" have similar meanings to one another. Building on this idea, a continuous bag of words model represents each word as a (long) vector, with the elements in each vector measuring the frequency with which other words are mentioned nearby (e.g., for the "nurse" vector, what fraction of the time in our corpus of vacancy posting text are "aardvark, "abacus," ... "zoo," or "zygote" mentioned in close proximity to the word "nurse"?). Given this vector representation, two words are similar if the inner product of their vectors is large. Short phrases, too, can be usefully represented as vectors as the sum of the vectors of the constituent words (for example, the vector representation of "construction manager" would equal the sum of the "construction" and "manager" vectors.) Taking stock, with the continuous bag of words model, we can represent any phrase—and, in particular, any job title—as a vector. As a result, we can also compute the similarity of any two job titles, as the inner product of the job titles' associated vectors.

Manually retrieving SOC codes for all of the job titles in our data set would be infeasible. Among ads posted on or after 1950, there are, after all, more than 306 thousand unique job titles which are mentioned in at least two job ads, and more than 75 thousand unique job titles which are mentioned in at least five job ads. We retrieve SOC codes using our continuous bag of words model. In particular, for each job title $\mathcal{N}$ in our newspaper data, we compute the similarity between $\mathcal{N}$ and all of the job titles, $\mathcal{O}$, which appear in O*NET's (version 22.1) either Sample of Reported Titles or Alternate Sample of Reported Titles. For each O*NET job title $\mathcal{O}$, we observe an SOC code. So, for the job title $\mathcal{N}$, we assign to $\mathcal{N}$ the SOC code of the O*NET job title $\mathcal{O}$ closest to $\mathcal{N}$. We do this for any job title that appears our newspaper data.

In a second step, we assign an SOC code of 999999 ("missing") if certain words or phrases appear—"associate," "career builder," "liberal employee benefit," "many employee benefit," or "personnel"—anywhere in the job title, or for certain exact titles: "boys," "boys boys," "men boys girls," "men boys girls women," "men boys men," "people," "professional," or "trainee." These words and phrases appear commonly in our newspaper ads and do not refer to the SOC code which our CBOW model indicates. "Associate" commonly appears the part of the name of the firms which are placing the ad. "Personnel" commonly refers to the personnel department to which the applicant should contact.

We also replace the SOC code for the job title "Assistant" from 399021 (the SOC code for "Personal Care Aides") to 436014 (the SOC code for "Secretaries and Administrative Assistants"). "Assistant" is the fourth most common job title, and judging by the text within the job ads refers to a secretarial occupation rather than one for a personal care worker. While we are hesitant to modify our job title to SOC mapping in an ad hoc fashion for any job title, mis-specifying this mapping for such a common title would have a noticeably deleterious impact on our data set.

In a final step, we amend the output of the CBOW model for a few ambiguously defined job titles. These final amendments have no discernible impact on aggregate trends in task content, on role within-occupation shifts in accounting for aggregate task changes, or on the role of shifts in the demand for tasks in accounting for increased earnings inequality. First, for job titles which include "server" and which do not also include a food-service-related word — banquet, bartender, cashier, cocktail, cook, dining, food, or restaurant — we substitute an SOC code beginning with 3530 with the SOC code for computer systems analysts (151121). Second, for job titles which contain the word "programmer," do not include the words "cnc" or "machine," we substitute SOC codes beginning with 5140 or 5141 with the SOC code for computer programmers (151131). Finally, for job titles which contain the word "assembler" and do not contain a word referring to manufacturing assembly work — words containing the strings "electronic," "electric," "machin," "mechanical," "metal," and "wire" — we substitute SOC codes beginning with 5120 with the SOC code of computer programmers (151131). The amendments, which alter the SOC codes for approximately 0.2 percent of ads in our data set, are necessary for ongoing work in which we explore the role of new technologies in the labor market. Certain words refer both to a job title unrelated to new technologies as well as to new technologies. By linking the aforementioned job titles to SOCs that have no exposure to new technologies, we would be vastly overstating the rates at which food service staff or manufacturing production workers adopt new information and communication technologies. On the other hand, since these ads represent a small portion of the ads referring to computer programmer occupations, lumping the ambiguous job titles with the computer programmer SOC codes will only have a minor effect on the assessed technology adoption rates for computer programmers.

Eliciting Skill- and Task-Related Information

Within the body of the job ads, similar words will refer to a common task or skill. For example, mathematical skills could appear in job ads using the words "mathematics," "math," or "quantitative." To study occupations' evolving skill requirements and task content, it is necessary to categorize these occupational characteristics into a manageable number of groups. Here, we construct three classification schemes.

Our main classification follows that of Spitz-Oener (2006) who, in her study of the changing task content of German occupations, groups activities into five categories: *nonroutine analytic, nonroutine interactive, nonroutine manual, routine cognitive,* and *routine manual.* In our main application of her categorizations, we begin with the words in each of her five lists of task-related words. For each list, we append words which are similar to those in footnote 14, where similarity is determined by our continuous bag of words model: We append words that have a cosine similarity greater than 0.55 to any of the words in footnote 14. We also append any additional words that have one of the ten highest cosine similarity scores in each task group. This is our primary classification, and we use it in each calculation that follows in the paper. In addition, as a robustness check, we will consider a narrower mapping between categories and words, one which only relies in Spitz-Oener (2006)'s definitions as enumerated in footnote 14.

For varying purposes, we also consider two additional complementary classifications. First, with the aim of emulating O*NET's database, we construct our own classification between words and phrases on the one hand and occupational work styles (corresponding to O*NET Elements beginning with 1C), skills (encompassing O*NET Elements 2A and 2B), knowledge requirements (corresponding to O*NET Elements 2C), and work activities (O*NET Elements 4A) on the other. For each O*NET Element, we begin by looking for words and phrases related to the O*NET Title and, refer to the O*NET Element Description to judge whether these synonyms should be included, as well as if other words should be included. For instance, for the "Production and Processing" knowledge requirement, our list of synonymous words includes the original "production" and "processing," as well as "process," "handle," "produce," "render," and "assembly." And since the O*NET Description for "Production and Processing" states that the skill is associated with the "Knowledge of raw materials, production processes, quality control, costs, and other techniques for maximizing the effective manufacture and distribution of goods," we also include "quality control," "raw material," "qc," and "distribution" in our list of words and phrases to search for when measuring this knowledge requirement. Admittedly, since this procedure is based on our own judgment, it is necessarily ad hoc. Moreover it will not be able to capture all of the words phrases which are indicative of a particular work style, skill, knowledge requirement, or work activity.

For this reason, we append to our initial lists of words and phrases an additional set of words, using a continuous bag of words model similar to the one constructed in Section 2.2, built from the newspaper and online (January 2012 and January 2016) job ads. We compute the similarity of the words in each O*NET Element Title and all of the other words in our corpus of newspaper and online vacancy postings. For instance, for "Production and Processing," our model yields: "process," "processes," "packaging," "preparation," and "manufacturing" as the words with the highest cosine similarity. We take the top 10 words, plus any additional words which have a cosine similarity greater than 0.45, to the O*NET Element Title and add these words to those words and phrases from our "judgment-based" procedure described in the previous paragraph.

Each of the two approaches, the "judgment based" procedure and the "continuous bag of words model based" procedure, has its strengths and weaknesses. On the one hand, the first procedure is clearly ad hoc. Moreover, the continuous bag of words model has the advantage of accounting for the possibility that employers' word choice may differ within the sample period.[51] On the other hand, the continuous bag of words model has the potential to identify words as synonyms even if they are not synonymous. For example, the vector representations in our bag of words model indicates that the five most similar words to the "Mathematics" O*NET Element Title are "math," "physics," "economics," "algebra," and "science." While the first five words strike us as reasonable, a word like "linguistics", which also appears in the list of similar words according to the CBOW model, seems more of a stretch.

Our second classification scheme applies the mapping between keywords and skills which Deming and Kahn (2018) define in their study of the relationship between firms' characteristics and the skill requirements in their vacancy postings.[52] To each of these lists of words, we append additional words which are sufficiently similar (those with a cosine similarity greater than 0.55 or among the 10 most similar words for each category) to any of the words in the original list.

[51]For instance, even though "creative" and "innovative" largely refer to the same occupational skill, it is possible that their relative use among potential employers may differ within the sample period. This is indeed the case: Use of the word "innovative" has increased more quickly than "creative" over the sample period. To the extent that our ad hoc classification included only one of these two words, we would be mis-characterizing trends in the O*NET skill of "Thinking Creatively." The advantage of the continuous bag of words model is that it will identify that "creative" and "innovative" mean the same thing because they appear in similar contexts within job ads. So, even if employers start using "innovative" as opposed to "creative" part way through our sample, we will be able to consistently measure trends in "Thinking Creatively" throughout the entire period. A second advantage of our CBOW model is that it allows us to partially undo the transcription errors generated in ProQuest's image scanning. Our CBOW algorithm, for example, identifies "adverhslng" as synonymous "advertising."

[52]See Table 1 of Deming and Kahn (2018) for their list of words and their associated skills. Building on their definitions, we use the following rules (1) cognitive: analytical, cognitive, critical thinking, math, problem solving, research, statistics; (2) social: collaboration, communication, negotiation, presentation, social, teamwork; (3) character: character, energetic, detail oriented, meeting deadlines, multi-tasking, time management; (4) writing: writing; (5) customer service: client, customer, customer service, patient, sales; (6) project management: project management; (7) people management: leadership, mentoring, people management, staff, supervisory; (8) financial: accounting, budgeting, cost, finance, financial; (9) computer (general): computer, software, spreadsheets.

Table 12: Summary of Robustness Checks

Table Number	Measure	Occupation Classification	Description of Exercise	Avg. Within Share
3	Spitz-Oener	6-Digit SOC	Benchmark	0.879
4	Spitz-Oener	Job Title	Benchmark	0.883
5	Deming and Kahn	Job Title	Benchmark	0.861
13	Spitz-Oener	4-Digit SOC	Benchmark	0.944
14	Spitz-Oener	Job Title	No Employment Weights	0.786
15	Spitz-Oener	Job Title	Sample: NYT Classified Ads	0.888
16	Spitz-Oener	Job Title	Sample: NYT Display Ads	0.899
17	Spitz-Oener	Job Title	No Words from CBOW	0.969
18	Spitz-Oener	Job Title	Account for Employment Turnover	0.846
19	Spitz-Oener	Job Title	Normalized Task Measures	0.759
20	Deming and Kahn	Job Title	Normalized Task Measures	1.000

Notes: This table summarizes the average "Within Share" for various decomposition. Within this table, the second column gives the task measure used in the decomposition, either Spitz-Oener (2006)'s or Deming and Kahn (2018)'s categorization. The third column gives the level of occupational aggregation. The fifth column describes other dimensions along which we vary the sample, weighting, or normalization of our decompositions. We provide the formula for the "Avg. Within Share" footnote 22.

E Robustness Checks on Section 3

In Section 3, we considered trends in the frequency with which different groups of words were mentioned in our newspaper text. We showed that the share of words related to routine cognitive and routine manual tasks have declined over the sample period, while words related to nonroutine tasks have increased in frequency. Moreover, nearly all of these changes have occurred within, rather than between, occupations. In this appendix, we assess the sensitivity of these results to applying different ways weighting occupations, to applying different normalizations for the task measures, to excluding words from our CBOW algorithm, and to examining different subsamples. We summarize the results of these robustness checks in Table 12. This table indicates that, across a wide variety of specifications, within-occupation shifts account for a majority of the overall changes in the types of tasks that workers perform. In the remainder of this appendix, we present the full decomposition results from each of the exercises summarized in Table 12.

In Section 3, our decompositions applied either a 6-digit occupation classification or a job-title based classification. In Table 13, we re-compute our decompositions using 4-digit SOC codes as our occupational category. We do so motivated by the relatively coarse occupational categorization at which certain versions and vintages of publicly available data sets categorize occupations.[53] Table 13 indicates that our decomposition results are similar when using either 4-digit or 6-digit SOCs as the occupation classification.

[53] For instance, versions of the American Community Survey—particularly so for vintages from the early 2000s—group multiple different 6-digit SOCs with one another.

Table 13: Trends in Keyword Frequencies: 4-Digit SOC

	Total	Within	Between	Within Share	Total	Within	Between	Within Share
	A. Nonroutine Analytic				B. Nonroutine Interactive			
1950 Level	2.76				5.11			
	(0.03)				(0.07)			
1950-2000	3.20	2.76	0.44	0.86	2.38	1.96	0.42	0.82
	(0.07)	(0.11)	(0.07)	(0.02)	(0.11)	(0.15)	(0.06)	(0.03)
	C. Nonroutine Manual				D. Routine Cognitive			
1950 Level	0.90				1.85			
	(0.03)				(0.03)			
1950-2000	-0.15	-0.13	-0.02	0.89	-1.02	-1.06	0.04	1.04
	(0.04)	(0.04)	(0.02)	(0.16)	(0.03)	(0.04)	(0.02)	(0.02)
	E. Routine Manual							
1950 Level	0.99							
	(0.03)							
1950-2000	-0.93	-0.89	-0.04	0.96				
	(0.03)	(0.03)	(0.01)	(0.01)				

Notes: See the notes for Table 3. Here, we use 4-digit SOC codes as opposed to 6-digit SOC codes as the occupational unit.

In our benchmark decompositions, we have used data from the decennial census to construct employment weights: Across 4-digit occupations, the weight of each occupation corresponds to the share of full-time workers employed in the occupation. In Table 14, we instead use the share of vacancies in job title j as our measure for ϑ_{jt}. As with our benchmark calculations in Table 4, the largest task shifts occurred away from routine manual tasks and toward nonroutine analytic tasks. The "Within Share" is now smaller for nonroutine analytic, nonroutine interactive, and routine cognitive tasks, and somewhat larger for the other two task measures. Overall, summing across the five measures, approximately 79 percent of the overall shifts in tasks have occurred within job titles.

Throughout the paper, we have pooled ads from our different samples of newspapers. Potentially, however, the trends in task mentions among the ads in the *Boston Globe* may differ from those in the *New York Times* or *Wall Street Journal.* Likewise, trends in task mentions among display ads and classify ads may differ from one another. In Tables 15 and 16, we perform our decomposition for two of the five subsamples of ads. (These two subsamples were present throughout our sample.) Comparing Tables 15 and 16, display ads contain a greater frequency of words referring to nonroutine analytic, nonroutine interactive, and routine manual task words, and a lesser frequency of words referring to other tasks. However, among both subsamples and similar to the pooled sample, the largest shifts occurred away from routine manual tasks and toward nonroutine analytic tasks. Also similar across the three subsamples, within job-title shifts in task mentions account for the primary share of overall task shifts. The average "Within Share" is 89 percent in Table 15 and 90 percent in Table 16.

When we produced Table 3, Table 4, and our other decomposition tables, we applied

Table 14: Trends in Keyword Frequencies: Vacancy Weights

	Total	Within	Between	Within Share	Total	Within	Between	Within Share
	A. Nonroutine Analytic				B. Nonroutine Interactive			
1950 Level	3.46				5.58			
	(0.03)				(0.11)			
1950-2000	2.82	1.80	1.01	0.64	2.26	1.07	1.19	0.47
	(0.06)	(0.14)	(0.13)	(0.05)	(0.15)	(0.23)	(0.24)	(0.10)
	C. Nonroutine Manual				D. Routine Cognitive			
1950 Level	0.66				2.64			
	(0.02)				(0.05)			
1950-2000	-0.09	-0.10	0.01	1.15	-1.68	-0.95	-0.73	0.56
	(0.02)	(0.04)	(0.04)	(0.53)	(0.05)	(0.15)	(0.13)	(0.08)
	E. Routine Manual							
1950 Level	0.64							
	(0.02)							
1950-2000	-0.60	-0.55	-0.05	0.92				
	(0.02)	(0.02)	(0.02)	(0.03)				

Notes: See the notes for Table 3. In Table 3, we weight 4-digit SOC codes according to their employment. In this table, instead, we do not apply this weighting method. Further, we use job titles as opposed to 6-digit SOC codes as the occupational unit.

Table 15: Trends in Keyword Frequencies: *New York Times* Classified Ads

	Total	Within	Between	Within Share	Total	Within	Between	Within Share
	A. Nonroutine Analytic				B. Nonroutine Interactive			
1950 Level	2.85				4.99			
	(0.03)				(0.07)			
1950-2000	2.56	2.16	0.40	0.84	2.08	1.79	0.29	0.86
	(0.06)	(0.28)	(0.27)	(0.10)	(0.12)	(0.29)	(0.29)	(0.14)
	C. Nonroutine Manual				D. Routine Cognitive			
1950 Level	0.98				2.00			
	(0.03)				(0.03)			
1950-2000	-0.23	-0.20	-0.02	0.90	-1.10	-0.95	-0.15	0.86
	(0.04)	(0.06)	(0.05)	(0.24)	(0.03)	(0.08)	(0.07)	(0.06)
	E. Routine Manual							
1950 Level	0.91							
	(0.04)							
1950-2000	-0.85	-0.77	-0.08	0.91				
	(0.04)	(0.04)	(0.02)	(0.03)				

Notes: See the notes for Table 3. Here, we compute our task measure only from the set of classified ads published in the *New York Times.* Further, we use job titles as opposed to 6-digit SOC codes as the occupational unit.

Table 16: Trends in Keyword Frequencies: *New York Times* Display Ads

	Total	Within	Between	Within Share	Total	Within	Between	Within Share
	A. Nonroutine Analytic				B. Nonroutine Interactive			
1950 Level	4.27				7.43			
	(0.41)				(1.05)			
1950-2000	2.87	0.43	2.44	0.15	2.00	-1.14	3.13	-0.57
	(0.55)	(0.83)	(0.74)	(0.26)	(1.29)	(1.34)	(1.47)	(57.66)
	C. Nonroutine Manual				D. Routine Cognitive			
1950 Level	0.63				0.84			
	(0.15)				(0.23)			
1950-2000	0.56	0.66	-0.10	1.18	-0.37	-0.45	0.07	1.19
	(0.20)	(0.77)	(0.69)	(2.19)	(0.24)	(0.34)	(0.19)	(1.41)
	E. Routine Manual							
1950 Level	1.88							
	(0.53)							
1950-2000	-1.84	-1.83	-0.00	1.00				
	(0.53)	(0.53)	(0.05)	(0.03)				

Notes: See the notes for Table 3. Here, we compute our task measure only from the set of display ads published in the *New York Times*. Further, we use job titles as opposed to 6-digit SOC codes as the occupational unit.

not only the Spitz-Oener (2006) mapping between words and task groups, but also our own continuous bag of words model to identify additional words to search for. In Table 17, we recompute trends in keyword frequencies, now using Spitz-Oener (2006)'s original mapping between words and task groups. In this table, trends in keyword frequencies—increasing for nonroutine analytic and interactive tasks, decreasing for routine tasks, and little change for nonroutine manual tasks—are similar to those depicted in Table 4. Moreover, as in Table 4, a large fraction of the overall changes in keyword frequencies occur within occupations.

Next, a possible limitation is that we are using job ads (which capture the task content of newly formed jobs) to measure stock of jobs existing at that point in time. Underlying our results is the assumption that job ads reflect the task content of all jobs within the occupation (both new and existing). Here, we make the opposite assumption, namely that once a job is formed its task content is fixed over time. With this assumption, and with knowledge of the rate at which jobs turn over within an occupation (call this ς_j), we can compute the evolution of the task content of the stock ($\check{T}_{jt}$) of a given task in occupation j using a perpetual inventory method:

$$\check{T}_{jt} = \widetilde{T}_{jt} \cdot \varsigma_j + \check{T}_{jt-1} \cdot (1 - \varsigma_j), \tag{6}$$

initializing $\check{T}_{jt} = \widetilde{T}_{jt}$ for $t = 1950$. In this equation $\widetilde{T}_{jt}$, equals a measure of the task content of occupation j in job ads at time t. To measure the job turnover rate, we take the sample (within the CPS-ASEC) of employed workers.[54] For workers employed in occupation j, we compute

[54] We restrict attention to workers who are between the age of 16 and 65, who work at least 40 weeks in the previous

Table 17: Trends in Keyword Frequencies, No CBOW

	Total	Within	Between	Within Share	Total	Within	Between	Within Share
	A. Nonroutine Analytic				B. Nonroutine Interactive			
1950 Level	1.65				1.76			
	(0.03)				(0.04)			
1950-2000	0.95	0.71	0.24	0.75	0.37	0.16	0.21	0.43
	(0.04)	(0.12)	(0.11)	(0.12)	(0.05)	(0.10)	(0.10)	(0.28)
	C. Nonroutine Manual				D. Routine Cognitive			
1950 Level	0.27				0.38			
	(0.01)				(0.01)			
1950-2000	-0.01	-0.05	0.04	6.11	-0.30	-0.29	-0.01	0.95
	(0.02)	(0.03)	(0.03)	(10.37)	(0.01)	(0.02)	(0.02)	(0.05)
	E. Routine Manual							
1950 Level	0.26							
	(0.01)							
1950-2000	-0.25	-0.24	-0.00	0.98				
	(0.01)	(0.01)	(0.01)	(0.03)				

Notes: See the notes for Table 3. In Table 3, we include not only the words mentioned in footnote 14, but also similar words according to our continuous bag of words model. Here, instead, we apply only the mapping between task groups and words mentioned in footnote 14. Further, we use job titles as opposed to 6-digit SOC codes as the occupational unit.

the turnover rate as the fraction of workers who were either in a different occupation in the previous year or who had more than one employer. Once we have computed $\check{T}_{jt}$, we recompute the overall and within-occupation changes in tasks in Table 18. The results from this table are that (i) the overall shifts in tasks are smaller than in the benchmark specification, and (ii) the "Within Share" is slightly smaller than in the benchmark specification, yet still above 70 percent for each task measure.

Finally, throughout the paper, our task measures were stated as task mentions divided per 1000 job ad words. As we have discussed in Section 3.2, our benchmark measures are not directly comparable with one another. Using T_{jt}^h to refer to the average number of mentions of task h in ads for job title j in year t, as an alternative to our benchmark measures, we place our task measures on a comparable scale via the following equations:

$$\widetilde{T}_{jt}^h = \frac{\widehat{T}_{jt}^h}{\sum_{h' \in \text{Spitz-Oener Tasks}} \widehat{T}_{jt}^{h'}} \text{, where} \tag{7}$$

$$\widehat{T}_{jt}^h = \frac{T_{jt}^h}{\sum_{t'=1950}^{2000} \sum_{j' \in \text{JobTitles}} S_{j't'} T_{j't'}^h} \text{, and} \tag{8}$$

S_{jt} equals the fraction of year t ads which have j as the job title. Within Equation 8, our first transformation requires that the Spitz-Oener (2006) tasks have the same mean. Our second

year, who have non-allocated information on age, race, gender, occupation, and number employers.

Table 18: Trends in Keyword Frequencies: Perpetual Inventory-based Weighting

	Total	Within	Between	Within Share	Total	Within	Between	Within Share
	A. Nonroutine Analytic				B. Nonroutine Interactive			
1950 Level	2.86				5.03			
	(0.03)				(0.07)			
1950-2000	2.51	1.87	0.64	0.74	2.01	1.49	0.51	0.74
	(0.06)	(0.23)	(0.21)	(0.08)	(0.12)	(0.25)	(0.25)	(0.12)
	C. Nonroutine Manual				D. Routine Cognitive			
1950 Level	0.97				1.99			
	(0.03)				(0.03)			
1950-2000	-0.21	-0.18	-0.03	0.85	-1.10	-0.92	-0.18	0.83
	(0.04)	(0.06)	(0.05)	(0.24)	(0.03)	(0.06)	(0.06)	(0.05)
	E. Routine Manual							
1950 Level	0.91							
	(0.03)							
1950-2000	-0.84	-0.75	-0.09	0.89				
	(0.04)	(0.04)	(0.02)	(0.02)				

Notes: See the notes for Table 3. In comparison, we here apply Equation 6 to impute occupations' task measures. Further, we use job titles as opposed to 6-digit SOC codes as the occupational unit.

transformation, in Equation 7, then ensures that the task measures for a given job title sum to 1. (A disadvantage of this normalization is that $\widetilde{T}^h_{jt}$ will be ill-defined for job title-year combinations for which $\sum_{h' \in \text{Spitz-Oener Tasks}} \widehat{T}^{h'}_{jt}$=0. This occurs for certain job titles which appear only in a few ads in the year t.) In our final set of robustness checks, we assess the sensitivity of our decompositions' results to these normalization. According to the first panel of Table 19, mentions of the nonroutine analytic task share more than doubled between 1950 and 2000, from 15 percent to 33 percent. The nonroutine interactive words also increased, but to a lesser degree. Conversely, the routine manual tasks share substantially declined, decreasing from 19 percent to 2 percent. The decline of routine cognitive tasks is also considerable, going from 27 percent to 14 percent. As with 4, these shifts have primarily occurred within rather than between job titles. Averaging over the five task groups, 76 percent of the overall shift in task mentions have occurred within job titles. (This is somewhat lower than the 88 percent figure that would correspond to the Table 4 decompositions.) Likewise, Table 20 indicates that large "Within Shares" obtain whether one applies our Equation 7-8 normalization to our Deming and Kahn (2018) measures or not. One difference as a result of the normalization: Some of Deming and Kahn (2018) measures decline over our sample period when applying Equations 7 and 8. In contrast, in Table 5 the frequency of mentions of all words related to Deming and Kahn (2018)'s measure increased between 1950 and 2000.

Table 19: Trends in Keyword Shares

	Total	Within	Between	Within Share	Total	Within	Between	Within Share
	A. Nonroutine Analytic				B. Nonroutine Interactive			
1950 Level	0.148				0.233			
	(0.003)				(0.003)			
1950-1960	0.051	-0.001	0.052	-0.029	0.038	-0.025	0.063	-0.669
	(0.004)	(0.004)	(0.003)	(0.076)	(0.004)	(0.004)	(0.003)	(0.207)
1960-1970	0.034	0.027	0.007	0.801	0.015	0.006	0.009	0.413
	(0.004)	(0.004)	(0.003)	(0.075)	(0.003)	(0.004)	(0.004)	(0.226)
1970-1980	0.014	0.003	0.011	0.220	0.020	0.015	0.004	0.773
	(0.004)	(0.006)	(0.006)	(0.531)	(0.004)	(0.009)	(0.007)	(0.344)
1980-1990	0.037	0.040	-0.003	1.086	0.061	0.064	-0.004	1.058
	(0.005)	(0.011)	(0.008)	(0.231)	(0.005)	(0.011)	(0.010)	(0.165)
1990-2000	0.051	0.080	-0.029	1.564	-0.003	0.003	-0.007	-0.909
	(0.006)	(0.014)	(0.014)	(0.293)	(0.004)	(0.015)	(0.015)	(7.819)
1950-2000	0.187	0.149	0.038	0.797	0.130	0.064	0.066	0.490
	(0.004)	(0.014)	(0.013)	(0.071)	(0.005)	(0.011)	(0.011)	(0.084)
	C. Nonroutine Manual				D. Routine Cognitive			
1950 Level	0.159				0.267			
	(0.004)				(0.004)			
1950-1960	0.001	0.016	-0.015	17.791	-0.063	-0.010	-0.053	0.155
	(0.007)	(0.007)	(0.002)	(76.382)	(0.006)	(0.007)	(0.003)	(0.099)
1960-1970	0.011	0.023	-0.012	2.093	-0.012	-0.004	-0.007	0.366
	(0.005)	(0.007)	(0.005)	(4.277)	(0.005)	(0.007)	(0.005)	(0.542)
1970-1980	0.046	0.057	-0.011	1.229	-0.046	-0.048	0.002	1.045
	(0.004)	(0.011)	(0.010)	(0.233)	(0.004)	(0.008)	(0.007)	(0.164)
1980-1990	-0.066	-0.082	0.015	1.234	0.019	0.059	-0.040	3.160
	(0.004)	(0.014)	(0.012)	(0.184)	(0.006)	(0.010)	(0.008)	(4.775)
1990-2000	-0.008	0.004	-0.013	-0.530	-0.020	-0.063	0.043	3.109
	(0.005)	(0.017)	(0.016)	(6.796)	(0.007)	(0.019)	(0.017)	(1.424)
1950-2000	-0.016	0.019	-0.035	-1.134	-0.122	-0.067	-0.056	0.545
	(0.005)	(0.013)	(0.011)	(0.901)	(0.004)	(0.017)	(0.015)	(0.132)
	E. Routine Manual							
1950 Level	0.193							
	(0.005)							
1950-1960	-0.027	0.020	-0.047	-0.763				
	(0.007)	(0.008)	(0.003)	(0.729)				
1960-1970	-0.049	-0.052	0.004	1.072				
	(0.004)	(0.007)	(0.004)	(0.094)				
1970-1980	-0.035	-0.028	-0.007	0.798				
	(0.004)	(0.007)	(0.006)	(0.169)				
1980-1990	-0.049	-0.081	0.031	1.632				
	(0.003)	(0.006)	(0.005)	(0.106)				
1990-2000	-0.019	-0.024	0.005	1.266				
	(0.003)	(0.006)	(0.005)	(0.258)				
1950-2000	-0.178	-0.165	-0.014	0.923				
	(0.005)	(0.006)	(0.003)	(0.016)				

Notes: See the notes for Table 3. In this table, we apply the normalizations given in Equations 7 and 8. Further, we use job titles as opposed to 6-digit SOC codes as the occupational unit.

Table 20: Trends in Keyword Shares: Deming and Kahn (2018) Measures

	Total	Within	Between	Within Share	Total	Within	Between	Within Share
	A. Character				B. Computer			
1950 Level	0.202				0.027			
	(0.003)				(0.001)			
1950-1960	-0.027	-0.036	0.009	1.323	0.030	0.022	0.008	0.725
	(0.004)	(0.005)	(0.002)	(0.133)	(0.002)	(0.002)	(0.001)	(0.045)
1960-1970	0.027	0.020	0.007	0.745	0.016	0.023	-0.007	1.460
	(0.003)	(0.004)	(0.003)	(0.114)	(0.001)	(0.003)	(0.002)	(0.158)
1970-1980	0.016	0.033	-0.017	2.034	0.022	0.026	-0.004	1.165
	(0.004)	(0.006)	(0.005)	(0.360)	(0.001)	(0.003)	(0.003)	(0.156)
1980-1990	-0.051	-0.056	0.006	1.116	0.031	0.050	-0.019	1.605
	(0.004)	(0.010)	(0.009)	(0.168)	(0.002)	(0.007)	(0.007)	(0.249)
1990-2000	-0.045	-0.058	0.013	1.298	0.041	0.017	0.024	0.414
	(0.003)	(0.008)	(0.008)	(0.168)	(0.003)	(0.009)	(0.009)	(0.209)
1950-2000	-0.079	-0.097	0.018	1.226	0.140	0.137	0.003	0.980
	(0.004)	(0.006)	(0.005)	(0.065)	(0.002)	(0.005)	(0.005)	(0.034)
	C. Customer Service				D. Financial			
1950 Level	0.149				0.149			
	(0.002)				(0.002)			
1950-1960	-0.006	-0.017	0.011	2.782	-0.022	-0.016	-0.006	0.717
	(0.002)	(0.002)	(0.001)	(1.719)	(0.003)	(0.004)	(0.001)	(0.086)
1960-1970	-0.011	-0.012	0.001	1.130	-0.010	-0.014	0.005	1.488
	(0.002)	(0.002)	(0.002)	(0.218)	(0.003)	(0.003)	(0.002)	(0.316)
1970-1980	0.004	0.009	-0.006	2.688	-0.033	-0.043	0.010	1.300
	(0.002)	(0.003)	(0.003)	(3.135)	(0.002)	(0.003)	(0.002)	(0.062)
1980-1990	0.015	0.010	0.004	0.707	0.001	-0.004	0.005	-5.623
	(0.003)	(0.004)	(0.004)	(0.251)	(0.002)	(0.003)	(0.002)	(803.716)
1990-2000	-0.008	-0.010	0.002	1.303	0.002	0.001	0.001	0.613
	(0.002)	(0.006)	(0.006)	(0.913)	(0.002)	(0.004)	(0.004)	(7.175)
1950-2000	-0.006	-0.019	0.013	3.074	-0.062	-0.076	0.014	1.229
	(0.003)	(0.006)	(0.005)	(14.792)	(0.003)	(0.004)	(0.004)	(0.062)
	E. People Management				F. Problem Solving			
1950 Level	0.112				0.102			
	(0.001)				(0.002)			
1950-1960	0.014	0.014	0.000	0.975	0.019	0.025	-0.006	1.314
	(0.002)	(0.003)	(0.002)	(0.125)	(0.003)	(0.004)	(0.002)	(0.101)
1960-1970	0.037	0.042	-0.005	1.149	-0.025	-0.019	-0.006	0.762
	(0.003)	(0.004)	(0.003)	(0.072)	(0.002)	(0.003)	(0.003)	(0.115)
1970-1980	-0.019	-0.038	0.018	1.955	-0.015	-0.019	0.004	1.291
	(0.002)	(0.003)	(0.002)	(0.157)	(0.002)	(0.004)	(0.003)	(0.215)
1980-1990	-0.030	-0.025	-0.006	0.816	-0.005	-0.011	0.006	2.185
	(0.002)	(0.008)	(0.007)	(0.257)	(0.002)	(0.004)	(0.004)	(1.753)
1990-2000	-0.028	-0.024	-0.004	0.855	0.001	-0.004	0.005	-2.539
	(0.002)	(0.009)	(0.009)	(0.304)	(0.002)	(0.005)	(0.005)	(23.262)
1950-2000	-0.027	-0.031	0.003	1.128	-0.025	-0.028	0.004	1.152
	(0.002)	(0.004)	(0.004)	(0.147)	(0.002)	(0.004)	(0.003)	(0.131)

Notes: Continued on the following page.

Table 20 (Continued): Trends in Keyword Shares: Deming and Kahn (2018) Task Measures

	Total	Within	Between	Within Share	Total	Within	Between	Within Share
	G. Project Management				H. Social			
1950 Level	0.111				0.045			
	(0.002)				(0.001)			
1950-1960	0.007	-0.009	0.016	-1.366	-0.003	0.001	-0.004	-0.200
	(0.002)	(0.002)	(0.001)	(1.501)	(0.002)	(0.002)	(0.001)	(5.626)
1960-1970	-0.009	-0.005	-0.004	0.568	0.005	0.008	-0.004	1.825
	(0.002)	(0.002)	(0.002)	(0.208)	(0.001)	(0.003)	(0.002)	(0.491)
1970-1980	0.001	-0.004	0.005	-2.775	0.022	0.020	0.002	0.917
	(0.002)	(0.003)	(0.003)	(47.545)	(0.001)	(0.004)	(0.003)	(0.147)
1980-1990	-0.016	-0.011	-0.004	0.712	0.038	0.044	-0.006	1.157
	(0.001)	(0.004)	(0.003)	(0.235)	(0.001)	(0.004)	(0.004)	(0.116)
1990-2000	0.012	0.043	-0.031	3.507	0.019	0.016	0.002	0.880
	(0.002)	(0.014)	(0.014)	(1.127)	(0.003)	(0.008)	(0.007)	(0.373)
1950-2000	-0.005	0.014	-0.019	-3.065	0.080	0.090	-0.010	1.121
	(0.002)	(0.013)	(0.013)	(17.250)	(0.003)	(0.008)	(0.006)	(0.076)
	I. Writing							
1950 Level	0.102							
	(0.002)							
1950-1960	-0.012	0.015	-0.027	-1.265				
	(0.003)	(0.003)	(0.002)	(0.615)				
1960-1970	-0.029	-0.042	0.013	1.466				
	(0.002)	(0.004)	(0.003)	(0.087)				
1970-1980	0.002	0.015	-0.013	7.759				
	(0.002)	(0.006)	(0.006)	(23.697)				
1980-1990	0.017	0.004	0.013	0.223				
	(0.002)	(0.007)	(0.007)	(0.432)				
1990-2000	0.006	0.019	-0.013	3.194				
	(0.003)	(0.007)	(0.007)	(18.920)				
1950-2000	-0.016	0.010	-0.027	-0.651				
	(0.003)	(0.006)	(0.005)	(0.446)				

Notes: See the notes for Table 3. In this table, we apply the normalizations given in Equations 7 and 8. Further, we use job titles as opposed to 6-digit SOC codes as the occupational unit.

F Robustness Checks on Section 4

This appendix compiles two robustness checks relative to our analysis in Section 4. First, we reproduce Table 6 using the normalizations introduced in Equations 7 and 8. Second, we re-estimate the relationship between job title vintages and tasks while controlling for year fixed effects.

Table 6 in the body of the paper characterized the evolution of Manager, Machinist, Cashier, and Real Estate Sales jobs by comparing each job title's task frequencies to the task frequencies in other job titles in our data set. In these calculations, we applied our baseline task measures, which is the frequency of Spitz-Oener (2006) task mentions per 1000 job ad words. Here, we assess the sensitivity of Table 6 to this measure of task intensity. Alternatively, Table applies Equations 7 and 8 to construct measures of the shares of each each Spitz-Oener (2006) task among the set of ads for each job title - decade pair.

Using these normalizations, we compute that 1950s Manager jobs were 12 percent nonroutine analytic, 20 percent nonroutine interactive, 17 percent nonroutine manual, 15 percent routine cognitive, and 36 percent routine manual. Managerial jobs in the 1950s closely mirrored—according to this five-dimensional representation—Pressman jobs. Averaging over all ads in our sample period, ads with Pressman as the job title were 14 percent nonroutine analytic, 19 percent nonroutine interactive, 20 percent nonroutine manual, 12 percent routine cognitive, and 36 percent routine manual. Over time, the nonroutine analytic and interactive task content of "Manager" jobs increased. Correspondingly, we find that 1960s Manager job ads were similar to Purchasing Agent ads. Later in the sample, Managers more closely resembled Editors (in the 1980s) and Recruiters (in the 1990s). The remaining three panels of Table 6 characterize the evolution of Machinist, Cashier, and Real Estate Sales job ads. Machinist job ads only meaningfully shifted between the 1980s and 1990s. In the last decade of our sample, Machinist ads began to resemble 1950-2000 Printer job ads. The Cashier job ads from the 1950s contained similar task combinations to Comptometer Operator ads. By the 1990s, Cashier job ads more closely resembled ads for Secretary Receptionists.

These patterns qualitatively mirror those in Table 6. Managers more closely mimic production-related occupations (i.e., Production Manager or Pressman) in the 1950s and jobs centered around interpersonal tasks (Recruiter or Coordinator) in the 1990s. Machinists are relatively unchanged in their task mix throughout the first four decades of our sample. There are also noteworthy differences: According to Table 6, Real Estate Sales only noticeably changed in the 1990s, when this job title's task mix approximated that of 1950-2000 Furniture Salespersons. In the bottom panel of Table 21 instead, Real Estate Sales closely mirrored Furniture Salespersons in the 1950s, Telephone Sales in the 1960s and 1970s, and Advertising Sales in the 1980s.

In Section 4.2, we document that the task content of job titles that emerge later in our sample period differs from the content of those that emerge earlier. Our key finding is that newer job titles have higher intensities of nonroutine analytic and interactive tasks, lower intensities of routine cognitive and manual tasks, and higher intensities of computer skills.

Table 21: Near Job Titles

	Shares	Similar Job Title	Shares of Similar Job Title
Panel A: Manager			
1950-1959	(0.12, 0.20, 0.17, 0.15, 0.36)	Pressman	(0.14, 0.19, 0.20, 0.12, 0.36)
1960-1969	(0.21, 0.24, 0.19, 0.12, 0.24)	Purchasing Agent	(0.17, 0.29, 0.17, 0.09, 0.27)
1970-1979	(0.29, 0.29, 0.19, 0.09, 0.15)	Manager	(0.27, 0.30, 0.18, 0.12, 0.13)
1980-1989	(0.29, 0.33, 0.19, 0.11, 0.08)	Editor	(0.30, 0.32, 0.18, 0.11, 0.10)
1990-2000	(0.32, 0.36, 0.18, 0.12, 0.02)	Recruiter	(0.32, 0.35, 0.17, 0.13, 0.03)
Panel B: Machinist			
1950-1959	(0.03, 0.03, 0.18, 0.05, 0.71)	Machinist	(0.03, 0.02, 0.15, 0.04, 0.75)
1960-1969	(0.03, 0.02, 0.14, 0.05, 0.76)	Machinist	(0.03, 0.02, 0.15, 0.04, 0.75)
1970-1979	(0.03, 0.01, 0.11, 0.01, 0.84)	Machinist	(0.03, 0.02, 0.15, 0.04, 0.75)
1980-1989	(0.04, 0.02, 0.16, 0.03, 0.76)	Machinist	(0.03, 0.02, 0.15, 0.04, 0.75)
1990-2000	(0.14, 0.12, 0.25, 0.03, 0.45)	Printer	(0.12, 0.15, 0.18, 0.10, 0.46)
Panel C: Cashier			
1950-1959	(0.06, 0.08, 0.07, 0.64, 0.15)	Comptometer Operator	(0.07, 0.10, 0.06, 0.62, 0.15)
1960-1969	(0.08, 0.09, 0.11, 0.55, 0.16)	Clerk	(0.07, 0.10, 0.08, 0.58, 0.17)
1970-1979	(0.07, 0.09, 0.24, 0.43, 0.18)	Teller	(0.14, 0.14, 0.16, 0.44, 0.13)
1980-1989	(0.11, 0.20, 0.17, 0.46, 0.07)	Claims	(0.16, 0.17, 0.13, 0.44, 0.10)
1990-2000	(0.21, 0.30, 0.06, 0.38, 0.05)	Secretary Receptionist	(0.15, 0.26, 0.08, 0.44, 0.06)
Panel D: Real Estate Sales			
1950-1959	(0.10, 0.63, 0.13, 0.03, 0.11)	Furniture Salesperson	(0.14, 0.54, 0.14, 0.07, 0.11)
1960-1969	(0.09, 0.69, 0.11, 0.07, 0.04)	Telephone Sales	(0.08, 0.70, 0.11, 0.07, 0.05)
1970-1979	(0.07, 0.74, 0.12, 0.02, 0.05)	Telephone Sales	(0.08, 0.70, 0.11, 0.07, 0.05)
1980-1989	(0.08, 0.74, 0.11, 0.06, 0.01)	Advertising Sales	(0.08, 0.76, 0.10, 0.04, 0.02)
1990-2000	(0.09, 0.61, 0.23, 0.07, 0.00)	Real Estate Sales	(0.09, 0.69, 0.14, 0.05, 0.04)

Notes: See the notes related to Table 6. In contrast to Table 6, we apply the normalizations given in Equations 7 and 8. Further, we use job titles as opposed to 6-digit SOC codes as the occupational unit.

These patterns hold both within and across conventionally defined SOC occupation codes.

To estimate Equation 2, we calculate task contents for each job title over our entire sample period, and hence the time time periods we use vary across job titles. The Section 4.2 specification is our preferred one. Much of the overall time trends in tasks is due to the arrival of new vintages of job titles. We prefer our estimates to reflect that channel.

However, one may wish to compare newer and older vintages at the same point in time, since other time trends in tasks may account for part of the observed differences between newer and older job titles. In this section we re-estimate Equation 2 at the job title-year level, and include year fixed effects. The comparison below is between newer and older job titles, observed in the same year.

We estimate the following regression:

$$\widetilde{T}_{jt}^{h} = \beta_o + \beta_t + \beta_1 v_j^p + \varepsilon_{jht} \tag{9}$$

Unlike Equation 2, Equation 9 exploits variation across job titles and over time. In this

Table 22: Relationship Between Task Measures and Job Title Vintages

Dependent Variable	Nonroutine Analytic	Nonroutine Interactive	Nonroutine Manual	Routine Cognitive	Routine Manual	Deming and Kahn Computer
Panel A: No SOC Fixed Effects, $p = 0.05$						
Coefficient	0.007	0.013	0.001	-0.015	-0.001	0.023
Standard Error	0.002	0.002	0.000	0.001	0.000	0.001
Panel B: 6-Digit SOC Fixed Effects, $p = 0.05$						
Coefficient	-0.011	0.003	-0.001	-0.007	-0.002	0.005
Standard Error	0.001	0.001	0.000	0.000	0.000	0.001
Panel C: No Fixed Effects, $p = 0.50$						
Coefficient	0.020	0.056	0.002	-0.027	-0.004	0.017
Standard Error	0.002	0.003	0.000	0.002	0.000	0.002
Panel D: 6-Digit SOC Fixed Effects, $p = 0.50$						
Coefficient	0.006	0.024	0.001	-0.005	-0.001	0.007
Standard Error	0.001	0.002	0.000	0.001	0.000	0.001
Panel E: No Fixed Effects, $p = 0.95$						
Coefficient	0.002	0.013	-0.001	0.007	-0.002	-0.002
Standard Error	0.002	0.002	0.000	0.002	0.000	0.001
Panel F: 6-Digit SOC Fixed Effects, $p = 0.95$						
Coefficient	0.008	0.008	0.001	0.008	0.001	0.003
Standard Error	0.001	0.001	0.000	0.001	0.000	0.001

Notes: Within each panel and column, we present coefficient estimates and standard errors corresponding to estimates of Equation 22. In this table, each observation is a job-title year combination. This contrasts with Table 7, in which each job title corresponds to a single observation.

regression, we include both occupation fixed effects (β_o) and year fixed effects (β_t). For most task and job title vintage measures, the results in Table 22 agree with those of Table 7. Nonroutine analytic tasks, nonroutine interactive tasks, and computer skills are more frequently mentioned in newer job titles. Routine manual tasks are more frequently mentioned in older vintage job titles. Not surprisingly, across all specifications, the estimated coefficients are somewhat smaller in absolute value than those in Table 7. Moreover, we note that the task versus vintage relationship is at times sensitive to the measure of job title vintage under consideration.

Appendix References

Autor, D. H., F. Levy, and R. J. Murnane (2003): "The Skill Content of Recent Technological Change: An Empirical Exploration," *Quarterly Journal of Economics*, 118(4), 1279–1333.

Autor, D. H., (2015): "Why Are There Still So Many Jobs? The History and Future of Workplace Automation," *Journal of Economic Perspectives*, 29(3), 3–30.

Bengio, Y., R. Ducharme, P. Vincent, and C. Jauvin (2003): "A Neural Probabilistic Language Model," *Journal of Machine Learning Research*, 3, 1137–1155.

Blei, D. M., A. Y. Ng, and M. I. Jordan (2003): "Latent Dirichlet Allocation," *Journal of Machine Learning Research*, 3, 993–1022.

Deming, D., and L. B. Kahn (2018): "Skill Requirements across Firms and Labor Markets: Evidence from Job Postings for Professionals," *Journal of Labor Economics*, 36(1), 337–369.

Fligstein, N., J. S. Brundage, and M. Schultz (2014): "Why the Federal Reserve Failed to See the Financial Crisis of 2008: The Role of Macroeconomics as a Sense making and Cultural Frame," Institute for research on labor and employment, working paper series, Institute of Industrial Relations, UC Berkeley.

Hansen, S., M. McMahon, and A. Prat (2018): "Transparency and Deliberation within the FOMC: A Computational Linguistics Approach," *Quarterly Journal of Economics*, 133(2), 801–870.

Hoffman, M. D., D. M. Blei, and F. R. Bach (2010): "Online Learning for Latent Dirichlet Allocation," in Advances in Neural Information Processing Systems 23: *24th Annual Conference on Neural Information Processing Systems 2010. Proceedings of a meeting held 6-9 December 2010, Vancouver, British Columbia, Canada.*, pp. 856–864.

Mikolov, T., K. Chen, G. Corrado, and J. Dean (2013a): "Efficient Estimation of Word Representations in Vector Space," Unpublished working paper.

Mikolov, T., I. Sutskever, K. Chen, G. S. Corrado, and J. Dean (2013b): "Distributed Representations of Words and Phrases and Their Compositionality," in *Advances in neural information processing systems*, pp. 3111–3119.

Rehurek, R., and P. Sojka (2010): "Software Framework for Topic Modeling with Large Corpora," in *Proceedings of the LREC 2010 Workshop on New Challenges for NLP Frameworks*, pp. 45–50, Valletta, Malta. ELRA.

Ruggles, S., K. Genadek, R. Goeken, J. Grover, and M. Sobek (2015): "Integrated Public Use Microdata Series: Version 6.0," Minneapolis, MN: Historical Census Projects, University of Minnesota.

Spitz-Oener, A. (2006): "Technical Change, Job Tasks, and Rising Educational Demands: Looking Outside the Wage Structure," *Journal of Labor Economics*, 24(2), 235–270.