

The Evolving U.S. Occupational Structure

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Abstract

Using the text from help wanted ads, we construct a new data set of occupational task content from 1960 to 2000. We document that within-occupation task content shifts are at least as important as employment shifts across occupations in accounting for the aggregate decline of routine tasks. Motivated by these patterns, we first apply our new task measures to a reduced-form statistical decomposition. We then embed our measures in an equilibrium model of occupational choice. These two exercises indicate that shifts in the relative demand for tasks account for a 25 log point increase in 90-10 earnings inequality over our sample period. **JEL Codes: J24, O33**

1 Introduction

Labor income inequality in the United States has increased considerably over the last several decades. Between 1960 and 2000, the ratio of earnings for the median worker, compared to the worker at the 10th percentile of the earnings distribution, has increased from 2.75 to 2.86. Over the same period, the 90-50 earnings ratio increased even more starkly, from 1.81 to 2.27. Alongside rising inequality, there have been dramatic changes in the composition of U.S. employment. For example, the employment share of occupations intensive in routine tasks has shrunk, while the share of occupations emphasizing nonroutine tasks, as well as social and cognitive skills, has grown (Autor, Levy, and Murnane, 2003; Autor, Katz, and Kearney, 2005; and Autor and Dorn, 2013).

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The evidence thus far points to the decline of employment in U.S. occupations intensive in routine tasks, but is largely silent on whether the content of occupations themselves has changed. Meanwhile, case studies of individual occupations have found considerable changes. For example, a report by the [National Research Council \(1999\)](#) suggests that managerial occupations over the second half of the twentieth century increasingly have emphasized team management, coaching skills and tasks, and interaction with customers. The rise in these skills and tasks were accompanied by a decline of managerial tasks related to direct control of subordinates.¹ These findings raise the question of whether managerial occupations are unique in experiencing changes in tasks, or if comparable changes have occurred elsewhere. Moreover, to the extent that the tasks that workers perform on the job have shifted, what are the implications for the distribution of earnings?

In this paper we show that, in fact, substantial changes in task composition did occur within occupations since 1960.² Moreover, we find that these within-occupation changes in task content account for much of the observed increase in earnings inequality. We start by constructing a new data set using the text content of approximately 4.1 million job ads appearing in three major metropolitan newspapers — the *New York Times*, the *Wall Street Journal*, and the *Boston Globe*. We then map the words contained in job ad text to different classifications of task content. Our main strategy relies on [Spitz-Oener’s \(2006\)](#) classification of words into routine (cognitive and manual) and nonroutine (analytic, interactive, and manual) tasks. We complement this approach using the classifications in [Deming and Kahn \(2017\)](#), [Firpo, Fortin, and Lemieux \(2014\)](#), and the Occupational Information Network (O*NET). This last mapping is useful, since O*NET is at present the de facto standard in the literature for measuring the content of occupations. To validate our new data set, we demonstrate that the measures that result from our mapping correlate, across occupations, with O*NET’s measures of the importance of different tasks.³

¹The National Research Council report chronicles the evolution of several other occupations. In Section 4, we link the changes within managerial, clerical, and assembly occupations documented in the report to the new measures we introduce in this paper.

²[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.

³We also perform several checks on the data to argue that neither the selection of ads into newspapers nor the fact that our data originate in metropolitan areas bias our results. First, we show that the distribution of ads across occupations is similar to the distribution of employment according to the decennial census (and our results largely agree with analogous comparisons made with online vacancies, e.g. [Hershbein and Kahn, 2016](#)). Second, we show that the educational requirements by occupation in our data set correlate reasonably well with those observed in the census (Appendix A). Third, 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 B). And, fourth, we show that our main results are not driven by the fact

We show that, in our database of newspaper ads, words related to interactive tasks have been increasing in frequency, while words related to routine tasks (especially routine manual tasks) have declined in frequency between 1960 and 2000. For instance, we find that the frequency of words related to routine cognitive tasks has declined by almost half from the early 1960s to the late 1990s, from 1.00 mentions per thousand job ad words to 0.54 mentions per thousand words. The frequency of routine manual tasks has declined even more starkly. On the other hand, the frequency of words related to nonroutine interactive tasks has increased by more than 54 percent, from 3.19 to 5.48 mentions per thousand of job ad words. Importantly, we find that a large fraction of the aggregate changes in both nonroutine and routine task related words has occurred within occupations, rather than through changes in the occupations’ employment shares.

Having documented these patterns, we provide two alternative quantifications of the relation between changes in the task content of occupations and the rise of inequality in the U.S. The first one relies on decomposition methods applied to the earnings distribution; the second, on an equilibrium model of worker occupational choices and comparative advantage.

In our first quantification, we incorporate our occupational measures into [Fortin, Lemieux, and Firpo \(2011\)](#)’s methodology for decomposing changes in the wage distribution across points in time. Using these methods, we break down changes in the distribution of earnings over time into changes in the attributes of workers and their occupations (the “composition” effect), as well as changes in the implicit prices of those observable characteristics (the “wage structure” effect). Next, we further break down changes in the distribution of earnings into the contributions of observable characteristics (e.g., the contribution of changes in educational attainment and of changes in the returns to education).

Our results suggest that, relative to the upper tail of the income distribution, tasks which were valued highly in low-wage jobs (in particular manual tasks) declined in importance. These task changes, however, come more from changes within the occupations themselves than from shifts of employment across occupations. In the decomposition, changes in occupational task content account, through composition effects, for a 32 log point increase in 90-10 male earnings inequality. Wage structure effects — changes in tasks’ implicit prices — account for a 6 percentage point decrease in 90-10 inequality. Among the 32 percentage points that are due to composition effects, routine manual and nonroutine interactive tasks respectively account for a 24 and 8 log point increase in inequality. (The contribution of changes in routine cognitive, nonroutine analytic, and nonroutine manual tasks is more modest.) If we instead ignore the evolution of occupational characteristics across time, and keep the task measures fixed, we can only account for a total of 3 percentage points of the

that most of our ads come from a selected number of large metro areas ([Appendix E.3](#)).

observed increase in 90-10 inequality. Hence occupational measures of task intensity account for a large component of the increase in earnings inequality between 1960 and 2000, but only if task measures are allowed to vary across time.

In our second quantification, which we view as complementary to the earnings distribution decomposition, we construct a general equilibrium model of occupational choice. In our model, individual occupations are represented as a bundle of tasks. Workers' skills govern their abilities to perform each of the individual tasks in their occupation, and give rise to comparative advantage. These skill levels are functions of workers' observable characteristics — like gender, education, and experience — but also contain an idiosyncratic component. Based on their skill levels and the demand for tasks within each occupation, workers select into the occupation with the highest payoff.

We estimate the skills by which each demographic group performs different groups of tasks, combining information on demographic groups' wages and occupation choices. Using our estimated model, we calculate that changes in the relative demands for tasks have led to a 25 log point increase in inequality among men, and a 22 log point increase in inequality among women and men. The intuition is that less educated workers both tend to be at the bottom of the wage distribution and have a comparative advantage in manual tasks, while the demand for the latter has declined.

Both the statistical decompositions and our model-based counterfactual exercises have their own advantages. In spite of their differences, however, both methods indicate that a relative decline in the demand for routine tasks has substantially increased earnings inequality between 1960 and 2000. Moreover, both of these exercises require information on changes in occupations' task content, something that our data set is suited to measure.

Our paper builds on two literatures, the first of which 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. More recently, [Firpo, Fortin, and Lemieux \(2014\)](#) decompose changes in the distribution of wages into the contribution of occupational characteristics and other factors (including de-unionization, changes in minimum wage, and changes in worker demographics). [Deming \(2017\)](#) documents that employment and wage growth has been confined to occupations which are intensive in both social and cognitive skills. [Michaels, Rauch, and Redding \(2016\)](#) extend [Autor, Levy, and Murnane \(2003\)](#) to study changes in employment shares by task content over a longer time horizon. They use a methodology that is related to ours, using the verbs from the Dictionary of Occupational Titles' occupational descriptions and their thesaurus-based meanings. [Burstein, Morales, and Vogel \(2015\)](#) quantify the

impact of the adoption of computers on between-group wage inequality.

Because commonly available data sets measuring occupational characteristics are infrequently and irregularly updated, in most of these papers occupational characteristics are fixed over time.⁴ One paper that focuses on within-occupation changes is [Spitz-Oener \(2006\)](#), which uses survey data from four waves of German workers to track skill changes within and between occupations, from the late 1970s to the late 1990s. One of our contributions is to study these changes in the U.S. context, extending the [Spitz-Oener \(2006\)](#) task classifications, and examining the implications of the observed changes in tasks for the wage distribution. Our paper contributes more generally to the measurement of time-varying task content of occupations by using newspaper job ads, a rich and largely untapped source of data.⁵ Newspaper data have the advantage of appearing in the field: Firms post these ads while they are actively searching for workers, meaning that, unlike survey data, our data are not subject to recall-bias or selective nonresponse. Our new data set contains rich information on U.S. occupations' skill requirements, technology usage, work activities, work styles, and other job characteristics, between 1960 and 2000. These data are complementary to existing data sources currently used to study the evolution of the U.S. labor market.⁶

A second related literature 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.⁷ Using data from CareerBuilder, [Marinescu and Wolthoff \(2016\)](#) document substantial variation in job ads' skill requirements and stated salaries within narrowly-defined occupation codes. Moreover, the within-occupation variation is to a large extent explained by the vacancy posting's job title. Using online job ads, [Hershbein and Kahn \(2016\)](#) and [Modestino, Shoag, and Ballance \(2016\)](#) argue that jobs' skill requirements have increased during the post-Great Recession period; [Deming and Kahn \(2017\)](#) find that firms that post

⁴[Ross \(2017\)](#) applies the 2003 to 2014 vintages of the O*NET database to construct a panel of occupations' skill and task intensity measures. In [Ross \(2017\)](#), within-occupation differences in task intensities are applied as an alternative source of variation, relative to previously used between-occupation trends, in identifying declines in the price of workers' routine task engagement in the last decade. In earlier work, [Autor, Levy, and Murnane \(2003\)](#) use the 1977 and 1991 versions of the Dictionary of Occupational Titles to compare changes in occupations' task content and computer adoption rates within these occupations.

⁵Also applying the text from newspaper ads, [DeVaro and Gurtler \(2017\)](#) document that before 1940 both job seekers and firms posted advertisements to match with one another. Only since 1940 has it been the case that firms were the primary party posting ads.

⁶Our new data set can be found at http://ssc.wisc.edu/~eatalay/occupation_data .

⁷Text analysis has been fruitfully applied in other branches of economics. [Gentzkow and Shapiro \(2010\)](#) study the text from newspapers and from the Congressional Record to construct an index of newspapers' partisan slant. [Hoberg and Phillips \(2016\)](#) use the text from publicly-traded firms' filings to the Securities and Exchange Commission to classify industries and to draw insights about the identities of firms' competitors.

ads with a high frequency of words related to social and cognitive skills have higher labor productivity and pay higher wages. By bringing in newspaper data, we contribute to this literature with measurement of long-run changes in tasks and skills in the labor market.

The rest of the paper is organized as follows. Section 2 outlines the construction of our data set of occupations and their skill and task content. We compare this new data set to existing data sources in Section 3. In Section 4, we document changes in the distributions of occupational skills and tasks. Section 5 links task changes to changes in the earnings distribution, first in a reduced-form exercise and then with the aid of a structural model. Section 6 reviews our results 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 originally published in the *New York Times*, *Wall Street Journal*, and *Boston Globe*. We complement these text files with a data set purchased from Economic Modeling Specialists International (EMSI) for the purpose of identifying each ad’s occupation code. We extract from the newspaper text information about the frequency of words related to occupations’ skill requirements and their work activities. The first step in our approach is to clean and process the raw newspaper data. Then, we map job ad titles to Standard Occupational Classification (SOC) codes. Finally, we map job ad text into tasks, by grouping sets of words according to their meaning. Once we describe these procedures, we present some simple descriptive statistics from our constructed data set.

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 newspaper into text files. Figure 1 presents a snippet of the raw text from a page of display ads from the 1979 *Boston Globe*. This text refers to three vacancy postings, one for a “Mutual Fund Clerk” position, a second for a “Payments Clerk,” and a third for a “Terminal Operator.” 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), there is still quite a lot of information to be extracted. Common work activities such as typing, processing applications, or maintaining client records are mentioned. In addition, one of the three advertisements includes an experience requirement. The raw text files that ProQuest has provided us allow us to

Figure 1: Unprocessed Text from the *Boston Globe*, November 4, 1979, Display Ad #133

rapid growth through continued innovation and diversification If you are highly motivated person who takes pride in your work and the company you work for consider career with Fidelity \n MUTUAL FUNDS CLERKS \n Individuals with 1-2 years funds transfer experience to process Keogh IRA accounts and adjustments \n PAYMENTS CLERKS \n Varied les processing new account applications and payments \n StI nt flt ner fr nlr ct tfl \n Mnirk \n and maintaining client \n strong record-keeping 50 wpm \n Data Control Department \n sorting and \n Brokerage \n environments with \n benefits package for our Boston convenient to the Market \n gr WilnliE lU5lty \n success \n -l 1?Q1.a1 ol P-1S1lv MPloV \n Fidelit \n Group \n 82 DEVONSHIRE STREET BOSTON MA 02109 \n 111 \n -l \n TERMINAL OPERATOR \n Position involves typing policy related information Into computer terminal No previous computer experience required Typing 5055 wpm Excellent benefits plus work Incentive program in addition to starting salary of S150-165.

Notes: The figure presents text from the first three vacancy postings in a page of display ads in the *Boston Globe*. An “\n” refers to a line break.

isolate the subset of text that come from advertisements, but do not directly allow us to identify which ads are job ads (as opposed to other types of advertisements). Nor does the text indicate when one job ad ends and another one begins. Therefore, in processing the ProQuest text files, we 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.

Distinguishing vacancy postings from other advertisements. To distinguish vacancy postings from other types of advertisements, we apply a Latent Dirichlet Allocation (LDA) model. An LDA model classifies documents to one of a number of topics. In these models, the probability that different words appear in a document depends on the hidden topic of that document. LDA model estimation yields estimates of these conditional probabilities.

In our context, the 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 document 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

Table 1: Results of the LDA Model

Topic 1	Topic 2	Topic 3	Topic 4	Topic 5
system	reg	car	day	street
experi	save	price	free	open
comput	store	new	new	inc
opportun	size	auto	one	ave
year	price	power	call	mass

Notes: The table provides the top five word stems for each of the five topics in our estimated LDA model performed on the *Boston Globe* display ad subsample.

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.”

To construct our LDA model, we take samples of pages of advertisements for each of our newspapers, separately: display ads in the *Boston Globe*, spanning 1960 to 1983; display ads in the *New York Times*, from 1940 to 2000; classified ads in the *Boston Globe*, from 1960 to 1983; classified ads in the *New York Times*, from 1940 to 2000; and classified ads in the *Wall Street Journal*, spanning 1940 to 1998.⁸

As an example of the partial output from our estimated model, Table 1 lists word stems which have the highest conditional probability of appearing in each of the five topics in our model. This model was estimated from pages of display ads appearing in the *Boston Globe*.⁹ Words in Topic 1 tend to appear frequently in job ads, while other topics contain words prevalent in other types of advertisements.

At this point, each page is defined by a probability distribution over the set of possible topics. We pick the pages for which the likelihood of belonging to the topic that we a priori identify with 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-

⁸These time spans correspond to the original data provided to us by ProQuest. While the data set which we have posted online contains data starting in 1940, throughout this paper we restrict attention to job ads which were published beginning in 1960. We make this restriction since the focus of our paper is on the implications of occupations’ task content on increasing labor income inequality, which began in earnest only in the 1960s.

⁹Computing the LDA model requires us to specify the number of topics present in the text. Since there is little a priori guidance in determining the optimal number of topics, for each source we choose the number of topics, one at a time, until we reach the largest number of topics which result in only one topic that is related to job vacancy postings. In Appendix C.1, we present the tables of predictive words for each newspaper in our sample.

related occupations) and including too many non-job ads in our data set.¹⁰ Appendix C.1 provides additional details regarding the LDA procedure, in general, and the application of this procedure to our particular problem. See, also, [Blei, Ng, and Jordan \(2003\)](#) and [Hoffman, Blei, and Bach \(2010\)](#).¹¹

Discerning the boundaries between vacancy postings and identifying each advertisement’s job title. 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. In particular, we use a rule that relies on certain common patterns across ads and relies on the presence of (i) street addresses, (ii) certain phrases (e.g., “send [...] resume” or “equal opportunity employer”), and (iii) the formatting of job titles. To search for job titles, we look for lines of text that are either i) all capitalized or ii) only one or two words appear. Within these lines, we search for words which appear in O*NET’s “Sample of Reported Job Titles.” If there is a match, we record the contents of the lines as the ad’s job title.

Sample of results Table 2 presents the result of our procedure applied to the unprocessed text from Figure 1. At least in this small snippet of text, our algorithm is able to correctly parse job titles and identify the boundaries between the three advertisements. In identifying the boundary between the first and second ad, line breaks before “payments clerks” were helpful. In addition to these line breaks, an address—82 Devonshire Street, Boston MA 02109—helps identify the boundary between the second and third job posting. Finally, our spell-checker is able to fix some transcription errors. At the same time, even after processing, a few transcription errors remain. Moreover, because part of the text of the first job ad appears before the job title, it is not included with the remaining text for the “mutual funds clerks” position.

To sum up, our process allows us to transform unstructured text into a set of distinct job ads and undo a portion of the error induced by ProQuest’s optical character recognition software. However, since our efforts to process the text are imperfect, our resulting data set will necessarily contain some measurement error. Still, as we will demonstrate in Section 3, given the massive number of vacancy postings which we have been able to process, our

¹⁰In practice, the model assigns low probabilities to intermediate likelihood values, and so the errors we make are relatively insensitive to our choice of cutoff.

¹¹Within economics, we are aware of one application of LDA, which classifies Federal Open Market Committee statements by topic. See [Fligstein, Brundage, and Schultz \(2014\)](#) and [Hansen, McMahon, and Prat \(2014\)](#).

Table 2: Processed Text from the *Boston Globe*, November 4, 1979, Display Ad #133

job title	text
	rapid growth through continued innovation and diversification If you are highly motivated person who takes pride in your work and the company you work for consider career with Fidelity
mutual funds clerks	individuals with 1 2 years funds transfer experience to process Keogh IRA accounts and adjustments
payments clerks	varied Les processing new account applications and payments stir nt flt near fr NLRB ct t fl mnirk and maintaining client strong record keeping 50 wpm data control department sorting and brokerage environments with benefits package for our Boston convenient to the market gr Willie lu5lty success 1 1 q1 a1 ol p 1sl1 vmplov fidelity group 82 devonshire street Boston ma 02109
terminal operators	position involves typing policy related information into computer terminal no previous computer experience required typing 5055 wpm excellent benefits plus work incentive program in addition to starting salary of 150 165

Notes: The table presents text from the first three of the 12 vacancy postings in a page of display ads in the *Boston Globe*.

database is still quite informative about occupations and their characteristics.

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 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 should all map to the same occupation — 291141 using the BLS Standard Occupational Classification (SOC) system.

From our list of job titles, we apply two complementary methods to group ads according to their SOC codes. First, for the most common 1000 job titles from our *Boston Globe*, *New York Times*, and *Wall Street Journal* job ads, we map the titles to their SOC codes using www.onetsocautocoder.com. These top 1000 job titles cover 2.2 of the 6.6 million ads from the previous subsection’s processed newspaper data.

For the remaining ads, we apply a *continuous bag of words* (CBOW) model, in combination with an ancillary data set provided to us by EMSI, to attempt to identify the ad’s SOC code.¹² Roughly put, this CBOW model allows us to find synonyms for words or phrases

¹²While onetsocautocoder.com is a useful, accurate tool to retrieve commonly occurring job titles, there are hundreds of thousands of unique titles occurring in at least two postings in our newspaper data, which

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,” “rn,” and “staff nurse” all tend to appear next to words like “patient,” “care,” or “blood” one would conclude that “rn” and “nurse” have similar meanings to one another. For additional background on CBOW models, and details on our implementation, see Appendix C.3.

This CBOW model is useful since we have an ancillary data set containing a large correspondence between job titles and SOC codes. EMSI has provided us a data set of the text from online job ads, originally posted between April 2011 and March 2017. These ads contain a job title, a SOC code, and text describing the job characteristics and requirements. We use the 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. We use this model at different points in the paper to find synonyms for words or phrases. At this stage, our CBOW model allows us to identify the closest job title in the EMSI data set for each job title in our newspaper text. Since job titles in the EMSI data set have an associated SOC code, we can obtain the SOC code for any job title in our newspaper text. We retrieve these SOC codes on all of the job titles which appear at least twice in our newspaper text. In combination with the first approach, we have been able to collect SOC codes for 4.1 million job ads.

2.3 Eliciting Skill- and Task-Related Information

Within the body of our job ads, we will 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 not only job titles, but also these occupational characteristics into a manageable number of groups. We follow four 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 analytic*.¹⁴ In our main application of these categories, we begin with the list of

makes manually retrieving them infeasible.

¹³Throughout this paper, we interpret the words as accurate representations of the positions the 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.

¹⁴The data set used in [Spitz-Oener \(2006\)](#) is a questionnaire given to West German workers. Building on

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 a CBOW model. 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 will consider a narrower mapping between categories and words, one which only relies in [Spitz-Oener \(2006\)](#)'s definitions as enumerated in footnote 14.

We also consider three 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. First, 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, refer to the O*NET Element Description to judge whether these synonyms should be included, as well as if other words should be included. As a second approach, we append to our initial lists of words and phrases an additional set of words, using our continuous bag of words model. Each of the two approaches, the "judgment-based" procedure and the "continuous bag of words model-based" procedure of identifying similar words, 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.¹⁵ On the other hand, there is a danger that the bag of words model will identify words as synonymous even if they are not.

Second, for the purpose of mapping our new task measures to changes in wage inequal-

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, manage, negotiate, negotiating, organize, organizing, presentation, presentations, presenting, purchase, sell, selling, teaching; 3) nonroutine manual: accommodate, accommodating, accommodation, renovate, renovating, repair, repairing, restore, restoring, service, serving; 4) routine cognitive: bookkeeping, calculate, calculating, correcting, corrections, measurement, measuring; 5) routine manual: control, controlling, equip, equipment, equipping, operate, operating.

¹⁵For 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 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. 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.

ity, we map our text to that in [Firpo, Fortin, and Lemieux \(2014\)](#). Firpo, Fortin, and Lemieux categorize Work Activities and Contexts into five groups: Information Content, Automation/Routine, Face-to-Face Contact, On-Site Job, and Decision-Making.¹⁶ Our last mapping is to skills in [Deming and Kahn \(2017\)](#)’s study of the relationship between firms’ characteristics and the skill requirements in their vacancy postings, which we explore in the Appendix to provide complementary results.

2.4 Descriptive Statistics

Using the text from the *Boston Globe*, *New York Times*, and *Wall Street Journal*, our algorithm from Section 2.1 results in a data set with 6.6 million vacancy postings.¹⁷ Among these vacancy postings, we have been able to retrieve a SOC code for 4.1 million ads. Table 3 lists the top occupations in our data set. The first two columns list common job titles among the 6.6 million total vacancy postings, while the last four columns present the top SOC codes. Across the universe of occupations, our newspaper data represents a broad swath of Management, Business, Computer, Engineering, Life and Physical Science, Healthcare, Sales, and Administrative Support occupations, but it under-represents Construction occupations and occupations related to the production and transportation of goods. See Appendices A and B for an analysis of the representativeness of our newspaper data relative to the decennial census and CPS. (These latter data sets we access via [Ruggles, Genadek, Goeken, Grover, and Sobek, 2015](#).)

Table 4 presents, for each task in [Spitz-Oener \(2006\)](#)’s classification, the most task-intensive occupations. Occupations which are intensive in nonroutine analytic tasks are concentrated in Architectural and Engineering occupations (SOC codes beginning with “17”) and Life, Physical, and Social Science Occupations (SOC codes beginning with “19”). Management (“11”) and Sales (“41”) occupations mention nonroutine interactive tasks frequently, while customer-service and maintenance related occupations (in a variety of SOC groups) have high nonroutine manual task intensities. Routine cognitive and routine manual task-related words are mentioned frequently in advertisements for clerical and production-related positions.

¹⁶See Appendix Table A.2 of [Firpo, Fortin, and Lemieux \(2014\)](#) for the mapping between their task groups and O*NET Work Activities and Work Contexts. Since our constructed data set includes only work activities, our corresponding measures of [Firpo, Fortin, and Lemieux \(2014\)](#)’s O*NET groups are based only off of work activity variables, and since the Automation/Routine task group is defined only by to O*NET work contexts, we will not be able to measure this variable.

¹⁷This 6.6 million figure excludes vacancy postings for which we cannot identify the job title or which contain a substantial portion, 35 percent or greater, of misspelled words. We also exclude ads with fewer than 15 words.

Table 3: Common Occupations

Job Title		6-Digit SOC Occupations		4-Digit SOC Occupations	
Description	Count	Description	Count	Description	Count
Secretary	117.3	436014: Secretary	275.6	4360: Secretary	408.6
Sales	55.4	439061: Office Clerk	182.2	4390: Oth. Admin. Support	340.3
Assistant	53.6	132011: Accountant	153.9	1320: Accountant	194.6
Accounting	51.0	412031: Retail Sales	149.8	1511: Computer Sci.	185.4
Clerk	50.0	433031: Bookkeeper	131.0	4330: Financial Clerks	174.8
Typist	50.0	439022: Typist	118.1	4120: Retail Sales	172.0
Salesperson	42.0	291141: Nurse	117.8	2911: Nurse	140.8
Engineer	41.6	111021: General Mgr.	91.6	1721: Engineers	132.1
Manager	41.3	172112: Ind. Engineer	88.1	1110: General Mgr.	127.7
Bookkeeper	40.5	113031: Financial Mgr.	68.1	1130: Financial Mgr.	101.8

Notes: This table lists the top ten 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. The counts are given in thousands of newspaper job ads.

3 Comparison of the New Data Set to O*NET

Before exploring trends in occupational task content and the implications for the distribution of earnings, we briefly compare our new data source to the widely used O*NET database. Our goal is to demonstrate the usefulness of newspaper text for measuring the task content of occupations.

Figure 2 plots the O*NET Importance measure and *Boston Globe*, *New York Times*, and *Wall Street Journal* keyword frequencies. Each panel plots this comparison for a separate O*NET Element. Within each panel, each data point represents a single 4-digit SOC occupation: For example, the “1920” (the code for Physical Scientists) in the top right panel indicates that the O*NET Importance of the skill of “Critical Thinking” is 4.0 (on a scale from 1 to 5), while in the newspaper data, we detect 0.11 Critical Thinking related keywords per ad. Figure 2 includes one work style (Independence), one skill (Critical Thinking), one knowledge requirement (Computers and Electronics), and one work activity (Interpreting for Others), each in a separate panel. The correlations (weighted by the number of vacancy postings in our newspaper data) in these four plots are 29 percent, 59 percent, 54 percent, and 51 percent, respectively.¹⁸ The relationship between our newspaper keyword frequencies and O*NET Importance measures appears to be nonlinear: For low-to-moderate O*NET Importance values, skill- and task-related keywords are very rarely mentioned in vacancy postings. Our algorithm detects skill- and task-related keywords only if the O*NET Impor-

¹⁸Across all 125 O*NET Elements, the unweighted correlations are lower by 7 percentage points on average.

Table 4: Top Occupations by **Spitz-Oener (2006)** Task Category

Nonroutine Analytic			Nonroutine Interactive		
1720: Engineers	69.3	0.89	1120: Sales Managers	70.1	1.11
1721: Engineers	132.1	0.89	4140: Sales Rep., Whole./Man.	64.1	0.80
1930: Social Scientists	5.2	0.70	4130: Sales Rep., Services	100.4	0.64
1910: Life Scientists	9.0	0.69	1110: Top Executives	127.7	0.61
1311: Business Operations	71.3	0.69	4120: Retail Sales	172.0	0.60
Nonroutine Manual			Routine Cognitive		
4930: Vehicle Mechanics	28.0	0.38	4330: Financial Clerks	174.8	0.22
4910: Maintenance Supervisors	14.1	0.29	4390: Other Admin. Support	340.3	0.10
4990: Other Maintenance	31.5	0.29	4320: Commun. Equip. Operators	11.0	0.09
4920: Electrical Mechanics	6.7	0.26	4310: Administrative Support	42.1	0.09
4340: Record Clerks	32.3	0.20	3730: Grounds Maintenance	1.4	0.08
Routine Manual					
5140: Metal and Plastic	32.0	0.14			
4990: Other Maintenance	31.5	0.07			
5141: Metal and Plastic	13.0	0.06			
4722: Construction Trades	2.6	0.05			
5120: Assemblers & Fabricators	9.8	0.05			

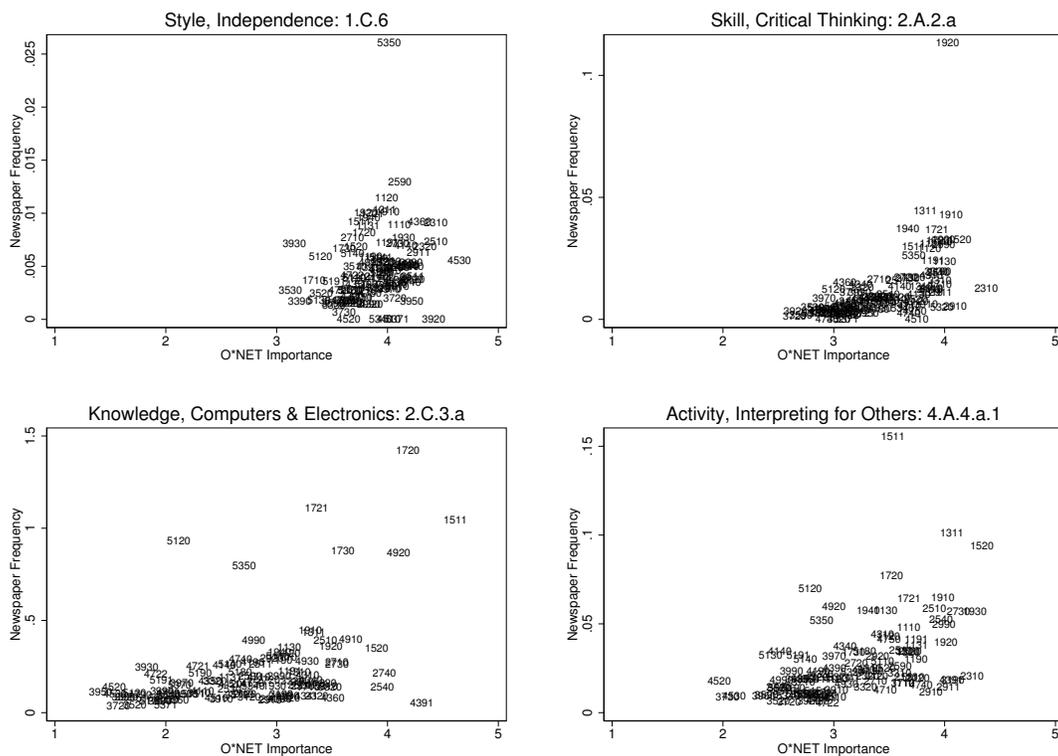
Notes: This table lists the top five 4-digit occupations according to the frequency with which different activity-related words are mentioned. Within each panel, the first column gives the SOC code and title; the second column gives the number of job ads in our data set (in thousands); and the final column gives the frequency (mentions per vacancy posting) of task-related words. Only occupations with at least 200 advertisements, representing 104 4-digit SOC codes, are included.

tance measures are sufficiently high, above 3 or 3.5.

The four relationships depicted in Figure 2 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 0.70 range, and are somewhat higher for knowledge requirements, skills, and activities (where the mean correlations are 0.58, 0.54, and 0.50, respectively) than for work styles (where the mean correlation is 0.33).¹⁹

¹⁹While we view O*NET as a useful and reliable benchmark, it too has its issues, which extend beyond its inability to track within-occupation changes in job characteristics over long time horizons. In their review of the design of the O*NET data collection program, the **National Research Council (2010)** identify several aspects of O*NET which may limit its usefulness as a research tool. Summarizing these issues, **Autor (2013)** writes that both the Dictionary of Occupational Titles 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 O*NET measures, but we interpret the correlations as reassuring evidence that the newspaper text is a valuable source of task data.

Figure 2: 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 20.1 of the O*NET database). The y-axis measures the number of keyword appearances per job ad, using data from the *Boston Globe*, *New York Times*, and *Wall Street Journal*.

4 Trends in Tasks

In this section, we document trends in occupational tasks from 1960 to 2000. The main results from these exercises are that i) between the 1960s and 1990s words related to non-routine interactive and analytic tasks have increased in frequency, while words related to routine manual and cognitive tasks have decreased in frequency, and ii) a large fraction of these changes are due to changes within occupations, rather than changes in employment shares across occupations. Lastly, we compare trends for three particular groups of occupations and show that our results resonate with previous findings in the literature.

4.1 Overall Trends

Table 5 present changes in task-related keywords, grouped according to the definitions introduced in Spitz-Oener (2006). The first column lists the task groups, while columns 2 through

Table 5: Trends in Keyword Frequencies

	Frequency								Within Share
	60-64	65-69	70-74	75-79	80-84	85-89	90-94	95-00	
Nonroutine	3.19	3.50	3.33	3.63	3.93	3.86	4.63	5.48	0.89
Analytic	[3.16]	[3.47]	[3.27]	[3.49]	[3.71]	[3.50]	[4.32]	[5.22]	(0.04)
Nonroutine	4.94	4.56	4.57	5.18	5.84	5.97	6.56	7.03	0.94
Interactive	[4.94]	[4.52]	[4.44]	[5.07]	[5.85]	[5.71]	[6.29]	[6.89]	(0.05)
Nonroutine	2.50	2.36	2.08	2.54	2.59	2.63	2.59	2.73	1.49
Manual	[2.52]	[2.40]	[2.04]	[2.56]	[2.65]	[2.67]	[2.54]	[2.86]	(0.68)
Routine	1.00	0.91	0.69	0.65	0.74	0.71	0.59	0.54	0.98
Cognitive	[0.99]	[0.90]	[0.67]	[0.61]	[0.73]	[0.76]	[0.61]	[0.54]	(0.04)
Routine	0.70	0.58	0.45	0.42	0.27	0.15	0.10	0.07	0.97
Manual	[0.71]	[0.60]	[0.51]	[0.50]	[0.31]	[0.18]	[0.11]	[0.10]	(0.04)

Notes: Occupations are defined using the 4-digit SOC classification. For each column, we compute average keyword frequencies (across occupations) for each five-year period. In these averages, occupations are weighted according to the number of workers in the decennial census, interpolating within-decade observations using counts from the 1960, 1970, 1980, 1990, and 2000 censuses. The numbers without square brackets represent the average keyword frequency in each five-year period. The numbers in square brackets represent the keyword frequencies which would prevail, holding fixed the number of workers in each occupation according to their values in 1960. The final “Within Share” column gives the ratio of the 1960-64 to 1995-2000 change according to the within-occupation component relative to the 1960-64 to 1995-2000 overall change. In this final column, the term within parentheses gives the bootstrapped (re-sampling ads from our newspaper text) standard errors of the “Within Share.”

9 compute two measures of task content, broken down in five year periods. The measure at the top of each row, which we interpret as the aggregate task content in the economy, presents average mentions in each occupation using census employment shares as weights. According to this measure, mentions of nonroutine tasks increased between the early 1960s and late 1990s by 54 percent for analytic tasks (3.19 versus 5.48 mentions per thousand ad words), 35 percent for nonroutine analytic tasks, and 9 percent for nonroutine manual tasks. Conversely, the largest decline in keyword frequency occurred for words related to routine manual tasks, decreasing from 0.70 to 0.07 mentions per thousand ad words. The decline of routine cognitive tasks is also considerable, going from 1.00 to 0.54 mentions per thousand words.

These changes reflect both between-occupation and within-occupation changes in task-related keywords. 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:

$$\bar{T}_t - \bar{T}_{1960} = \sum_j \vartheta_{j,1960} (\tilde{T}_{jt} - \tilde{T}_{j,1960}) + \sum_j (\vartheta_{j,t} - \vartheta_{j,1960}) \tilde{T}_{jt}. \quad (1)$$

In this equation, \tilde{T}_{jt} is a measure of task-related word frequency in postings for occupation j in year t . The ϑ_{jt} terms measure the share of workers in occupation j at time t , while \bar{T}_t denotes the share-weighted average frequency of the task-related word at time t . On the right-hand side of Equation 1, the first sum represents the change in overall keyword frequencies due to within-occupation changes in task-related word mentions. The second sum represents the contribution of changes in the share of workers in different occupations on overall keyword frequencies. We use a 4-digit SOC classification to perform this decomposition separately for each of the five tasks introduced in [Spitz-Oener \(2006\)](#). The final column of Table 5 lists the proportion of the overall changes in keyword frequencies, comparing the 60-64 column to the 95-00 column, which are due to the within-occupation component. For every task, within-occupation changes account for a predominant share of the overall changes.

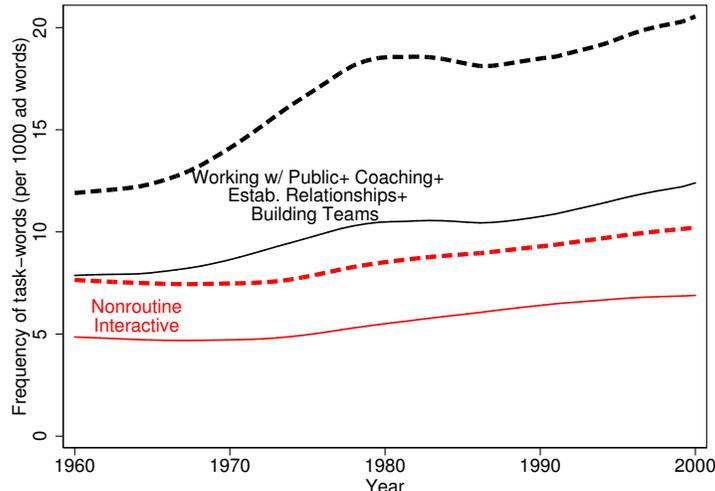
Sensitivity Analysis

In Appendix D we consider the sensitivity of the results given in Table 5 to the mapping of words to tasks, as well as to the level of detail of the occupation codes used.

First, we recompute Table 5 with [Spitz-Oener \(2006\)](#)'s original mapping between tasks and words (i.e., excluding the words which we have appended from our continuous bag of words model). Second, we consider two alternate measures of occupational characteristics, one introduced by [Firpo, Fortin, and Lemieux \(2014\)](#) and the other by [Deming and Kahn \(2017\)](#). Using each of these three alternate measures of occupational characteristics, the predominant share of the overall changes in occupational characteristics occurs within rather than between 4-digit SOC codes.

The extent to which between-occupation changes are responsible for overall changes in keyword frequencies may potentially be sensitive to the coarseness of occupation definitions. If occupations are coarsely defined, one will tend to estimate that between-occupation changes are relatively unimportant. In a second robustness check, we re-estimate Equation 1 first using a 6-digit SOC codes to classify occupations and alternatively using individual job titles to classify occupations. Instead of a median within share of 0.97, which we obtain from averaging over the final columns of Table 5, one would arrive at a median within share of 0.99 with a 6-digit classification and 0.68 with a job-title-based classification. For all three classifications, within-occupation changes are the primary source of the overall shift in task content.

Figure 3: Task Measures: Managers and All Occupations



Notes: The figure above plots the average number of task-related word mentions for two different types of tasks, both for managerial occupations (dashed lines) and for all occupations (solid lines). We apply a local polynomial smoother. Managerial occupations are defined as those with a SOC code between 1100 and 1199.

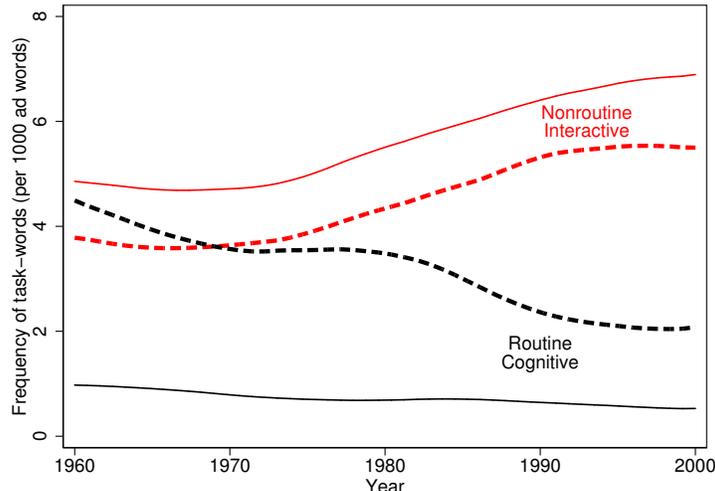
4.2 Narratives of Occupational Change

In this section, we present three vignettes that demonstrate how individual occupation groups have evolved over our sample period. Our goal is to provide concrete, illustrative examples of occupational change, through the lens of our task and skill measures. We emphasize that these examples represent a portrait of long-run occupational change that was previously unobserved by researchers.

In Figure 3, we present two separate task measures for managerial occupations (in thick, dashed lines) and all occupations (in thin, solid lines). Between 1960 and 2000, the frequency of words related to nonroutine interactive tasks in managerial occupations increased by approximately one-third, from 7.5 to 10.0 mentions per 1000 ad words.²⁰ This measured trend aligns with the [National Research Council \(1999\)](#)’s characterization of the changing nature of managerial work. Summarizing the contemporaneous literature, the [National Research Council \(1999\)](#) write 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 also plot trends in the mentions of four O*NET work activities:

²⁰While it is true that some of these changes reflect trends in the relative sizes of different managerial occupations, in Appendix D.3 we plot changes in task intensities within 4-digit SOC occupations. The results look quite similar.

Figure 4: Task Measures: Office Clerks and All Occupations

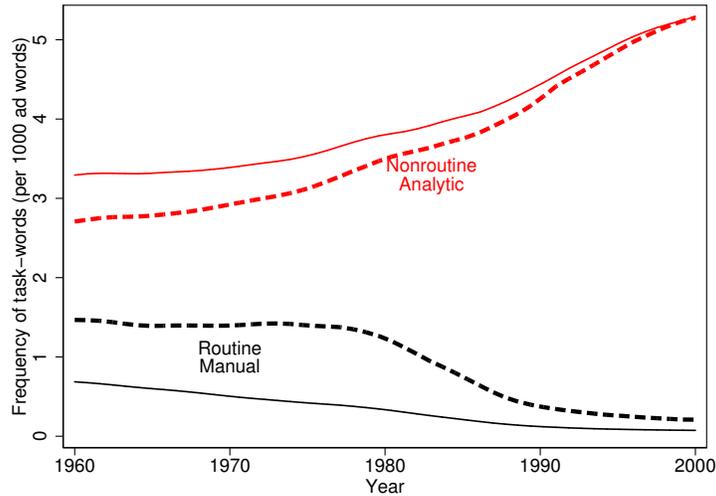


Notes: Office clerical occupations are those which have a SOC code between 4330 and 4341. We apply a local polynomial smoother. Averages across all occupations are depicted as the solid lines, and those across office clerical occupations are plotted as dashed lines.

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). Mentions of these four activities increased by more than 50 percent in managerial occupations, increasing more quickly than for the workforce as a whole. In sum, while interactive tasks have always been a requirement for managerial occupations, the importance of such tasks has widened since 1960.

Second, Figure 4 contrasts trends in tasks measures for office clerks compared to all occupations. While mentions of routine cognitive tasks has decreased for both office clerks and more generally for all occupations, the drop off has been more pronounced in clerical positions. Concurrently, the frequency of nonroutine interactive task-related words has increased in clerical ads roughly at the same pace as in other occupations. Both trends are consistent with Autor (2015)’s account of changes experienced by bank tellers (one particular office clerk occupation). He writes: “Increasingly, banks recognized the value of tellers enabled by information technology, not primarily as checkout clerks, but as salespersons, forging relationships with customers and introducing them to additional bank services like credit cards, loans, and investment products.” (p. 7) (Unplotted, the frequency of nonroutine analytic-related keywords increased in office clerical occupations, partially closing the gap between these occupations and others.) Hence, much of the overall decline in routine cognitive tasks occurred in occupations like clerical occupations that were previously specialized in these tasks. The remaining jobs in these occupations increasingly contain nonroutine analytic and

Figure 5: Task Measures: Non-Supervisory Production Workers and All Occupations



Notes: Non-supervisory production occupations have an SOC code between 5120 and 5199. We apply a local polynomial smoother. Averages across all occupations are depicted as solid lines, and those across non-supervisory production occupations are plotted as dashed lines.

interactive tasks.

Finally, compared to the beginning of the sample period, the frequency of routine manual tasks has declined considerably, particularly in non-supervisory production occupations. Figure 5 presents these trends along with changes in the frequency of nonroutine analytic task related words. Nonroutine analytic task keywords have been increasingly mentioned in job ads for production workers. The trends in keyword frequencies in this figure are consistent with case studies of manufacturers' adoption of new information technologies (e.g., [Bartel, Ichniowski, and Shaw, 2007](#)). These new technologies substitute for workers who were previously performing routine manual tasks. The surviving production workers are those who have high levels of technical and problem-solving skills.

5 Implications for the Earnings Distribution

In this section, we use our new time-varying task measures to explore the implications of changes in occupations' task content for the earnings distribution. First, we bring our measures of occupations' task content to the decomposition methods of [Fortin, Lemieux, and Firpo \(2011\)](#). The goal of this exercise is to determine which occupational characteristics account for changes in the distribution of earnings between 1960 and 2000. Next, in Section 5.2, we develop a framework for interpreting occupations as a bundle of tasks. We embed this framework into a quantitative general equilibrium model of occupational sorting based

on comparative advantage (akin to Heckman and Sedlacek, 1985, Heckman and Scheinkman, 1987, or more recently Burstein, Morales, and Vogel, 2015). We estimate this model and then use it to quantify the impact of changes in the demand for tasks on earnings inequality.

We view the two approaches as complementary methods for understanding the sources of increasing inequality, each approach with its own advantages and disadvantages. The statistical decompositions developed by Firpo, Fortin, and Lemieux (2014) are a flexible accounting device, helpful in determining whether observable characteristics of workers and occupations can account for changes in the earnings distribution. But it has some limitations. One is that the residual in the wage equation contains the contribution to wages of workers' sorting optimally across occupations. A second limitation resides in the interpretation of the decomposition in the face of general equilibrium adjustments. As noted by Firpo, Fortin, and Lemieux (2014), in response to a shock to the task demands, worker mobility across occupations will tend to limit changes in occupation prices, and this approach will attribute wage variation to changes in the returns to skills. Our Section 5.2 model is designed to grapple both with occupational sorting and general equilibrium effects. On the other hand, the model imposes parametric assumptions on workers' idiosyncratic ability to work in each potential occupation. Despite their differences, both approaches demonstrate that changes in occupations' task content generate a large fraction of the increase in 90-10 earnings inequality observed between 1960 and 2000.

5.1 Decompositions Using RIF Regressions

In this section, we perform a statistical decomposition due to Fortin, Lemieux, and Firpo (2011) to assess the role of occupations' task content on earnings inequality. Fortin, Lemieux, and Firpo introduce a method with which to decompose changes in the distribution of earnings across points in time on the basis of worker and occupational attributes. This method, which can be thought of as an extension of a Oaxaca-Blinder decomposition, breaks down changes over time in any quantile of the earnings distribution into the contribution of observable changes in worker and occupational characteristics (the "composition" effect) and the contribution of implicit changes in the rewards to those characteristics (the "wage structure" effect). One can further break down the composition and wage structure effects into the parts belonging to each of these characteristics (e.g. worker's educational attainment, occupational task content, etc.).

The basis of the decomposition is the following specification of workers' earnings as a function of their observed characteristics and the tasks of the occupations in which they work:

$$\log W_{ijt} = \log \pi_{0t} + \sum_{h=1}^H T_{hjt} \log \pi_{ht} + \sum_{k=1}^K \alpha_k \tilde{S}_{kg} + \log \epsilon_{ijt}. \quad (2)$$

In this equation, i is an individual, W_{ijt} is the individual’s wage, and \tilde{S}_{kg} is an observable skill characteristic k for an individual who is in group g . And, $\log \pi_{ht}$ is a regression coefficient that represents the (log) price of task h in period t .

To perform our decompositions, we compute recentered-influence-function (RIF) regressions that describe, for workers in each quantile, the relationship between real log earnings and different occupational and worker characteristics. In these RIF regressions, the coefficient estimates will vary by quantile; coefficient estimates for the 10th and 90th percentiles are given in Appendix E.1. The worker characteristics include a race indicator and an indicator for marital status, along with education and potential experience categorical variables.²¹

Our occupational characteristics are the measures based on Spitz-Oener (2006) and Firpo, Fortin, and Lemieux (2014) that we have discussed in Section 4. Since the different task measures (e.g., routine cognitive versus nonroutine interactive) are scaled differently — not only because employers tend to systematically mention some types of words more frequently than others, but also because our algorithm may be better at detecting certain types of words than others — it is necessary to standardize our task measures. We normalize $T_{hjt} \equiv (\tilde{T}_{hjt} - \mu_h) / \sigma_h$; here μ_h is the mean and σ_h is the standard deviation of keyword frequencies for task group h across years and occupations. Standardizing variables this way eliminates permanent cross task variation in mentions but retains the ability to do comparisons both across occupations at a point in time and within occupations across time.

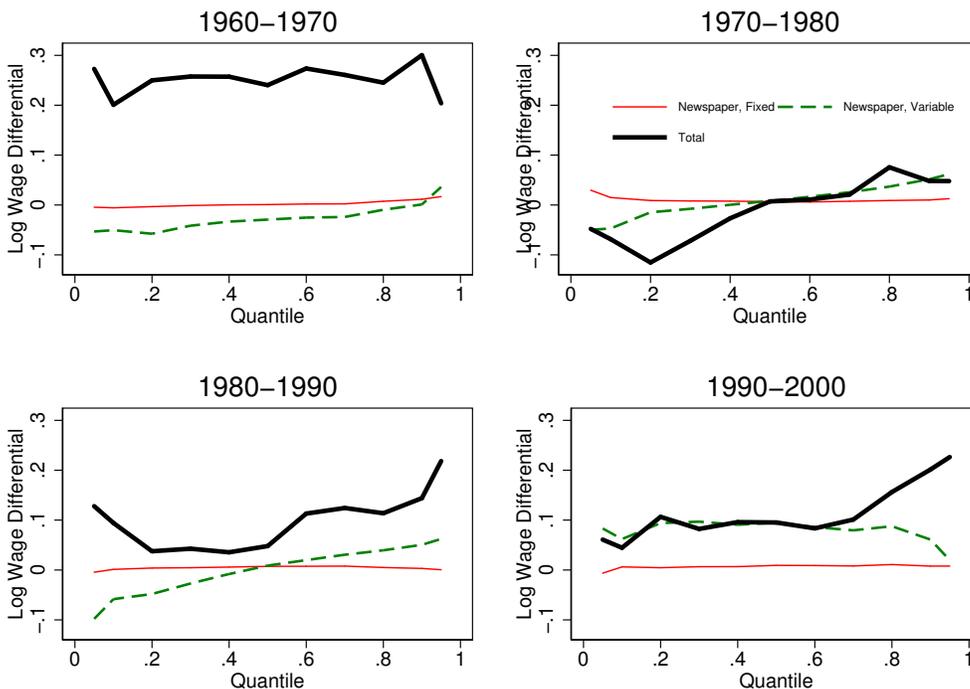
Decompositions Using Spitz-Oener’s (2006) Classification

We begin by grouping tasks into nonroutine analytic, nonroutine interactive, nonroutine manual, routine cognitive, and routine manual categories. We highlight the importance of our time-varying occupational measures by employing two sets of decompositions. In the first, T_{hjt} is fixed to its sample mean for each occupation-task combination (thus eliminating time

²¹The education categories are Some High School; High School; Some College (which is the omitted group); College; and Post-graduate. The potential experience categories are defined by ten-year intervals (with individuals with 20 to 29 years of potential experience belonging to the omitted group.) These education and potential experience categories are more coarsely defined than in Firpo, Fortin, and Lemieux (2014). We adopt this classification to be consistent with our analysis in Section 5.2.

The sample includes only males with age between 16 and 65. We restrict the sample to male workers since the RIF regression decompositions are ill-equipped to handle the large increase in female labor force participation observed in the first half of our sample period. Appendix E.2 presents our decompositions for samples that include female workers. When females are included in the sample, the (unexplained) “wage structure” effects of our task measures are considerably larger in the 1960s, but similar in other decades. The composition effects are also similar to what we report here.

Figure 6: Decomposition of Real Log Earnings



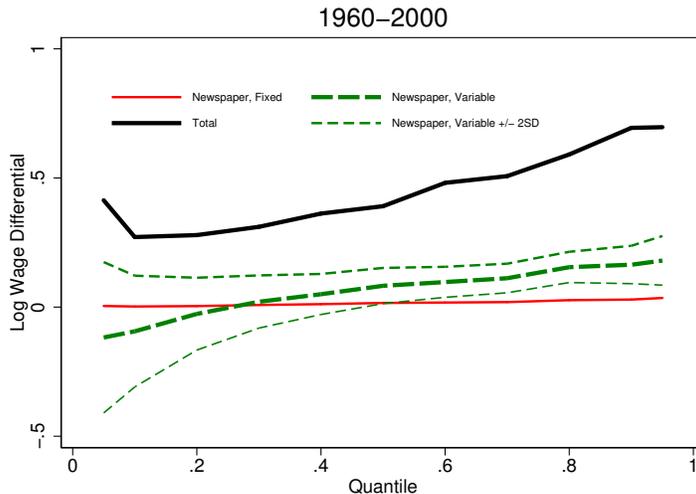
Notes: The thick solid line presents changes in log wage income of workers at different quantiles of the income distribution. The thin solid line and the dashed line give the contribution of occupations (combining the composition effects and wage structure effects) using two different measures of occupational characteristics.

variation), and in the second, T_{hjt} is allowed to freely vary across time within occupations.

Figure 6 presents our decompositions, together with the total change at each percentile of the distribution, for each decade between 1960 and 2000. The thick solid line shows total observed changes for each percentile. According to the top-left panel, average earnings increased between 1960 and 1970, with little change in earnings inequality. In the following decades, from 1970 to 2000, inequality increased more sharply, while average earnings increased less. To what extent can occupational characteristics account for these changes?

We plot the contribution of occupational task content, combining both the composition and wage structure effects, in the dashed and thin solid lines in Figure 6. The thin solid line — computed using task measures that are fixed throughout the sample — accounts for a small part of the changes in the earnings distribution. According to this measure, occupational characteristics account for a 2 percentage point increase in 90-10 inequality between 1960 and 1970 and no change in the 1970s, 1980s, or 1990s.

Figure 7: Decomposition of Real Log Earnings



Notes: The thick solid line presents changes in log earnings of workers at different quantiles of the distribution. The thin solid line and dashed lines give the contribution of occupations (both through the composition effects and wage structure effects) using two different measures of occupational characteristics.

By contrast, when we allow task measures to vary across time, occupational characteristics account for a substantial increase in the median and 90-10 inequality. Between 1960 and 2000, with our preferred, time-varying measure of tasks, occupational changes can account for a large increase in male earnings 90-10 inequality: 5 percentage points in the 1960s, 10 percentage points in the 1970s, 11 percentage points between 1980 and 1990, and no change between 1990 and 2000.

In Figure 7, we sum up the decompositions in the four panels of Figure 6. Over these four decades, the 90-10 ratio of earnings inequality increased by 42 log points among male workers. Of this change in earnings inequality, our measures of occupational changes account for a 26 log point increase. In this figure, we also plot the two standard deviation confidence interval of the wage structure and composition effects. The two standard deviation confidence interval for the increase in 90-10 earnings inequality that is due to our task measures spans 4 to 48 log points.²² On the other hand, the contribution of occupational characteristics to 90-10 earnings inequality is a modest 3 log point increase when using measures which are fixed within occupations throughout the sample period. We conclude that variation in

²²These confidence intervals aim to measure the uncertainty surrounding our sampling of newspaper text. We construct 20 bootstrapped samples from our newspaper text. For each of these bootstrapped samples, we re-estimate our RIF regression based decompositions. To construct the dashed lines in Figure 7, we compute the standard deviation at each quantile of the RIF regression estimated contribution of our task measures to changes in the earnings distribution.

task content that includes changes within occupations across time can account for a large fraction of the rise in inequality. The contribution of occupational changes coming only from differences in task content between occupations is comparatively smaller.

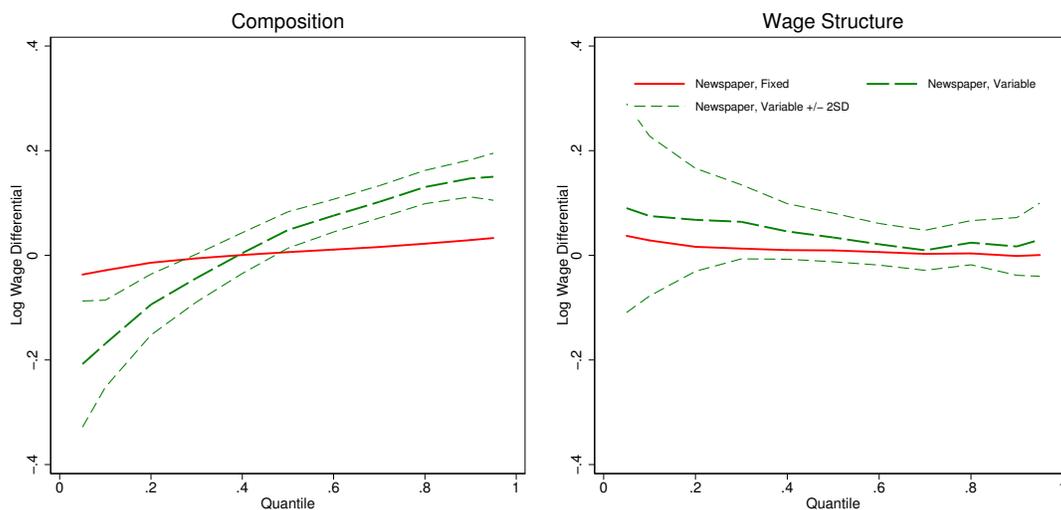
To better understand the role of occupational changes in accounting for increased inequality, we plot the composition and wage structure effects separately for each newspaper-based measure (Figure 8). Occupational measures in which task measures are fixed yield modest composition and wage structure effects. Changes in the composition of tasks, as measured via fixed-over-time measures, account for a 6 percentage point increase in 90-10 inequality. On the other hand, the composition effect is substantially larger using our measure in which occupations' task measures vary as time progresses. In fact, for workers above the 90th percentile of the earnings distribution, these composition effects account for at least a 15 percentage point increase in earnings; for workers below the 10th percentile, the same composition effects account for at least a 17 percentage point decline. In sum, given the large changes in workers' activities within occupations that we uncovered in the previous sections, decompositions which rely only on between-occupation changes in task or skill-intensity understate the contribution of composition effects on changes in the earnings distribution.²³

In Figure 9, we present the composition and wage structure effects, broken down by task. The key result from this exercise is that, among the estimated compositional effects, changes in routine manual tasks generate the largest changes in labor income inequality. Nonroutine interactive tasks also contribute to the increase in inequality, although to a lesser extent. These composition effects are due to a combination of i) a large decline in economy-wide routine manual and cognitive task content and a corresponding increase in nonroutine interactive and analytic task content; ii) a stronger association between workers' earnings and their occupations' tasks (a larger estimated $\log \pi$) for routine manual tasks at the bottom of the distribution than in the top; and iii) a stronger association between earnings and nonroutine interactive task content at the top of the distribution than in the bottom. Finally, changes in the "price" of tasks, as measured by the wage structure effects, account for a 6 percentage point decline in 90-10 inequality.

The U.S. economy experienced several consequential changes since 1960, including dramatic technological progress and an increasing openness to trade. These developments have induced a shift in the composition of tasks which workers perform, and has re-shaped returns to these tasks. Our results suggest that changes in the task content of occupations translated

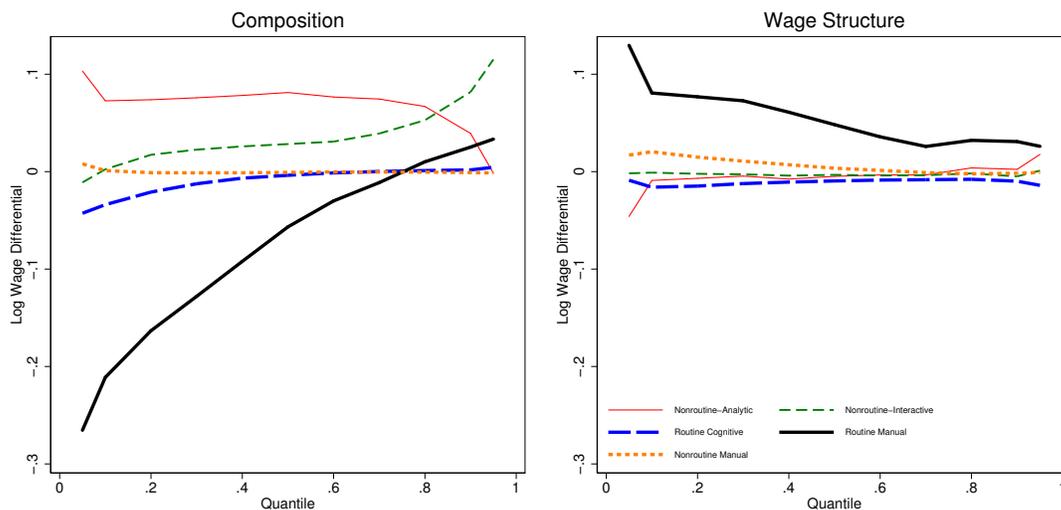
²³There are analogous wage structure and composition effects for the demographic, experience, and education variables. We do not plot these here. Throughout the entire distribution, but especially across the right tail of the distribution, the composition effect for education is positive, indicating that increases in male workers' educational status is associated with higher earnings and earnings income inequality. These results are consistent with those of [Firpo, Fortin, and Lemieux \(2014\)](#).

Figure 8: Decomposition of Real Log Earnings: Composition and Wage Structure



Notes: The left panel describes the contribution of occupational characteristics through compositional changes. The right panel describes the contribution of occupational characteristics through wage structure effects.

Figure 9: Detailed Decompositions of Real Log Earnings



Notes: The panels describe the contribution of individual occupational characteristics, through compositional changes (left panel) and wage structure effects (right panel) to changes in the earnings distribution. In this panel, we use the newspaper-based task measures which are allowed to vary within occupations across time.

shocks to trade and technology into widening inequality. Changes in the task returns played a more modest role. The implication is that, relative to the top of the distribution, the tasks which declined in importance over the sample period (routine manual tasks) were highly priced at the bottom of the wage distribution. Concurrently, tasks priced relatively highly for high-wage jobs (nonroutine analytic and interactive tasks) increased in importance between 1960 and 2000. A second implication follows from a comparison of the decompositions based on fixed and time-varying task content measures. With fixed task content, shifts in the tasks performed by workers can only arise via changes in the prevalence of occupations at different points of the distribution. Our decompositions indicate that such between-occupation shifts were of secondary importance in accounting for widening inequality, relative to the large within-occupation changes in task content that we have documented.

Decompositions Using Firpo, Fortin, and Lemieux (2014)’s Classification

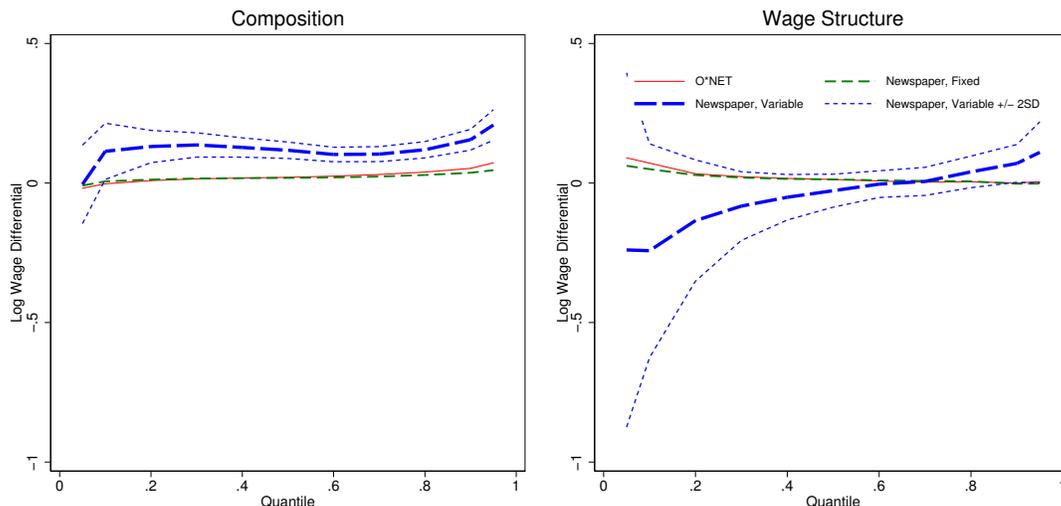
We now perform a similar set of decompositions using [Firpo, Fortin, and Lemieux \(2014\)](#)’s task classification. Figure 10, analogous to Figure 8, plots the composition and wage structure effects of our technology and offshoring measures on the earnings distribution between 1960 and 2000. Here, composition effects account for a 4 log point increase in 90-10 inequality. Wage structure effects account for a more substantial increase in inequality of 31 log points. In combination, [Firpo, Fortin, and Lemieux \(2014\)](#)’s task measures account for a 35 log point increase in 90-10 inequality.

Using fixed-over-time occupational measures yields much smaller results. Note that because there is a direct mapping between [Firpo, Fortin, and Lemieux \(2014\)](#)’s classifications and O*NET work activity measures, we can include measures based on O*NET. Results from decompositions based on our fixed-over-time newspaper task measures mirror those based on O*NET’s measures, confirming that our newspaper-based measures track similar task content as those based on O*NET.

Sensitivity Analysis

In the appendices, we consider three sets of exercises to examine the sensitivity of our results. First, in Appendix E.2, we examine the robustness of our benchmark results to changes in the way we construct mappings — from newspaper text to Spitz-Oener’s task groupings, to our transformation of the frequency of task-related words to T_{hjt} , and, finally, to the inclusion of women in the sample. Second, given the current discordance between the regions of the United States from which we are characterizing occupational characteristics (New York and Boston) and the regions we use to measure workers’ income and demographic variables are

Figure 10: Decomposition of Real Log Earnings: Composition and Wage Structure



Notes: The left panel describes the contribution of occupational characteristics through compositional changes using [Firpo, Fortin, and Lemieux \(2014\)](#)’s task definitions. The right panel describes the contribution of occupational characteristics through wage structure effects.

measured (the entire U.S.), we re-compute Figures 7 through 10 using only census data from the New York and Boston MSAs (see Appendix E.3). Third, in Appendix E.4, we apply hourly wage data from the CPS Merged Outgoing Rotation Group, instead of annual labor income data from the decennial census, to analyze changes in income inequality.²⁴ These three different samples present a consistent depiction on the relationships between our job characteristics and trends in labor income inequality.

5.2 Decompositions in an Estimated Equilibrium Model

In this section we take an alternative approach to calculating changes in the earnings distribution. We begin with a quantitative model in which workers sort based on comparative advantage, along the lines of [Burstein, Morales, and Vogel \(2015\)](#). We consider the effect of changes in the parameters of occupations’ production functions, and interpret these changes as reflecting exogenous shifts in the demand for worker-produced tasks.

We consider a closed economy with many time periods $t = 1, 2, \dots$ and a continuum of workers. Each individual worker i belongs to one of a finite number of groups, indexed by $g = 1, \dots, G$. The mass of workers in group g is L_{gt} . Workers of type g are endowed with

²⁴We acknowledge a trade-off here: While we would prefer to use hourly wages as the basis for our measurement of income inequality, we wish to take advantage of the longer sample which the decennial census offers.

a set of skills S_{gh} , $h \in 1 \dots H$, where h indexes different tasks which workers perform in their occupations. Worker i produces task h by combining skills and time: $q_{iht} = S_{gh}l_{iht}$. Here, l_{iht} equals the amount of time the worker allocates to task h . Each worker has a total of one unit of time, which she supplies inelastically in one of $j \in 1, \dots, J$ occupations.

Worker i , if she works in occupation j , produces

$$V_{ijt} = \epsilon_{ijt} \prod_{h=1}^H \left(\frac{q_{iht}}{T_{hjt}} \right)^{T_{hjt}} \quad (3)$$

units of output. In Equation 3, ϵ_{ijt} is an occupation-worker unobserved efficiency, and T_{hjt} gives the importance of task h in occupation j . We fix $\sum_h T_{hjt} = 1$ for each occupation and time period. Variation in T_{hjt} across occupations captures, for example, that some occupations are more intensive in routine analytic tasks than others. To match our time-varying measures of task content, we allow the parameters T_{hjt} to evolve exogenously through time. Such changes could reflect, again as an example, declines in the demand for worker-performed routine manual or routine cognitive tasks caused by a decline in the price of computers, or increases in nonroutine interactive tasks related to the increased importance of team management.

We assume that worker i 's wages, W_{ijt} , equal the value of the output she produces, $P_{jt}V_{ijt}$, which represents the product of the output produced and the price of the occupation j specific output. Taking P_{jt} as given, each worker chooses the amount of time spent on each of the H tasks to maximize the value of her output. The solution to this problem implies that $l_{ijt} = T_{hjt} \cdot \left(\sum_{h'=1}^H T_{h'jt} \right)^{-1} = T_{hjt}$.²⁵

Plugging the optimal time allocation back into Equation 3 yields worker i 's log wages

$$\log W_{ijt} = \log P_{jt} + \sum_{h=1}^H T_{hjt} \log S_{gh} + \log \epsilon_{ijt}. \quad (4)$$

We assume that workers are freely able to choose their occupations to maximize their wages. Workers take as given each occupation-specific output price, and the task activities associated with each occupation. The idiosyncratic component of worker i 's returns from working in occupation j , ϵ , is a Frchet-distributed random variable, drawn independently across occupations and workers, with shape parameter θ , i.e., $\Pr[\epsilon_{ijt} < z] = \exp(-z^{-\theta})$. The parameter θ is an inverse measure of the dispersion of ϵ_{ijt} within group-occupation pairs.²⁶

²⁵Due to the assumption that the production function of occupation- j specific output is Cobb-Douglas, individual abilities do not shape the time spent in each task, although they will affect occupational choice.

²⁶In Appendix F, we outline the extra assumptions necessary to derive from Equation 2, the basis of our

The Frechet formulation conveniently generates expressions for the fraction of group g workers which work in occupation j and the average wage of group g workers. The probability that a worker of type g sorts into occupation j is

$$\lambda_{gjt} = \frac{\left(P_{jt} \prod_{h=1}^H (S_{gh})^{T_{hjt}}\right)^\theta}{\sum_{j'} \left(P_{j't} \prod_{h=1}^H (S_{gh})^{T_{hj't}}\right)^\theta}. \quad (5)$$

Moreover, the average wages of group g workers equals

$$\bar{W}_{gt} = \Gamma\left(1 - \frac{1}{\theta}\right) \cdot \left(\sum_j \left(P_{jt} \prod_{h=1}^H (S_{gh})^{T_{hjt}}\right)^\theta\right)^{1/\theta}, \quad (6)$$

where $\Gamma(\cdot)$ is the Gamma function.

To close the model, we assume that there is a representative consumer who has CES preferences over the output produced by the different occupations:

$$V_t = \left[\sum_{j=1}^J (\sigma_j)^{\frac{1}{\rho}} \cdot (V_{jt})^{\frac{\rho-1}{\rho}} \right]^{\frac{\rho}{\rho-1}},$$

with V_{jt} representing the sum of the output of individual workers, i , who produce occupation j output. Here, σ_j parameterizes the consumer's preferences for occupation j output, and ρ gives the preference elasticity of substitution across occupations' output. Given these preferences, we can write the market-clearing condition for occupation j output, equating expenditures on the occupation's output to the wage bill of workers who are employed in occupation j :

$$\underbrace{\frac{\sigma_j \cdot (P_{jt})^{1-\rho}}{\sum_{j'} \sigma_{j'} (P_{j't})^{1-\rho}}}_{(A)} \underbrace{\sum_g \bar{W}_{gt} L_{gt}}_{(B)} = \sum_{g=1}^G \underbrace{\Gamma\left(1 - \frac{1}{\theta}\right) \left(\sum_{j'} \left(P_{j't} \prod_{h=1}^H (S_{gh})^{T_{hj't}}\right)^\theta\right)^{1/\theta}}_{(C)} \underbrace{\lambda_{gjt} L_{gt}}_{(D)}. \quad (7)$$

The left-hand side of Equation 7 contains two terms: the share of total expenditures on occupation j output (term A), multiplied by total expenditures (term B). On the right-hand side, the total wage bill of workers in occupation j is computed as the sum of the wage bill of group g workers in occupation j ; which in turn equals the product of the average wage of group g workers (term C) and the number of group workers (term D).

statistical decompositions, from Equation 4, in the previous section.

An equilibrium of our economy is the solution to $\{\lambda_{ij}\}$ and $\{P_j\}$, as determined by Equations 5 and 7.

With this model, we evaluate the impact of change in the demand for tasks on the equilibrium wage distribution. To do so, we first use data from a single period (1960) in combination with Equations 5 and 6 to estimate demographic groups’ skills in producing tasks. Then, with our measures of changes in occupations’ task content, we compute the counterfactual change in the distribution of wages, between 1960 and 2000, that is due only to changes in the demand for tasks. Appendix F details the equilibrium of the model, and delineates our algorithm to recompute the equilibrium to in response to changes in the T s. Throughout the remainder of the section, we fix $\theta = \rho = 1.78$, following [Burstein, Morales, and Vogel \(2015\)](#).

In estimating our model, we need to map task-related keyword frequencies, as observed in the newspaper data (\tilde{T}_{hjt}), to our production function parameters (T_{hjt}). To ensure that our production function parameters sum to one for each occupation-year, we apply the following transformation: $T_{hjt} = \tilde{T}_{hjt} / (\sum_{h'} \tilde{T}_{h'jt})^{-1}$.

Estimation of task-related skills

For each task h , we parameterize the relationship between skills and educational and demographic observables as follows:

$$\log S_{gh} = a_{h,gender} D_{gender,g} + a_{h,edu} \cdot D_{edu,g} + a_{h,exp} \cdot D_{exp,g}. \quad (8)$$

Here, $D_{gender,g}$, $D_{edu,g}$, and $D_{exp,g}$ are dummies for gender, education and experience, which define the categories g . We estimate these a parameters via a method of moments procedure.²⁷

Our estimation recovers $a_{h,gender}$, $a_{h,edu}$, and $a_{h,exp}$ to minimize

$$\sum_g \sum_j \omega_{gj}^\lambda \left(\log \lambda_{gj,1960} - \log \lambda_{gj,1960}^{\text{data}} \right)^2 + \sum_g \omega_g^W \left(\log \bar{W}_{g,1960} - \log \bar{W}_{g,1960}^{\text{data}} \right)^2. \quad (9)$$

In Equation 9, $\lambda_{gj,1960}^{\text{data}}$ and $\log \bar{W}_{g,1960}^{\text{data}}$ refer to the observed occupational shares and average wages.²⁸ The ω_{gj}^λ and ω_g^W are weights, characterizing the relative importance of each moment

²⁷As in the previous subsection, we have two gender, five educational, and four experience groups, with “male” as the omitted gender category, “Some College” as the omitted educational category, and 20-29 years as the omitted experience category.

²⁸Our estimation relies on data from 3240 (=40 · 81) moments—representing information from 40 groups (2 genders, 5 educational categories, and 4 experience categories) and 81 occupations—to identify 121 parameters: 81 occupation-fixed effects plus 40 a coefficients.

in our estimation. We compute these weights as the inverse of the variance of the moment (in the decennial census) across 40 bootstrapped samples.

Table 6 quantifies the patterns of comparative advantage across groups and tasks. For example, relative to other groups, workers with higher educational attainment tend to have a comparative advantage at performing nonroutine analytic tasks; high school graduates and workers with some college tend to have a comparative advantage in routine cognitive tasks; and high school dropouts have an advantage in routine and nonroutine manual tasks. Also, more experienced workers are more skilled in performing nonroutine interactive, and less skilled in routine cognitive tasks.

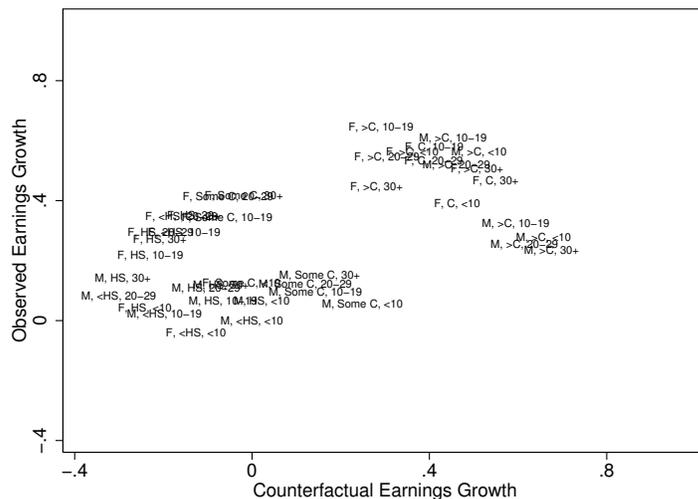
Table 6: Estimates of Skills

	Nonroutine Analytic	Nonroutine Interactive	Nonroutine Manual	Routine Cognitive	Routine Manual
Gender					
Female	-1.384 (0.004)	-0.473 (0.004)	0.269 (0.005)	3.472 (0.006)	-7.420 (0.017)
Education					
< HS	-1.981 (0.007)	-1.155 (0.005)	2.628 (0.011)	-2.199 (0.012)	4.461 (0.034)
High School	-0.785 (0.008)	-0.498 (0.005)	0.905 (0.011)	-0.006 (0.010)	2.757 (0.033)
College	1.449 (0.008)	0.106 (0.006)	1.414 (0.017)	-1.002 (0.016)	-8.438 (0.057)
Post-Graduate	1.394 (0.008)	-0.215 (0.007)	3.222 (0.011)	-2.778 (0.020)	-7.300 (0.059)
Experience					
0-9 Years	-0.068 (0.005)	-0.602 (0.005)	-0.365 (0.007)	0.586 (0.010)	-2.560 (0.020)
10-19 Years	-0.002 (0.006)	-0.219 (0.005)	0.216 (0.007)	0.354 (0.012)	-0.906 (0.018)
30+ Years	-0.063 (0.006)	0.153 (0.004)	-0.026 (0.007)	0.239 (0.011)	-0.767 (0.020)

Notes: To compute the standard errors, we re-sampled 40 times from the 1960 decennial census. For each bootstrapped sample, we recomputed the empirical occupational shares and group wages and then found the combination of parameters that minimized Equation 9. The omitted demographic groups are males, workers with Some College, and workers with 20-29 years of potential experience.

With the aim of substantiating these estimates, we make two points. First, as an assessment in-sample fit of the model, we compare $\log \lambda_{gj,1960}$ and $\log \lambda_{gj,1960}^{\text{data}}$ (across the 3240 group-occupation observations), and $\log \bar{W}_{g,1960}$ and $\log \bar{W}_{g,1960}^{\text{data}}$ (across the 40 groups). The correlation between the model-estimated occupational shares and the observed shares is

Figure 11: Counterfactual and Observed Earnings Growth, 1960-2000, By Demographic Group



Notes: Each point gives the growth in wages for one of the 40 g groups. The first character—“M” or “F”—describes the gender; the second set of characters—“<HS,” “HS,” “Some C,” “C,” or “>C”—the educational attainment; and the third set of characters the number of years of potential experience for the demographic group.

0.52, while the correlation between $\log \bar{W}_{g,1960}$ and $\log \bar{W}_{g,1960}^{\text{data}}$ is 0.95. Second, identification of the parameters in Table 6 follows transparently from workers’ sorting patterns. Based on our set-up, the share of workers will be high for occupations in which their skills will be used intensively. For example, mirroring the estimates in Table 6, the correlation between the average number of words related to routine cognitive tasks in occupation j and an occupation-group’s $\log \lambda_{gj,1960}$ is substantially higher for women compared to men (0.34 versus 0.00); for high school graduates compared to post-graduates (0.17 versus 0.10); and for workers with fewer than 10 years of experience compared to workers with 30+ years of experience (0.14 versus 0.09).²⁹

Counterfactual earnings distribution

Having estimated the distribution of skills, we now compute the counterfactual dispersion in wages that would otherwise have been obtained in succeeding decades—in 1970, 1980, 1990, and 2000—as a result of changes in the demand for tasks over our sample period. To do so, we consider an exogenous change in the T_{hjt} production function parameters (which, again, we measure through the changes in task-related keyword frequencies). Stemming from these

²⁹As a second example, the correlation between the frequency of words related to nonroutine analytic tasks and $\log \lambda_{gj,1960}$ is increasing across the five education groups: -0.31, -0.18, -0.01, 0.30, 0.39.

changes in the demand for tasks, we compute the counterfactual equilibrium that would have obtained, fixing $\log S_{gh}$ to the values we estimated in the previous subsection, but allowing T_{hjt} to change over time.³⁰

Figure 11 plots the growth in \bar{W}_{gt} between 1960 and 2000, both as observed in the data and according to our counterfactual exercise. Wages increase most quickly for workers with college degrees or with post-graduate education. According to our estimated model, wage growth is fastest for high-education demographic groups because these groups have an advantage in nonroutine analytic and interactive tasks as of 1960, and the relative demand for these tasks has increased over the subsequent 40 years.

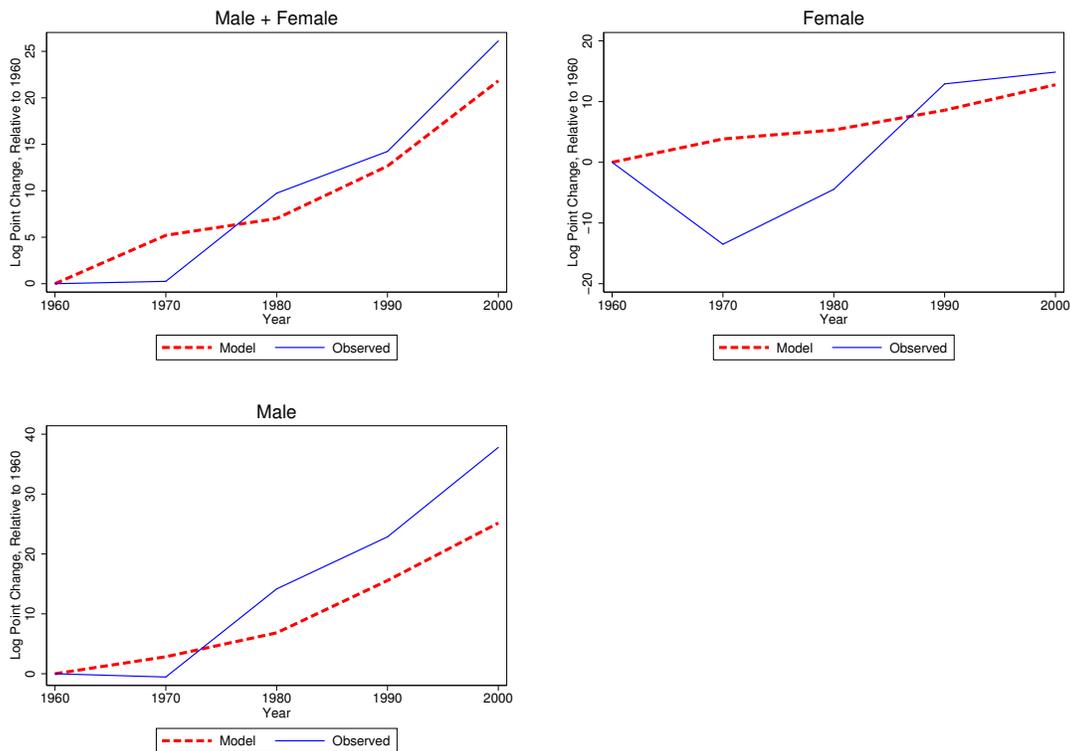
Increases in between-group inequality signify larger overall inequality. Figure 12 plots changes in 90-10 inequality, both the observed growth rate and the counterfactual growth rates that are due only to changes in T_{hjt} . Between 1960 and 2000, 90-10 inequality increased by 26 log points for the entire population, 38 log points for male workers, and 15 log points for female workers. According to our counterfactual exercises, within occupation changes in task demand account for much of the observed increase in 90-10 inequality: 22 log points for the entire sample, 13 log points for female workers, and 25 log points for male workers.

Discussion Occupational choice and wage data from the beginning of our sample suggest that workers with certain demographic characteristics (e.g., workers with a college degree) have an advantage in the tasks which have happened to grow over the subsequent forty years. Since these demographic groups were already highly remunerated in 1960, changes in the demand for tasks have increased earnings inequality.

Where do these shifts in the demand for tasks come from? Our model omits capital as an input in the production of tasks. Likely, some of the differential growth rates of T_{hjt} across task groups epitomize, at a more fundamental level, changes in capital prices. To the extent that the elasticity of substitution between workers and capital is relatively high in the production of routine tasks, a decline in the price of capital will be equivalent to a reduction in the demand for worker-performed routine tasks. Moreover, insofar as employers' innovation and technology adoption decisions are a function of the supply of workers of different skill types, changes in the T_{hjt} not only embody exogenous changes in the demand for tasks (which has been our interpretation here), but also reflect changes in the skill composition of labor supply. An interesting topic for future work would be to build on our model of occupations as a bundle of tasks, endogenizing changes in the T_{hjt} while acknowledging that

³⁰In the exercises in this section, we also fix the sizes of the 40 different demographic groups to their 1960 values. An alternate procedure would allow these labor supplies to vary throughout the sample according to observed demographic changes. This alternate procedure yields similarly large increases in 90-10 inequality in the counterfactual equilibrium, compared to those reported in Figure 12.

Figure 12: Counterfactual and Observed 90-10 Inequality, 1960-2000



Notes: Each panel plots the change in 90-10 earnings inequality, as observed in the decennial census (solid line), and are due only to changes in the demand for tasks (dashed line).

workers and capital combine to perform each individual task and that innovations which lead to these declines in capital prices are potentially a response to the changing composition of the workforce.

The statistical decomposition in the previous section and the counterfactual exercise in this section, while markedly different in their approach and assumptions, result in comparable assessments of the role that task measures play in explaining increasing inequality. On the one hand, in contrast to the statistical decomposition, worker sorting plays a key role in the equilibrium model. Rewards to skills are occupation specific (and determined by the occupations' associated task content). Sorting amplifies the effect of observed changes in tasks on inequality.³¹ Moreover, while heavily parameterized, the model takes into account the labor responses to changes in task prices induced by the shifts to the T_{hjt} . These general

³¹In principle, sorting on unobservable characteristics could lead the statistical decomposition to either overstate or understate the role of tasks in accounting for increased inequality. If, over time, there is increased sorting of workers with high unobserved ability into jobs at the top of the distribution, then the decomposition's wage structure effects will under-represent the contribution of task price changes to inequality. [Firpo, Fortin, and Lemieux \(2014\)](#) argue that this is likely the case. See their Section I.B.

equilibrium effects also tend to generate more inequality explained by the model relative to the statistical decomposition.

On the other hand, in the model, we only evaluate the effect of within-occupation changes in task demands, while other shocks to fundamentals could also shape the income distribution. These other shocks include changes in the demand for occupations (measured by σ_j in the model), and potentially represent a source of widening income inequality that is encapsulated by the statistical decompositions and not the counterfactual exercises. Moreover, to the extent that the price of individual tasks vary within occupations, the RIF regressions will capture a source of inequality that the model cannot.

6 Conclusion

In this paper, we chronicle the changes in the U.S. occupational structure between 1960 and 2000. We document that a predominant share of changes in the skill and task composition of the workforce has occurred within rather than between occupations. Not only is it the case that occupations intensive in routine tasks have declined as a share of the workforce — a central pattern of the existing task literature — but also individual occupations’ routine task content has declined as well.

We then demonstrate that within-occupation task changes are fundamentally important in an examination of the evolution of income inequality. We first perform a statistical decomposition on the earnings distribution and find that compositional changes associated with occupational characteristics can explain a 26 log point increase in labor income inequality (as measured by the 90-10 ratio) between 1960 and 2000. We then construct and estimate a Roy model in which changes in the demand for tasks determine workers’ comparative advantage. Our estimated model accords with the results from our statistical accounting exercise.

Beyond this project, our newspaper data have the potential to address other economic questions related to the labor market. For example, in ongoing work we use the text to measure the adoption of new computer technologies, to study how these technologies interact with the task content of jobs. More generally, we view our newspaper-based job vacancy text as offering an opportunity to study questions that have been examined using online job vacancy text over a longer time horizon than previously possible (Hershbein and Kahn, 2016; Modestino, Shoag, and Ballance, 2016).

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