The Geography of Job Tasks

Enghin Atalay   Sebastian Sotelo   Daniel Tannenbaum*

January 13, 2023

Abstract

We introduce new measurement tools to understand the sources of earnings differences across space. Based on the natural language employers use in job ads, we develop granular measures of job tasks and of worker specialization. We find that jobs in larger commuting zones involve greater interpersonal interactions and have higher computer software requirements. Between 10 and 50 percent of task and technology variation between large and small commuting zones exists within occupations. Further, workers in larger markets are more specialized. Tasks, technologies, and worker specialization account for a substantial portion of the market size premium even within occupations.

JEL Codes: J20, J24, R12, R23

*Atalay: Research Department, Federal Reserve Bank of Philadelphia. Sotelo: Department of Economics, University of Michigan-Ann Arbor. Tannenbaum: Department of Economics, University of Nebraska-Lincoln.
We thank Reid Gahan, Billy Huang, and Ryan Kobler for outstanding research assistance and Barbara Nordin for excellent editorial assistance. We thank seminar participants at the 2019 Society of Labor Economists conference, the 2019 Urban Economics Association conference, the UNL labor reading group, the Federal Reserve Bank of Philadelphia, the 2022 ASSA annual meetings, and the Bureau of Labor Statistics, as well as Adrien Bilal, Jeffrey Lin, and Gregor Schubert for valuable feedback. We thank the Washington Center for Equitable Growth and the Russell Sage Foundation (grant #92-18-05) for financial support. Sotelo thanks the IES at Princeton for its hospitality during part of this research. The views expressed in this paper are solely those of the authors and do not necessarily reflect the views of the Federal Reserve Bank of Philadelphia or the Federal Reserve System.

1 Introduction

Geographic inequality is pervasive in the U.S. labor market. Average wages, the college wage premium, and the wage gap between white-collar and blue-collar occupations increase with labor market size. Furthermore, different labor markets foster distinct types of work. For example, managerial, financial, and computer occupations are over-represented in large labor markets, and maintenance, production, and material moving occupations in smaller ones.

While economists have studied how jobs vary with market size, prior research has been unable to fully characterize spatial differences in the nature of work. Job content analysis applied to national datasets, such as O*NET, cannot directly measure the extent to which occupations vary across markets. This approach might be apt for some occupations: For example, food preparation workers may perform similar activities in Ann Arbor as in Philadelphia. But for other occupations, job tasks and technologies likely vary with the size of the labor market. For example, financial analysts in Hastings, Nebraska may perform fundamentally different tasks compared to those in New York City. Existing datasets do not speak to these differences.

In this paper, we study the geography of job tasks and technology requirements in the United States. We develop a novel approach to measurement applied to an increasingly popular data source: the text of online job ads. We use natural language processing to extract job tasks and technologies from job ads and provide new evidence for three mechanisms behind the commuting zone (CZ) size-wage premium: interpersonal interactions and coordination, the adoption of new technologies, and worker specialization. Our measures are not fixed at the occupation level, and capture differences in task content within and across regions. We find that work differs across CZs, even within occupations, and this heterogeneity is important for understanding both the CZ size-wage premium and the increased skill premium in larger CZs.

We take two approaches to task measurement. The first approach, following our prior work on newspaper job postings (Atalay et al., 2018, 2020), maps words from job ads into task categories used in previous literature (Spitz-Oener, 2006; Autor, 2013). In our second, novel approach, we use tools from natural language processing to define tasks as the verb-noun pairs that appear in job descriptions. This approach yields more granular measures and reduces the level of researcher discretion in classifying tasks. In addition, it allows us to measure how specialized jobs are—i.e., how far apart workers are in task space, within firms or occupations.

Our main empirical analysis introduces several facts regarding the geography of work in the United States. We first show that analytic and interactive tasks increase steeply with market size: Relative to jobs in the bottom population decile, jobs in the top decile have 0.30 standard deviations (s.d.) higher intensity of non-routine analytic tasks and 0.24 s.d. higher intensity of non-routine interactive tasks. In addition, these jobs have 0.18 s.d. lower intensity of routine manual tasks. Even after conditioning on narrowly defined occupation (six-digit SOC) categories, about 16 percent of the gradient between largest and smallest CZs for non-routine analytic tasks, 26 percent of the gradient for non-routine interactive tasks, and 53 percent of the gradient for routine manual tasks remains. We further decompose interactive tasks into those that capture interactions outside the firm and those that capture interactions within the firm. The CZ size gradient is positive for both external and internal interactive tasks, and these relationships are more pronounced for jobs requiring a college degree. Our subsequent analysis using our granular task measures echoes these findings at a much higher resolution. The verb-noun pairs with the steepest gradients with CZ size demonstrate the importance of problem-solving ("managing projects," "developing strategies," "problem-solving skills") and communication and worker interactions ("written communication," "maintaining relationships") in large CZs.

Building on our understanding of differences in job tasks across market size, we consider whether computer software technologies are more likely to be mentioned in job descriptions in larger markets, and how this gradient differs by whether a job requires a college degree. We find that technology requirements increase steeply with market size, with approximately one-and-a-half times as many mentions of technologies in the largest CZs as in the smallest. About 12 percent of the gradient remains after conditioning on six-digit occupational categories. Moreover, the technology gradient is present only for jobs requiring a college degree. Technologies with the steepest gradient for college degree holders involve computer programming (e.g., Python, JavaScript, and Linux), while those for high school diploma holders involve data entry and word processing (e.g., Microsoft Excel, Microsoft Outlook, Microsoft Word).[1]

Our paper also introduces a novel approach for measuring worker specialization, using the content of job descriptions. We represent each job as a vector of verb-noun pairs appearing in the text, and we then compute the average cosine similarity among the vectors associated with a given occupation-CZ (or, alternatively, firm-CZ or industry-CZ) pair. We show that task specialization is increasing in market size, and this relationship holds within occupations, within firms, and between firms. These relationships are stronger for firms in the nontradable sector.

Workers in top population decile CZs earn 31.4 log points more than those residing in

[1]These results complement an expanding literature on the spatial distribution of technology adoption (Eckert et al., 2020; Bloom et al., 2020; Eeckhout et al., 2021).

bottom decile CZs. Even within occupations, this premium is 27.4 log points. In a final step of our analysis, we show that our new technology and specialization measures are associated with large differences in wages and skill premia between smaller and larger labor markets. Within-occupation heterogeneity in interactive tasks, technology usage, and specialization account for 20 percent (5.5 log points out of a total of 27.4) of the difference in wages between workers in top and bottom population decile commuting zones and 22 percent (8.5 log points out of a total of 38.2) when we restrict our data to white-collar occupations. While we interpret these regressions descriptively—since the premia on tasks and technologies may in part reflect worker sorting on unobservable characteristics—they nevertheless show that jobs differ between large and small labor markets in ways that have been previously unmeasured and are reflected in wages. In addition, our evidence suggests that worker sorting is driven in part by the particular job tasks and technologies that employers demand.

Our paper contributes to research on geographic inequality (Glaeser and Maré, 2001; Moretti, 2013a; Diamond, 2016; Frank et al., 2018) by using job postings data to study the geography of tasks and technologies. Worker interactions have long been pointed to as a source of productivity gains in cities (Marshall, 1890; Jacobs, 1969), and recent research studies worker interactions as a source of agglomeration, both theoretically (Davis and Dingel, 2019) and empirically (Bacolod et al., 2009b; Michaels et al., 2018; Rossi-Hansberg et al., 2019). Prior research also shows that new patents and occupational titles are more likely to appear in cities (Carlino et al., 2007; Lin, 2011), suggesting that innovation and technology adoption is concentrated in larger CZs. Using the text of job vacancies, we introduce a new approach to task measurement, which uses natural language processing and requires fewer ex ante restrictions relative to widely used O*NET scales and categories. We show that worker interactions and the adoption of new technologies increase in CZ size, and the gradients are particularly strong for college-educated workers. We find substantial within-occupation heterogeneity that is important for explaining CZ size-wage premia and the differential returns to work faced by white- and blue-collar workers.

We also contribute to the literature that relates productivity and the division of labor to the extent of the market (Young, 1928; Stigler, 1951; Kim, 1989; Becker and Murphy, 1992). Recent work finds greater occupational diversity in cities (Duranton and Jayet, 2011; Tian, 2019). Moretti (2013b) and Dauth et al. (2022) provide evidence for more efficient matching of workers and firms in cities. Our contribution is to measure specialization directly in task space. We show that specialization increases in CZ size and that it accounts for a substantial portion of the CZ size-wage premium.

2 Data and Measurement

We use a comprehensive database of online job ads posted between January 2012 and March 2017, which we purchased from Economic Modeling Specialists International (EMSI, 2017). This dataset is similar to data from Burning Glass Technologies (Burning Glass), which has been used in recent work to study the labor market (Hershbein and Kahn, 2018; Deming and Kahn, 2018; Modestino et al., 2020). Like Burning Glass, EMSI data are proprietary and assembled using web crawlers that extract job vacancy postings from all major online job boards; EMSI also removes duplicate postings that appear across boards. An advantage of the EMSI data for our purposes is that it contains all of the original job ad text. To reduce computational time, we use a 5 percent random sample of the data (7.2 million ads).[2]

In addition to the full text content of each ad, EMSI provides fields for the educational requirement of the job, the firm name, the firm's industry (six-digit NAICS), the occupation code (six-digit SOC), and the job location (county FIPS code). We map FIPS codes to commuting zones (CZs) following Autor et al. (2019). We adopt the CZ as our geographic unit of analysis and refer to CZs throughout this paper as local labor markets. Appendix A.1 provides descriptive statistics for the CZs in the sample, including population and number of ads by CZ decile. We exclude ads with fewer than the 1st and greater than the 95th percentile word count.[3] We make a few additional minor restrictions, which are detailed in Appendix A.2, leaving us with a sample of 6.3 million ads for the occupational analysis and 5.6 million ads for the firm-level analysis.

For the several exercises that require wages at the occupation level and for the construction of employment weights, we use the 2010-2017 American Community Survey (ACS) (Ruggles et al., 2020), and we restrict the sample to individuals who worked at least 40 weeks in the past year and report at least 35 usual hours worked per week. Our measure of wages is total annual pre-tax wage and salary income ("wages" throughout the paper), which we adjust by CPI-U to constant 2012 dollars before averaging to the four-digit SOC-by-CZ cell. We link job ads data to the ACS by four-digit SOC and CZ; we use four-digit SOCs for our wage analysis because of the greater number of observations per cell. In a robustness analysis, we use Burning Glass data, which contains wages extracted from job ads (see Appendix C.5).

[2] We prefer EMSI for our purposes because it contains each ad's complete job description text, which is ideal for extracting job tasks and measuring specialization. By contrast, the version of Burning Glass to which we also have access provides a combination of tasks, skills, and technologies. As a robustness check, we reproduce our main results using Burning Glass data and report them in Appendix C.4. Our results are similar with this alternate data source.

[3] Dropping extremely short ads removes those that are unlikely to have meaningful task information, while dropping exceedingly long ads helps reduce computation time.

2.1 Measuring Tasks: Extraction and Classification

We extract job tasks from the job descriptions using two approaches. Following our prior work (Atalay et al., 2018, 2020), we map keywords in the job descriptions to five task categories: non-routine interactive, non-routine analytic, non-routine manual, routine cognitive, and routine manual, following the categorization of Spitz-Oener (2006). We also map words into O*NET work activities, to validate our text-based task measures and to study different types of interactive tasks. See Appendix A.5 for more details on the word mappings. For job ad j and task category k, our measure of task intensity is the number of distinct task-specific word mentions per 1,000 ad words.[4] We standardize each task to have mean zero and standard deviation one across all ads.

In our second, novel approach, we define tasks as verb-noun pairs. This allows us to distinguish between different types of activities. For example, "develop relationships" is distinct from "develop strategies," and "lead team" is distinct from "lead customers." This approach also allows us to measure specialization among jobs within the same occupation, industry, or firm.

There are two steps to the task extraction process. First, we define a task as a (verb stem, noun stem) pair that occurs within the same sentence, and second, we vectorize ads according to tasks. In the first step, we aim to ensure the verb-noun pairs that we extract are tasks and not firm or worker characteristics. To do so, we isolate the section of the text that pertains to job tasks through to the end of the ad. We search for the keywords "duties," "summary," "description," and "tasks," which suggest a list of tasks will follow.[5] Then, we use the sentence tokenizer and parts-of-speech tagger available in Python's NLTK library to extract each verb and the noun that follows in each sentence, ignoring other parts of speech that may appear in between. Hence, whether the job ad says, "perform commercial, residential, and industrial electrical maintenance," as it does in the sample ad of Table B.1, or simply "perform maintenance," our algorithm will record "perform maintenance" as the task. If multiple verbs correspond to the same noun (for instance, "serve and assist customers"), our algorithm extracts two distinct tasks: "serve customers" and "assist customers."[6] Verbs and

[4] We count repeated use of the same word only once. Hence, the repetitiveness of the job description does not inflate the task intensity of the ad. The use of different task keywords, such as "analyze" and "evaluate," will each be counted and will increase the task intensity measure.

[5] This step significantly improves the precision of the task extraction. Note that not all ads will have these keywords. Hence, an important check is whether the presence of these words varies systematically with CZ size. Figure A.11 investigates this relationship and finds little evidence for a systematic pattern.

[6] We do not perform the analogous procedure when a verb is followed by a list of nouns (for instance, "assist customers and staff"); in this situation, our algorithm extracts one task—the verb and the first noun ("assist customers").

nouns are stemmed so that variation in verb and noun forms do not affect the analysis (e.g., "assist customers" and "assisting customers" are treated as the same task).

We use the 500 most common tasks to balance the advantage of comprehensively characterizing jobs' tasks against the costs of computational time. We reproduce the key results using the 2,000 most common tasks (a higher resolution) and using the 300 most common tasks (a lower resolution) in Appendices C.1 and C.3 and obtain nearly identical results. We also show that when we aggregate granular tasks that are similar in meaning (e.g., "identifies problems" and "resolves issue"), we get nearly identical results (Appendix C.2).

In the second step, we search through the full text of each ad for the appearance of each of these 500 verb-noun pairs and vectorize each job ad.[7] Verb-noun pairs that appear multiple times in an ad are counted only once, meaning each element of the vector is a zero or one. Table B.1 provides two example job ads with their full text, along with the verb-noun pairs extracted by the algorithm.

In our main analysis, we exclude 101 verb-noun pairs that in our judgment do not correspond to job tasks, such as "send resume" and "is position," reducing the number of tasks to 399. Appendix B.1 lists these 399 verb-noun pairs and the 101 excluded pairs.[8]

The 10 most common tasks, from most to least frequent, are: "written communication," "working team," "provide customer-service," "provide service," "lifting pounds," "providing support," "build relationships," "ensure compliance," "assisting customers," and "provide customer." A key strength of our approach is that it allows the text used by employers, describing the jobs they intend to fill, to define the set of tasks.

To illustrate the value of natural language processing for extracting job tasks, Table 1 lists the most common tasks for each of four occupations: Electricians, Supervisors of Retail Sales, Registered Nurses, and Lawyers. The tasks are broadly aligned with our prior intuition for what workers in these different occupations do. For instance, Electricians need to "use hands," "ensure compliance," and "perform maintenance," while Supervisors of Retail Sales must "provide customer-service," "drive sales," and "maintain inventory." Registered Nurses "provide care," "provide service," and "make decisions," while Lawyers must use "written communication," "provide guidance," "conduct research," and "meet deadlines." These descriptive results lend confidence to the approach of using these tasks to study the labor market.

[7]We use the entire job ad text when vectorizing, rather than a subset of the text. The reason is that not all ads have a section of text with keywords that indicate job tasks will follow. As a result, there is a tradeoff between being able to vectorize all ads and reducing bias from potentially counting instances of verb-nouns that do not refer to job tasks.

[8]In our robustness exercises with 2,000 tasks, we do not exclude any verb-noun pairs and confirm that our main analysis is not sensitive to the exclusion of selected verb-noun pairs.

2.2 Job Ads: Coverage, Representativeness, and Selection

We evaluate the coverage of job ads across geographic space and whether online job ads are a reasonable representation of overall vacancies in Appendices A.3 and A.4. We first document that our 5 percent sample of ads span four-digit SOC by CZ cells representing 98.3 percent of ACS employment. We then evaluate the representativeness of our data, comparing it to the Job Openings and Labor Turnover Survey (JOLTS) dataset. Consistent with a similar check in Hershbein and Kahn (2018), we find broad concurrence in the industry composition between the EMSI data and JOLTS. Finally, we use the Current Population Survey (CPS) Computer and Internet Use Supplement to study whether the propensity of workers to find employment through online job ads relative to other methods varies with CZ size and find no significant relationship.

2.3 Beyond O*NET: The Usefulness of Job Ads for Studying the Labor Market

O*NET is one of the most widely used data sources for measuring job tasks and has been a valuable resource for research on topics ranging from the changing nature of work (Deming, 2017) to the labor market effects of technology (Acemoglu and Autor, 2011) and immigration (Peri and Sparber, 2009). However, O*NET is based on surveys with small sample sizes—approximately 39 respondents per occupation and item (Handel, 2016)—and offers measures at the occupation-level only.

Despite these limitations, we use O*NET as a benchmark to examine how well job ads can approximate an O*NET-based analysis of tasks and market size. Note that job ads represent vacancies—a flow—whereas O*NET is a survey of employed workers—a stock. Therefore, we consider the extent to which vacancies capture information about employed workers. We construct O*NET measures of job tasks following the selection of survey items and categorization of Acemoglu and Autor (2011), and construct occupation-level tasks using job ads following the Spitz-Oener (2006) categorization described above. We then study the task gradient with market size using the two distinct occupation-level task measures (O*NET versus job ads), where the variation in tasks across markets is due solely to variation in employment shares. We demonstrate in Appendix A.5 that the task gradients are strikingly similar across data sources.

Second, we extract occupation-level tasks from the text of job ads to mimic O*NET work activities. For this exercise, we rely on words from O*NET task descriptions and construct tasks in the job ads data based on these words. We show in Appendix A.5 that the tasks extracted from the job ads reflect occupation-level content that is similar to the occupation-level content of O*NET. Of course, job ad data have additional within-occupation variation in tasks that we are shutting down for these two validation exercises; in our main analysis, we leverage the additional within-occupation variation.[9]

Finally, we show in Appendix B.6 that occupation-CZ task measures, constructed using job ads, account for variation in average wages at the occupation-CZ level, above and beyond what is captured by occupation fixed effects. The job ads data therefore capture occupational characteristics beyond what is available in O*NET, and these characteristics are reflected in market wages.

3 The Geography of Tasks and Technologies

This section presents the gradients of tasks, technologies, and worker specialization across market size.

3.1 Job Tasks Across Space

We begin with our first approach to task measurement and study how the five task categories (non-routine interactive, non-routine analytic, non-routine manual, routine cognitive, and routine manual) differ across labor markets of different sizes. For each task k, we regress task intensity $t_{jn}^{(k)}$ of job ad j in market size decile n on indicators for market size decile. CZs are placed in market size deciles using employment weights so that each decile n has approximately the same number of employed workers. We estimate:

$$t_{jn}^{(k)} = \beta_0 + \sum_{n=2}^{10} D_{jn}\beta_n^{(k)} + \gamma' x_j + \epsilon_j, \tag{1}$$

where D_{jn} are indicators for market size decile n, with the 1st decile serving as the reference group, and x_j represents a control for ad length and, in some specifications, six-digit SOC fixed effects. The coefficients of interest, $\beta_n^{(k)}$, capture the task intensities relative to the 1st decile market size. Standard errors are clustered at the CZ level.

Figure 1, panel I, plots the coefficients on market size decile, $\beta_n^{(k)}$. The primary takeaway is that non-routine interactive and non-routine analytic tasks increase in market size, while routine manual tasks decrease in market size. Jobs in population decile 10 have 0.24 s.d. greater intensity of non-routine interactive tasks, 0.30 s.d. greater intensity of non-routine

[9] The Princeton Data Improvement Initiative (PDII) also permits within-occupation variation in measurement, although with much smaller sample sizes and less granular geographic and task measures. In Appendix A.5, we study the within-occupation correlation of tasks measured in the PDII and tasks measured in job vacancies and find broad alignment between the two.

analytic tasks, and 0.18 s.d. lower intensity of routine manual tasks relative to jobs in decile 1. Panel II includes six-digit SOC fixed effects and shows that the gradients diminish. This weaker gradient is unsurprising and indeed reassuring, since occupational categories are designed to group jobs by their work activities. Nevertheless, even within occupations, non-routine interactive and analytic tasks are mentioned more frequently (by 0.06 s.d. and 0.05 s.d., respectively), and routine manual tasks are mentioned less frequently (by 0.09 s.d.), in top population decile CZs relative to bottom decile CZs. Hence, while much of the variation in job tasks across geography is captured by the composition of occupations, a strong gradient remains even within occupations, which is missed in standard data sources such as O*NET. Taking the ratio of the point estimate for decile 10 in Panel II relative to the estimate for decile 10 in Panel I, about 16 percent of the gradient remains with six-digit SOC fixed effects for non-routine analytic tasks and 26 percent remains for non-routine interactive tasks. For routine manual tasks, about 53 percent of the gradient remains.[10]

Our findings deepen our knowledge of how work differs across labor markets of different sizes, going beyond standard educational and occupational classifications. Bacolod et al. (2009a) document that the urban wage premium is partly a premium on cognitive and interactive skills and that there is no urban premium on physical skills. In related work, Bacolod et al. (2009b) document that agglomeration increases the demand for interactive skills and the opportunities for specialization. These papers use a hedonic model, worker-level skill data, and occupation-level task data to study how the demand for tasks varies with geography. In contrast, we directly observe how jobs themselves vary across labor markets within occupations. We show that the extent to which occupations themselves vary across CZs accounts for a sizable share of these premia.

In addition, Panels III through VI of Figure 1 show that jobs requiring a college degree in large CZs are far more intensive in interactive and analytic tasks compared with those in smaller CZs, while this gradient is flat for jobs requiring only a high school diploma. Both within and between occupations, jobs in large CZs require different tasks of workers with different education levels.

Finally, Figure C.1 shows that jobs that are *jointly* intensive in interactive and analytic tasks represent a greater share in large markets. Jobs that are intensive in both analytic and interactive tasks make up 12.4 percentage points more of jobs in the highest decile compared with the lowest decile. Jobs that are intensive in only analytic tasks but not interactive tasks make up only about 3.4 percentage points more of jobs in the highest decile. These qualitative findings hold within occupations. In sum, the increasing importance over time of

[10] In Appendix C.1, we perform a decomposition to further evaluate how much of the variation in tasks across geography is due to within- versus between-occupation variation in task content.

jobs that are jointly analytic and interactive, as documented by Deming (2017), is mirrored in these jobs' overrepresentation in large labor markets.

Interactive Tasks Inside and Outside the Firm

Having demonstrated the importance of interactive tasks in large labor markets, we assess the importance of interactions inside the firm relative to those outside.

We use task measures that map to O*NET task categories that separately measure external and internal interactive tasks.[11] We regress each task-intensity measure on CZ size deciles, with controls for ad length and, where indicated, six-digit SOC fixed effects. Figure 2 plots the coefficients on market size decile. This figure shows that both external and internal interactive tasks increase with market size. Compared with ads in the bottom population decile, ads in the top population decile mention internal interactive tasks (by 0.21 s.d.) and external interactive tasks (by 0.26 s.d.) more frequently. When we include six-digit SOC fixed effects, the gradients are 0.07 for both—about 30 percent as large.

Our results indicate that both types of interactive tasks increase with market size. As far as we are aware, this is the first exercise to separately measure the CZ size gradient of external and internal interactions. Moreover, in Figure C.2 we show that these gradients are largely driven by jobs requiring a college degree.

These results provide direct evidence about the micro mechanisms behind the structure of the firm and the spatial agglomeration of economic activity. Recent work, for example, has emphasized how productivity gains at the firm level are related to the ability to facilitate information flows within the firm (Garicano and Rossi-Hansberg, 2015), which we show happens more intensively in large labor markets. Other work, including Arzaghi and Henderson (2008) and Davis and Henderson (2008), argues that communication across firms—either among firms within the same industry or between customers and suppliers—is a key source behind agglomeration of economic activity. More broadly, we add to the evidence discussed in Davis and Dingel (2019) about cities as loci of interaction, showing that both internal and external interactions matter, and that skilled workers are key to these information flows. Underpinning all this work is the idea that large markets reduce the cost of face-to-face meetings, facilitating tacit knowledge flows across economic agents (Storper and Venables, 2004). Our empirical evidence demonstrates that both theories emphasizing information flows between and across firm boundaries are necessary to fully characterize labor markets,

[11] We define *external interactive tasks* as O*NET activities "Selling or Influencing Others" and "Communicating with Persons Outside Organization," and we define *internal interactive tasks* as O*NET work activities "Guiding, Directing, and Motivating Subordinates," "Developing and Building Teams," "Coaching and Developing Others," "Coordinating the Work and Activities of Others," and "Communicating with Supervisors, Peers, or Subordinates." We list the word mappings in Appendix A.5.

but with the proviso that the tacit knowledge flows shared in large CZs are primarily among college-educated workers.

A Granular Approach to Measuring Tasks

Turning to our second approach to measuring tasks, we study the verb-noun pairs extracted from the text. We estimate equation (1) separately for each of the tasks, and collect the coefficients $\hat{\beta}_{10}^{(k)}$, which we normalize by dividing by the standard deviation of the task and sorting by magnitude. Table 2 presents the largest positive and largest negative estimates across all tasks, both with and without SOC f.e.

Our results echo, at a much higher resolution, what we found in Figure 1. Placing little guidance on the categorization of tasks, and using the natural language of the job ad descriptions to measure tasks, this exercise reveals that non-routine and abstract tasks have the steepest positive gradient. Examples include "managing projects," "problem-solving skills," and "developing strategies." Communication and group interactions are important, too, as illustrated by the gradients of "written communication" and "maintaining relationships." The tasks with the steepest negative gradient reflect more routine activities and emphasize following directions, including "operate cash-register," "greeting customers," and "maintaining inventory." Table 2 also shows the steepest positive and negative gradients with six-digit SOC fixed effects and the patterns are similar. The correlation of task rankings with and without SOC f.e. is 0.66.[12]

3.2 Technology Requirements Across Space

We next explore the importance of new technologies in large CZs and study how this relationship varies with the educational requirements of jobs.

We measure the technology requirements of a job by searching for each of O*NET's Hot Technologies. The list is originally derived from job postings and includes 180 different technologies.[13] Figure 3 presents a job ad-level regression of the number of technologies that

[12]For robustness, we report the steepest positive and negative gradients with respect to a continuous measure of log population in Table B.5. In addition, we reproduce the table measuring tasks as verbs only (from Michaels et al., 2018); see Table B.7. Both robustness exercises reveal a similar pattern of increased abstract tasks, personal interactions, and teamwork in large CZs.

[13]We list the technologies in Appendix B.3. We retrieved this list from https://www.onetonline.org/search/hot_tech/ on August 27, 2019. The O*NET Hot Technologies are periodically updated. The initial list contains 182 technologies, but we exclude R and C from our main analysis since they are likely to lead to false positives. We also flag and exclude false positives of social media technologies (Facebook, YouTube, and LinkedIn) in our main analysis, since these technologies are likely to be mentioned in the context of encouraging the job applicant to visit the firm's social media page. We describe our criteria for identifying false positives of social media technologies in Appendix B.3. In Appendix B.5, we reproduce our main results

are a job requirement, on CZ size deciles, controlling for log ad length. Panel I, estimated without any occupational controls, shows that technological requirements increase with labor market size. Panel II includes six-digit SOC fixed effects. In both, the gradient is stronger for jobs requiring a college degree.

The results in Figure 3 provide three main conclusions. First, technology intensity is a dimension along which work varies greatly across labor markets: A job in population decile 10 has 0.15 more mentions of technologies relative to a job in the lowest decile, which has a mean of 0.09 mentions per ad. Second, the gap in technology intensity between college and non-college work becomes larger with labor market size.[14] Finally, a substantial fraction of this correlation with market size—but crucially not all—is contained in differences in occupations. The point estimate for decile 10 is 12 percent as large in Panel II as in Panel I, implying that 12 percent of the CZ size premium reflects within-occupation differences.

We next examine gradients of individual technologies with market size. We estimate equation (1), replacing the dependent variable with $tech_{jn}^{(\ell)}$, an indicator for job ad j being located in market size decile n requiring technology ℓ. We run this regression for each of the 180 technologies, and sort by $\beta_{10}^{(\ell)}$, after normalizing the estimates by dividing by the standard deviation of $tech_{jn}^{(\ell)}$. The results are presented in Table 3. The technologies with the steepest positive gradient with market size are Microsoft Excel, Python, JavaScript, Microsoft Project, and Linux. Furthermore, both more established technologies, such as the Microsoft suite, and newer ones, such as Ajax and Git, are more prevalent in larger CZs. Jobs requiring a college degree have the steepest gradients for technologies involving computer programming (e.g., Python, JavaScript, Linux), while jobs requiring a high school diploma have the steepest gradients for technologies involving data entry and word processing (e.g., the Microsoft Office suite).[15]

Our results complement the findings in the literature that new patents and new occupational titles appear with greater frequency in cities (Carlino et al., 2007; Lin, 2011). Unlike prior work, our data allow us to observe technology use at the job-level, technology-by-technology. Importantly, while new technologies are adopted more intensively by workers in large CZs, we find a large education gap in technology adoption between college and non-college workers, one that widens with CZ size.[16] Hence, new technologies and education are

with R and C included in our list of technologies.

[14] In Appendix C.1, we show that our results are virtually unchanged if we study two approximately equal time periods, which addresses the potential concern that gradients change over time due to technological change.

[15] Table 3 omits technologies with the steepest negative gradient because the estimates are small in magnitude and the vast majority are statistically insignificant.

[16] Spitz-Oener (2008) and Atalay et al. (2018) find that new technologies tend to complement analytic

complements, and more so in large CZs.

3.3 Specialization in Tasks Across Space

In this section, exploiting our granular task measures, we provide a new and more detailed measure of worker specialization: the dissimilarity in tasks that workers perform relative to their peers within the same firm-market, industry-market, or occupation-market. We then demonstrate that this measure of specialization increases with market size.

We first define distance between jobs in task space. We characterize each job j as a vector of tasks, T_j, with each element corresponding to a distinct task. Each element takes a value of one if job ad j's description contains the corresponding task, and zero otherwise. We normalize the task vectors to have unit length: $V_j = \frac{T_j}{\sqrt{T_j \cdot T_j}}$. The normalization ensures that our measures of specialization are unaffected by job ad length.

The inner product between two task vectors is their cosine similarity, which takes a value between zero and one. Intuitively, if two jobs have perfect overlap in tasks, their similarity is one, and if they have no tasks in common, their similarity is zero. We define the task dissimilarity between job ads j and j' as one minus their cosine similarity: $d_{jj'} = 1 - V_j \cdot V_{j'}$.

We define specialization within a firm-market as the average task dissimilarity between job ad j and other ads in the firm-market pair. For this analysis, we denote a firm f as a firm name × six-digit industry NAICS code.[17] Define $d_{jfm} = 1 - V_{jfm} \cdot \overline{V}_{(-j)fm}$, where $\overline{V}_{(-j)fm}$ is the vector of task content in firm-market fm, averaged over all ads in the firm-market excluding job ad j. If the term d_{jfm} is larger, job ad j has less overlap in task content with other ads in the firm-market fm. At the firm level, the degree of specialization is $d_{fm} = \frac{1}{n_{fm}} \sum_{j \in fm} d_{jfm}$, where n_{fm} is the number of job ads in the firm-market.[18]

Note that we can define task dissimilarity more generally, $d_{jcm} = 1 - V_{jcm} \cdot \overline{V}_{(-j)cm}$, where c may represent job ad j's firm or its occupation. Below, we explore dissimilarity along these two dimensions. We estimate the following regression:

$$d_{cm} = \alpha_0 + \sum_{n=2}^{10} D_{mn}\alpha_n + x_{cm}^{'}\delta + \epsilon_{cm}, \tag{2}$$

tasks. To the extent that analytic tasks are more intensive for college workers (compared to non-college workers) we uncover here that these complementarities are stronger with CZ size.

[17]Cases where the same firm appears in two industries are rare, and therefore our results are essentially unchanged when grouping by firm name only.

[18]In constructing the firm-market sample, we drop ads that contain zero tasks—approximately 15 percent of ads—and ads that are singletons in the firm-market cell, another 4 percent. In constructing the occupation-market sample, the respective numbers are 17 percent and 0.11 percent. The average number of job ads in a firm-market cell is 8.3, and the median is 5.

where d_{cm} is the mean task dissimilarity in group c and market m (where c refers to either firm or occupation), D_{mn} is an indicator that market m is in size decile n, and x_{cm} are our main controls averaged to the group-market cell. In specifications in which c refers to occupation, x_{cm} may also include occupation fixed effects.[19]

Figure 4 plots the estimates for α_n. Panels I and II illustrate that task dissimilarity within firms increases in market size, with a steeper gradient for nontradable sector firms, which supports the classic theoretical point that the degree of specialization is limited by the extent of the market. Since the market for tradable sector firms extends beyond their CZs, the gradient of specialization with respect to local market size will be flatter for workers in these sectors. Panels III and IV show that specialization within occupations is also increasing in market size.

We perform several checks on the measurement of worker specialization and reexamine the gradient in Appendix C.2. First, we note that some tasks are intuitively similar, such as "provide feedback" and "provide recommendations." We aggregate tasks with similar meaning, using a modeling approach from natural language processing to group tasks, and demonstrate the robustness of our results on specialization and CZ size. Within the same appendix, we apply three exercises to investigate whether the sampling of job postings may lead to measurement error in specialization measures, since small markets may have fewer job ads in an occupation-market or firm-market cell.[20]

So far, we have demonstrated that workers are more specialized, within their firm or occupation, in larger markets. The same is true for firms: The distance in task space among firms within the same (six-digit NAICS) industry increases in market size. To see this, first define the dissimilarity between firm f in industry i and market m and other firms in the industry-market as $d_{fim} = 1 - \overline{V}_{fim} \cdot \overline{V}_{(-f)im}$. In this equation, $\overline{V}_{fim}$ is the vector of average tasks for the firm-industry-market, and $\overline{V}_{(-f)im}$ is the vector of average tasks for all firms other than f in the industry-market. For each industry-market pair, the average across-firm specialization is $d_{im} = \frac{1}{n_{im}} \sum_{f,m} d_{fim}$; here, n_{im} is the number of firms in industry i and market m.

[19]In our analysis of specialization within occupations, we use four-digit (rather than six-digit) SOCs as our unit of analysis, to have more job ads in cells with which to calculate task dissimilarity.

[20]First, we confirm that the patterns in Figure 4 are robust to controlling for the number of ads in the cell (Figure C.11). Second, we reproduce Figure 4, panel A, for firm-markets with above the median number of postings and for those with below the median number of postings (Figure C.12). The results for the two groups look quite similar. Third, we do a placebo-type analysis of national chains and show that these chains have a flattened specialization gradient, as we might expect given the relative homogeneous organizational structure of national chains across space (see Figure C.13).

We compare market size and between-firm specialization using the following regression:

$$d_{im} = \alpha_0 + \sum_{n=2}^{10} D_{mn}\alpha_n + x_{im}^{'}\delta + \epsilon_{im}. \tag{3}$$

Here, d_{im} is the mean task dissimilarity in industry i and market m, D_{mn} is an indicator that market m is in size decile n, and x_{im} includes controls for the average (log) length among ads posted by industry i firms in market m. In certain specifications, x_{im} also includes industry fixed effects. These industry-market regressions are weighted by the number of firms in the cell.

Figure 5 presents our estimates. Firms are located further apart in task space in larger markets, especially in nontradable industries.

These results together reveal that, as market size grows, so does within- and between-firm task specialization. Our approach to measuring specialization has several advantages. It is comprehensive, allowing us to go beyond case studies that focus on specific occupations (e.g., Baumgardner, 1988; Garicano and Hubbard, 2009). We also complement the literature that measures specialization as occupational diversity (Bacolod et al., 2009b; Duranton and Jayet, 2011; Tian, 2019) in that we construct specialization measures based directly on job tasks and are thus able to speak about specialization in tasks themselves.[21] As we show in Section 3.5, these differences have implications for wages.

3.4 Elasticities with Respect to Log Population

Our main figures present the intensity of tasks, technologies, and the degree of specialization by market size deciles. Researchers may be interested in a single number that summarizes the elasticity of each of these outcomes with respect to log population. We next present elasticities of tasks with respect to a continuous measure of log population, following a two-step procedure (Combes and Gobillon, 2015).

The first step is an ad-level regression of task intensity $t_{jn}^{(k)}$ (or technology intensity, or the degree of specialization) on controls (ad length and, where indicated, six-digit SOC fixed effects) and CZ indicators. In the second step, we regress the CZ effects on log CZ population, weighted by the number of ads in the cell. Table 4 reports the estimates resulting from this second step. Most elasticities diminish with the inclusion of occupation fixed effects, but important differences remain: About 29 percent of the elasticity for non-routine interactive

[21] In Appendix C.2, we show that a greater number of distinct job titles are present in larger labor markets, and that "rare" job titles and occupation codes are over-represented in larger markets, reproducing the findings of Duranton and Jayet (2011) and Tian (2019) in our data.

tasks remains with SOC fixed effects, and about 15 percent of the elasticity for non-routine analytic tasks remains. The elasticity for occupation-market specialization does not diminish with SOC fixed effects.

3.5 Tasks, Technologies, and Wages

In previous sections, we have documented that interactive tasks, technology use, and worker specialization all increase with CZ size.[22] In this section, we demonstrate that earnings are positively associated with these three factors and, as a result, help explain differences in earnings observed between large and small CZs.

We estimate:

$$log(wage)_{om} = \gamma_0 + \gamma_1 t_{om} + \gamma_2 tech_{om} + \gamma_3 d_{om} + \gamma_4 ba_{om} + \xi_o + \epsilon_{om}. \quad (4)$$

In equation (4), t_{om} is the occupation-market sum of internal and external interactive tasks, normalized to have mean zero and standard deviation one across jobs; $tech_{om}$ is the mean number of technological requirements in the occupation-CZ pair; d_{om} is the mean task dissimilarity within each occupation-CZ; and ba_{om} is the fraction of employed workers in the occupation-CZ with a four-year college degree (henceforth, BA) or above (computed in the ACS). Finally, we include four-digit occupation fixed effects, ξ_o, in some specifications to highlight the role of tasks and technologies in accounting for within-occupation wage differences across markets.[23]

One should be cautious in interpreting the γ coefficients as causal, since, for example, workers may sort endogenously into occupations by unobservables in local labor markets that may correlate with wages. However, to the extent that these parameters are statistically and economically significant, they convey suggestive evidence that job tasks and technologies are a mechanism behind the CZ size premium. In addition, they demonstrate the value of using job ad text to measure job characteristics beyond occupational categories.

Table 5 reports the results. Column 1 shows that a one-standard-deviation increase in interactive tasks is associated with an increase in wages by approximately 12.5 percent, while

[22]We have also documented that analytic tasks increase with CZ size. In what follows, we only focus on three key channels— interactive tasks, technologies, and specialization—motivated by the theories we have discussed earlier in the paper and to have a parsimonious accounting of the wage premium.

[23]Our preferred specification excludes CZ fixed effects, since our aim is to account for differences in wages across CZs of different sizes, an exercise that the inclusion of CZ fixed effects would preclude. Nevertheless, Appendix C.3 presents the results with CZ fixed effects, showing that, consistent with Adam Smith's theory, which works through market size, the relationship between specialization and wages is diminished, although it remains significant for white-collar occupations. Technology intensity remains significantly positively related to occupation-CZ wages.

a 0.1 increase in the number of technology mentions increases wages by 3.8 percent. A one-standard-deviation increase in task dissimilarity is associated with an increase in wages by 2.6 percent. Adding SOC fixed effects (in column 2) and controls for education (in column 3) each weaken the coefficients on interactive tasks and technologies, but these estimates remain economically and statistically significant. These results emphasize the importance of measurement within occupational categories for understanding wage inequality across geography.

Columns 4-7 re-estimate equation (4) separately by occupational category. We classify workers into white-collar and blue-collar workers by two-digit SOC, as described in the table note.[24] Within-occupation differences in interactive tasks play an important role in accounting for the wage premium, particularly for white-collar occupations. Similarly, white-collar workers have a within-occupation premium for technological requirements, while blue-collar workers do not. Lastly, within occupation-CZ task dissimilarity is associated with a wage premium for white-collar occupations, but is not for blue-collar occupations.[25]

We use these coefficient estimates to gauge the importance of interactive tasks, technologies, and worker specialization in accounting for the market size premium. After controlling for occupation fixed effects, workers in the top population decile have wages that are 27.4 log points higher than those in the bottom decile. The intensity of the interactive task measure, aggregating internal and external interactions, is approximately 0.15 standard deviations higher in top relative to bottom decile CZs. Hence, column 2 of Table 5 indicates that interactive tasks account for 0.48 ($\approx 0.15 \cdot 0.032$) log points of the within-occupation difference in wages for workers living in top and bottom population deciles. Specialization in top decile CZs is 1.30 standard deviations greater than in bottom decile CZs (Figure 4, panel IV). Our specialization measure accounts for 4.0 ($\approx 1.30 \cdot 0.031$) log points of the difference in wages for workers living in top and bottom population deciles (Table 5, column 2). The technology measures account for an additional 0.98 ($\approx 0.03 \cdot 0.328$) log points, where the 0.03 comes from the estimate reported in Figure 3, panel II. Together, the three variables account for 20 percent ($\approx 5.5/27.4$) of the CZ size-wage premium. Furthermore, using the coefficient estimates from column 4, the three measures account for 22 percent (8.5 log points) of the 38.2 log point CZ size-wage premium in white-collar occupations.[26] In sum, our interactive

[24] We analyze white- and blue-collar occupations to study two occupation groups that have, respectively, higher-educated and lower-educated workers. This analysis relies on subgroups at the occupation level (and not according to education), since specialization measures are defined at the occupation-market level.

[25] Wages are available only in a subsample of job ads in the Burning Glass data. We discuss the selection of job ads with posted wages in Appendix C.5. Despite these selection concerns, we reproduce Table 5 using wage data from Burning Glass in Table C.12 and find similar estimates.

[26] Between top and bottom population deciles, the white-collar interactive task gap is 0.20 standard deviations, the technology gap is 0.045 mentions, the task dissimilarity gap is 1.06 standard deviations, and

task, technology, and specialization measures account for a substantial portion of the CZ size-wage premium as well as the steeper CZ size-wage premium for highly skilled workers that exists within occupations.[27]

4 Interpretation of Our Results

Our main result is that jobs are fundamentally different in large CZs. They involve more human-to-human interaction, greater use of information and communication technologies, and increased worker specialization. Moreover, these differences are more pronounced for higher-educated workers, and their association with wages are larger for higher-skilled, white-collar occupations.

An ongoing debate in the labor literature is whether the market size premium primarily reflects the sorting of workers (Card et al., 2021) or the productivity benefits of workers' locations (De la Roca and Puga, 2017), with significant implications for the effectiveness of place-based versus worker-based policies (Kline and Moretti, 2014). A key limitation of existing research is that even the best administrative datasets in the U.S., such as the Longitudinal Employer-Household Dynamics program used in Card et al. (2021), lack information on the content of work activities. Our paper adds to this debate: Jobs themselves differ, and the CZ size-wage premium is not just a reflection of workers' unobservable characteristics. To the extent that the selection of workers is important—e.g., workers with communication skills or greater facility with new technologies may sort into large CZs—our paper provides evidence that this sorting is a response to demand.[28]

Our results offer insight not only into the sources of the CZ size gradient, but also into why the gradient differs according to workers' education. There is limited evidence on the mechanisms behind the college-non-college gap in the CZ size premium because existing data sources do not allow researchers to comprehensively measure the content of jobs separately by worker education. We show that while college workers have a positive gradient for interactive tasks and the adoption of new technologies, these gradients are flat for non-college workers.

the wage gap is 38.2 log points. Thus, using the estimates from Table 5, the three components account for $(0.20 \cdot 0.047 + 0.045 \cdot 0.35 + 1.06 \cdot 0.056)/0.382 \approx 22.2\%$ of the wage gap between bottom and top population decile CZs.

[27] The corresponding calculations conditional on education (Table 5, columns 3 and 5) imply that interactive tasks, technologies, and specialization measures account for 16.1 percent of the 16.7 log point conditional CZ size-wage premium, and 16.6 percent of the 24.4 log point conditional CZ size-wage premium for white-collar workers.

[28] While employers undoubtedly respond to supply conditions, and the job description content may reflect these conditions, the fact that employers explicitly mention interactive tasks and technologies suggests that employers demand these types of workers.

In addition, our wage regressions show that these three mechanisms are far more important for white-collar occupations than for blue-collar occupations.

Lastly, our results provide the most direct empirical evidence to date that the degree of worker specialization increases with market size and is an important component of the CZ size-wage premium. While the relation between specialization and productivity is one of the oldest ideas in economics, direct measurement of specialization has remained elusive. The state-of-the-art method is to count the number of distinct, or rare, occupations in a market without directly using information on tasks. Our approach provides finer measures and allows us to measure within- and between-firm specialization using a common methodology. Our empirical evidence shows that both coordination within firms and worker specialization increase together with market size, lending empirical support to the theoretical insight of Becker and Murphy (1992).

5 Conclusion

By applying tools from natural language processing to rich textual data from online job ads, we examine in detail the differential task and technology content of jobs between large and small commuting zones. We also characterize the relationship between market size and specialization. We have shown that the task content of occupations is critical to understanding why average wages and the skill premium rise with CZ size. Application of the type of fine-grained analysis we develop in this paper can shed light on a large set of economic phenomena, ranging from the limits to human capital mobility across regions to the design of policies aimed at enhancing labor market fluidity.

References

Acemoglu, D. and Autor, D. (2011). Skills, Tasks and Technologies: Implications for Employment and Earnings. In Ashenfelter, O. and Card, D., editors, *Handbook of Labor Economics*, volume 4 of *Handbook of Labor Economics*, chapter 12, pages 1043–1171. Elsevier.

Arzaghi, M. and Henderson, J. V. (2008). Networking Off Madison Avenue. *Review of Economic Studies*, 75(4):1011–1038.

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

Atalay, E., Phongthiengtham, P., Sotelo, S., and Tannenbaum, D. (2020). The Evolution of Work in the United States. *American Economic Journal: Applied Economics*, 12(2):1–34.

Autor, D. and Handel, M. (2013). Putting Tasks to the Test: Human Capital, Job Tasks, and Wages. *Journal of Labor Economics*, 31(S1):S59 – S96.

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

Autor, D. H., Dorn, D., and Hanson, G. (2019). When Work Disappears: Manufacturing Decline and the Falling Marriage-Market Value of Young Men. *American Economic Review: Insights*, 1(2):161–178.

Bacolod, M., Blum, B. S., and Strange, W. C. (2009a). Skills in the City. *Journal of Urban Economics*, 65(2):136–153.

Bacolod, M., Blum, B. S., and Strange, W. C. (2009b). Urban Interactions: Soft Skills Versus Specialization. *Journal of Economic Geography*, 9(2):227–262.

Baumgardner, J. (1988). Physicians' Services and the Division of Labor Across Local Markets. *Journal of Political Economy*, 96(5):948–982.

Becker, G. S. and Murphy, K. M. (1992). The Division of Labor, Coordination Costs, and Knowledge. *Quarterly Journal of Economics*, 107(4):1137–1160.

Blau, F. D. and Kahn, L. M. (2013). The Feasibility and Importance of Adding Measures of Actual Experience to Cross-Sectional Data Collection. *Journal of Labor Economics*, 31(2):S17–S58.

Bloom, N., Hassan, T., Kalyani, A., Lerner, J., and Tahoun, A. (2020). The Geography of New Technologies. Technical report, Institute for New Economic Thinking.

Card, D., Rothstein, J., and Yi, M. (2021). Location, Location, Location. Working Paper 21-32, Center for Economic Studies, U.S. Census Bureau.

Carlino, G. A., Chatterjee, S., and Hunt, R. M. (2007). Urban Density and the Rate of Invention. *Journal of Urban Economics*, 61(3):389–419.

Combes, P.-P. and Gobillon, L. (2015). The Empirics of Agglomeration Economies. In Duranton, G., Henderson, J. V., and Strange, W. C., editors, *Handbook of Regional and Urban Economics*, volume 5 of *Handbook of Regional and Urban Economics*, chapter 5, pages 247–348. Elsevier.

Dauth, W., Findeisen, S., Moretti, E., and Suedekum, J. (2022). Matching in Cities. *Journal of the European Economic Association.*

Davis, D. and Dingel, J. (2019). A Spatial Knowledge Economy. *American Economic Review*, 109(1):153–70.

Davis, J. C. and Henderson, J. V. (2008). The Agglomeration of Headquarters. *Regional Science and Urban Economics*, 38(5):445–460. In Honor of Masahisa Fujita: A Special Issue.

De la Roca, J. and Puga, D. (2017). Learning by Working in Big Cities. *The Review of Economic Studies*, 84(1):106–142.

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

Deming, D. J. and Kahn, L. B. (2018). Skill Requirements Across Firms and Labor Markets: Evidence from Job Postings for Professionals. *Journal of Labor Economics*, 36(S1):S337–S369.

Diamond, R. (2016). The Determinants and Welfare Implications of US Workers' Diverging Location Choices by Skill: 1980-2000. *American Economic Review*, 106(3):479–524.

Duranton, G. and Jayet, H. (2011). Is the Division of Labour Limited by the Extent of the Market? Evidence from French Cities. *Journal of Urban Economics*, 69(1):56–71.

Eckert, F., Ganapati, S., and Walsh, C. (2020). Skilled Scalable Services: The New Urban Bias in Recent Economic Growth. Technical report.

Eeckhout, J., Hedtrich, C., and Pinheiro, R. (2021). IT and Urban Polarization. Technical Report 21-18, Federal Reserve Bank of Cleveland.

EMSI (2017). Data source: Economic Modeling Specialists International (EMSI) www.economicmodeling.com.

Frank, M. R., Sun, L., Cebrian, M., Youn, H., and Rahwan, I. (2018). Small Cities Face Greater Impact from Automation. *Journal of the Royal Society Interface*, 15(139).

Garicano, L. and Hubbard, T. N. (2009). Specialization, Firms, and Markets: The Division of Labor Within and Between Law Firms. *Journal of Law, Economics, and Organization*, 25(2):339–371.

Garicano, L. and Rossi-Hansberg, E. (2015). Knowledge-Based Hierarchies: Using Organizations to Understand the Economy. *Annual Review of Economics*, 7(1):1–30.

Glaeser, E. and Maré, D. (2001). Cities and Skills. *Journal of Labor Economics*, 19(2):316–342.

Hallock, K. F. (2013). Data Improvement and Labor Economics. *Journal of Labor Economics*, 31(S1):S1–S16.

Handel, M. J. (2016). The O*NET Content Model: Strengths and Limitations. *Journal for Labour Market Research*, 49(2):157–176.

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

Jacobs, J. (1969). *The Economy of Cities*. Random House.

Kim, S. (1989). Labor Specialization and the Extent of the Market. *Journal of Political Economy*, 97(3):692–705.

Kline, P. and Moretti, E. (2014). People, Places, and Public Policy: Some Simple Welfare Economics of Local Economic Development Programs. *Annual Review of Economics*, 6(1):629–662.

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

Marshall, A. (1890). *Principles of Economics*. Macmillan.

Michaels, G., Rauch, F., and Redding, S. J. (2018). Task Specialization in U.S. Cities from 1880 to 2000. *Journal of the European Economic Association*, 17(3):754–798.

Modestino, A. S., Ballance, J., and Shoag, D. (2020). Upskilling: Do Employers Demand Greater Skill When Workers are Plentiful? *Review of Economics and Statistics*, 102(4):793–805.

Moretti, E. (2013a). Real Wage Inequality. *American Economic Journal: Applied Economics*, 5(1):65–103.

Moretti, E. (2013b). *The New Geography of Jobs*. Mariner Books/Houghton Mifflin Harcourt.

Peri, G. and Sparber, C. (2009). Task Specialization, Immigration, and Wages. *American Economic Journal: Applied Economics*, 1(3):135–169.

Rossi-Hansberg, E., Sarte, P.-D., and Schwartzman, F. (2019). Cognitive Hubs and Spatial Redistribution. NBER Working Papers 26267, National Bureau of Economic Research, Inc.

Ruggles, S., Flood, S., Goeken, R., Grover, J., Meyer, E., Pacas, J., and Sobek, M. (2020). IPUMS USA: Version 10.0 [dataset]. Minneapolis, MN: IPUMS.

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

Spitz-Oener, A. (2008). The Returns to Pencil Use Revisited. *Industrial and Labor Relations Review*, 61(4):502–517.

Stigler, G. J. (1951). The Division of Labor is Limited by the Extent of the Market. *Journal of Political Economy*, 59(3):185–193.

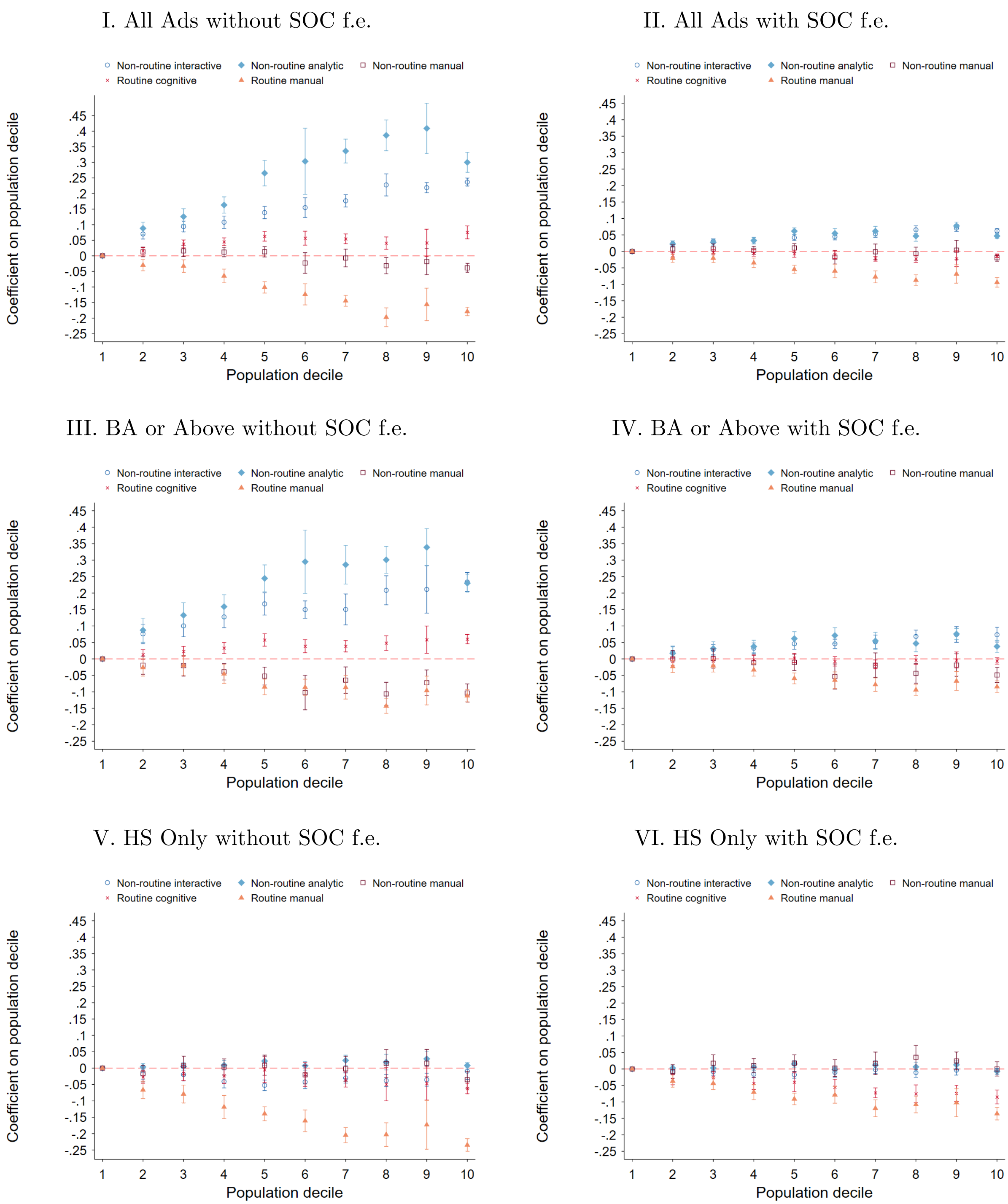
Storper, M. and Venables, A. J. (2004). Buzz: Face-to-Face Contact and the Urban Economy. *Journal of Economic Geography*, 4(4):351–370.

Tian, L. (2019). Division of Labor and Productivity Advantage of Cities: Theory and Evidence from Brazil. Technical report.

Young, A. A. (1928). Increasing Returns and Economic Progress. *Economic Journal*, 38(152):527–542.

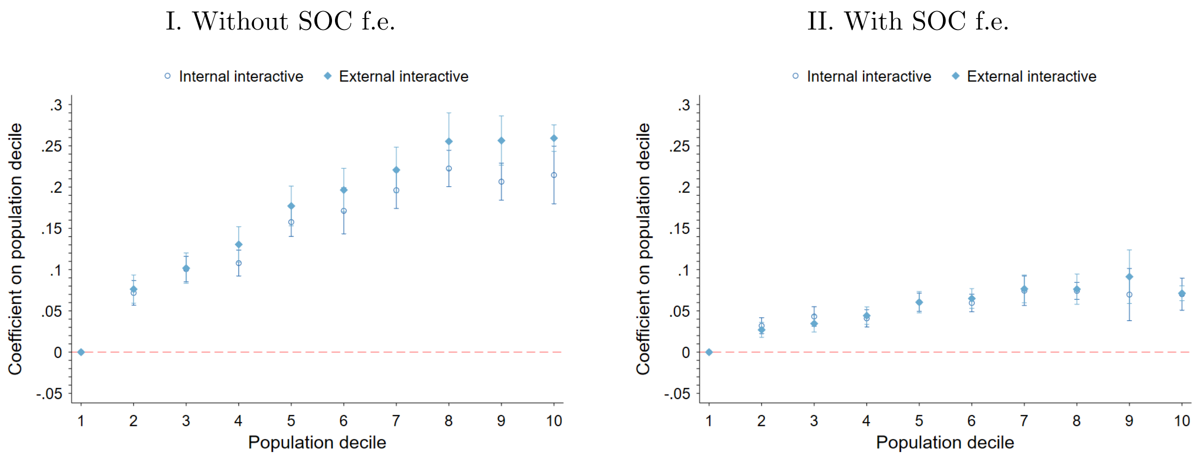
Figures and Tables

Figure 1: Tasks and Market Size



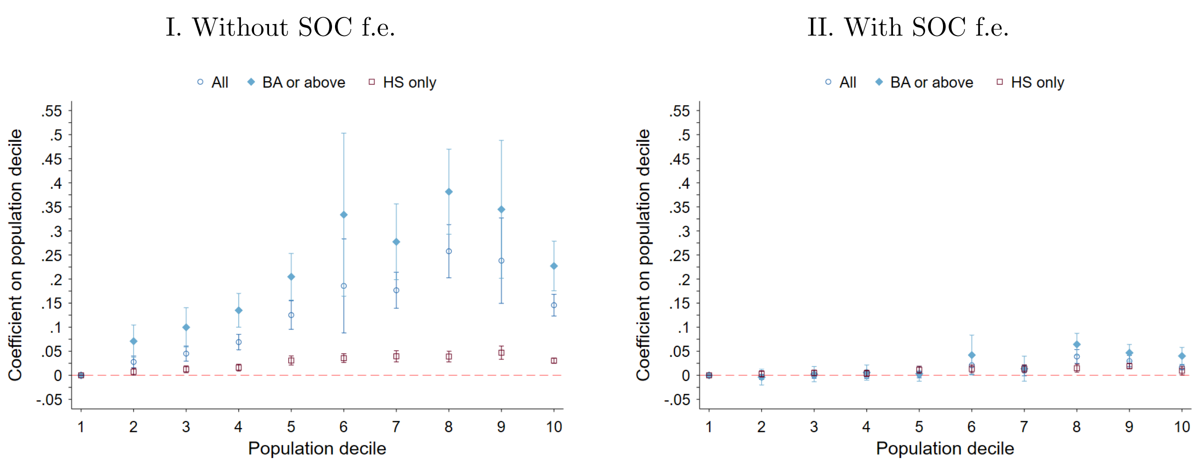
This figure presents estimates of equation (1). We control for log total ad words and, in the right panels, six-digit SOC fixed effects. The dependent variable is task intensity. Standard errors are clustered at the CZ level.

Figure 2: O*NET Interactive Tasks Gradient



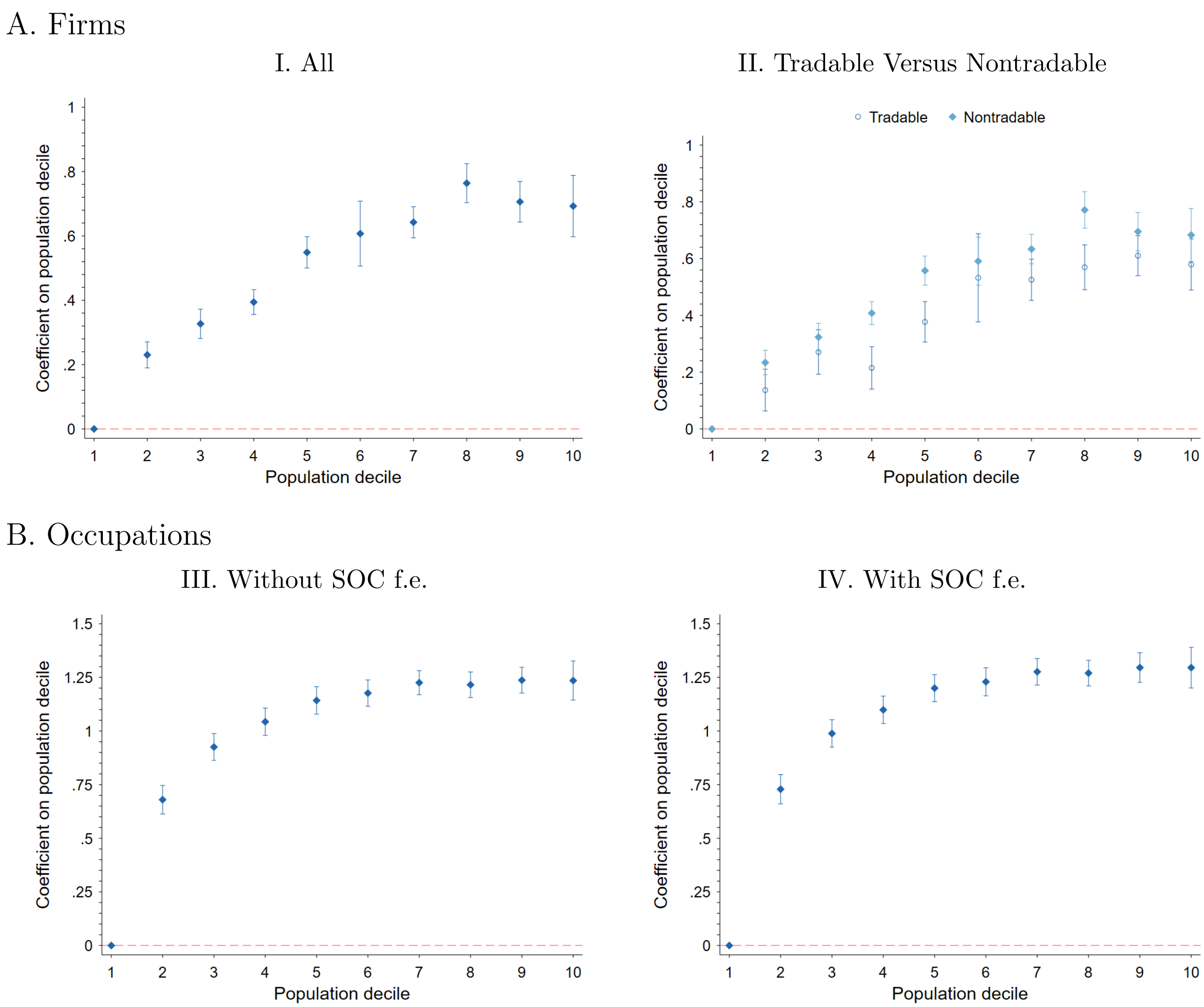
This figure presents estimates of equation (1). We control for log total ad words and, in the right panel, six-digit SOC fixed effects. The dependent variable is task intensity. Standard errors are clustered at the CZ level.

Figure 3: The Technology Gradient



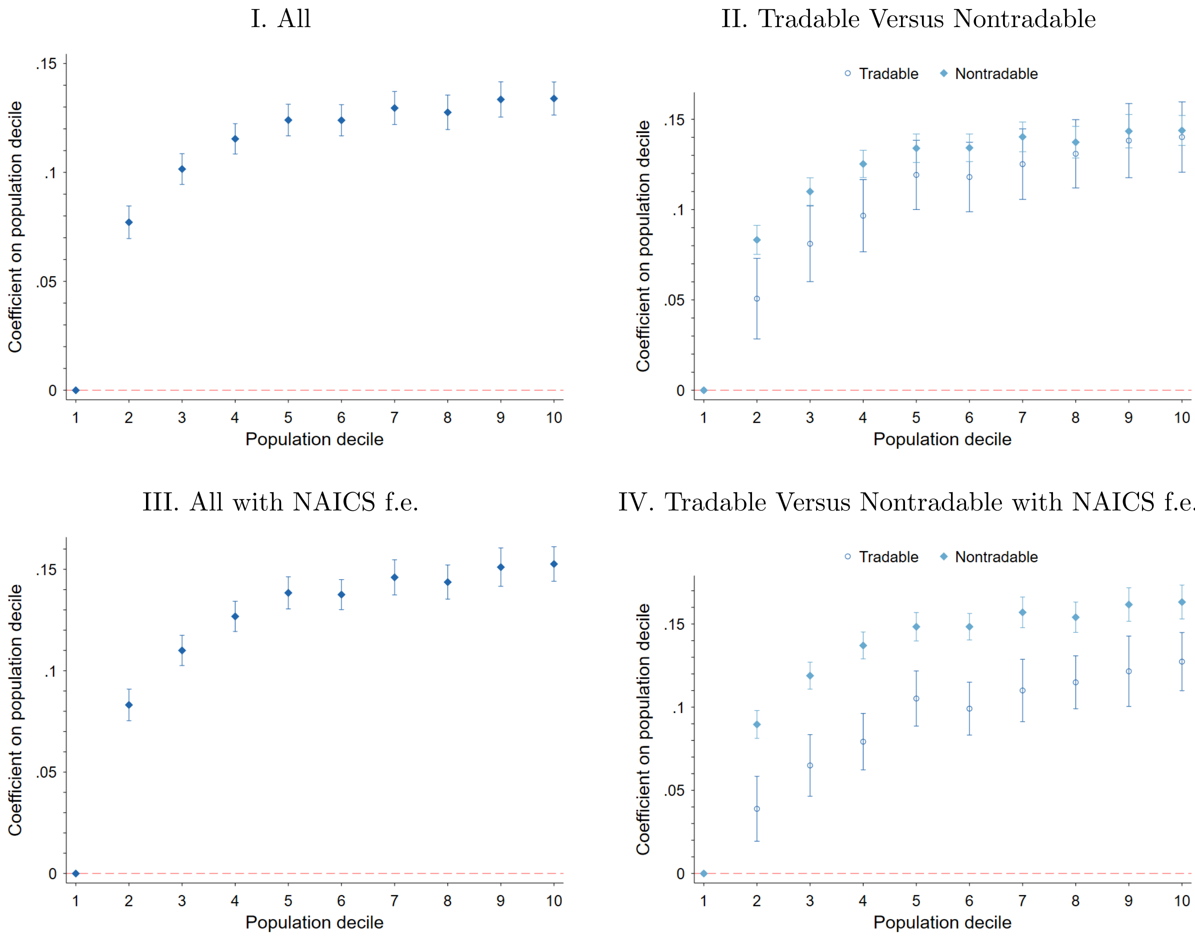
The dependent variable is the number of O*NET Hot Technologies mentioned in the ad, which is regressed on a vector of deciles for CZ size. For reference, the 1st population decile mean is 0.09 across all job ads, 0.25 for BA or above, and 0.08 for HS only. We control for log total ad words. Panel II includes six-digit SOC fixed effects. Standard errors are clustered at the CZ level.

Figure 4: Specialization Gradient: Task Dissimilarity Within Firms and Occupations



The figure presents estimates of equation (2) and studies how task dissimilarity within the firm (panel A) and within the occupation (panel B) vary with market size. Panel A uses the firm-market sample, and the dependent variable is the mean task dissimilarity in the firm-market, while panel B uses the occupation-market sample, and the dependent variable is mean task dissimilarity in the occupation-market. We control for log total ad words, which is averaged at the cell level. Firm-market regressions are weighted by number of ads in the cell; occupation-market regressions are weighted by ACS employment in the cell. Standard errors are clustered at the CZ level. For reference, the 1st population decile mean for the top left panel is -0.52; for the top right panel, it is -0.55 for the nontradable sample, and it is -0.06 for the tradable sample. The 1st population decile mean for the bottom two panels is -1.03. We define tradable by two-digit NAICS code: agriculture, forestry, fishing and hunting (11), mining, quarrying, and oil and gas extraction (21), and manufacturing (31-33).

Figure 5: Specialization Gradient: Task Dissimilarity Across Firms



The figure presents estimates of equation (3). The panels above use the industry-market sample, and the dependent variable is the mean task dissimilarity in the industry-market. We control for log total ad words, which is averaged at the cell level. The industry-market regressions are weighted by number of firms in the cell. Standard errors are clustered at the CZ level.

Table 1: Most Common Tasks for Selected Occupations

	Electricians		Supervisors of Retail Sales		Registered Nurses		Lawyers	
Rank	Task	Mean	Task	Mean	Task	Mean	Task	Mean
1	use hands	0.1230	provide customer_service	0.2973	providing care	0.1564	written communication	0.1497
2	build relationships	0.0990	assist store	0.2082	continuing education	0.0858	providing support	0.0928
3	written communication	0.0940	written communication	0.1643	written communication	0.0682	working team	0.0665
4	ensure compliance	0.0933	ensure stores	0.1483	provides quality	0.0597	meet requirements	0.0580
5	perform maintenance	0.0787	maintain store	0.1435	demonstrate knowledge	0.0462	provide service	0.0517
6	lift lbs	0.0571	driving sales	0.1269	working team	0.0411	writing skills	0.0463
7	work shift	0.0518	closes store	0.1258	provide service	0.0408	provide guidance	0.0451
8	preferred ability	0.0429	assisting customers	0.1251	develop planning	0.0393	ensure compliance	0.0417
9	lifting pounds	0.0417	maintaining inventory	0.1243	establish policies	0.0358	conducting research	0.0365
10	provides leadership	0.0383	lifting pounds	0.1048	making decisions	0.0338	meet deadlines	0.0306
N		8,073		320,882		241,859		14,400

The table above lists the most common verb-noun pairs and their mean frequency per ad for each of four occupations: Electricians (47-2111), Supervisors of Retail Sales (41-1011), Registered Nurses (29-1141), and Lawyers (23-1011). The number of job ads for each occupation is reported in the bottom row.

Table 2: Tasks with the Steepest Gradient: Extracting Tasks Directly from Ads

Positive Gradient				Negative gradient			
No SOC f.e.		SOC f.e.		No SOC f.e.		SOC f.e.	
Task	$\hat{\beta}_{10}$	Task	$\hat{\beta}_{10}$	Task	$\hat{\beta}_{10}$	Task	$\hat{\beta}_{10}$
written communication	0.1619	achieving sales	0.0712	maintain store	-0.1767	maximizes profitability	-0.1607
managing projects	0.1170	ensure safety	0.0699	maximizes profitability	-0.1703	protect company	-0.1504
meet deadlines	0.1077	written skills	0.0585	operating cash_register	-0.1654	maintain store	-0.1340
providing support	0.0973	driving sales	0.0579	protect company	-0.1646	operating cash_register	-0.1252
maintaining relationships	0.0959	stand walk	0.0575	make changes	-0.1417	make changes	-0.1233
written skills	0.0931	exceed sales	0.0554	provide customer_service	-0.1393	greeting customers	-0.1093
problem_solving skills	0.0893	providing environment	0.0536	preventing trafficking	-0.1383	procedures cash	-0.1077
working relationships	0.0864	providing coaching	0.0510	greeting customers	-0.1346	skating carhop	-0.1064
develop business	0.0834	prioritize tasks	0.0510	skating carhop	-0.1337	ensure employees	-0.1035
developing strategies	0.0759	working relationships	0.0506	procedures cash	-0.1260	unloading trucks	-0.1017
identify opportunities	0.0758	according company	0.0503	maintaining inventory	-0.1235	drive_in employees	-0.0984
prioritize tasks	0.0751	handle tasks	0.0492	assist store	-0.1210	maintaining inventory	-0.0948
develop relationship	0.0737	using eye	0.0474	unloading trucks	-0.1206	assigned store	-0.0862
make recommendations	0.0733	including nights	0.0452	ensure employees	-0.1136	working store	-0.0856
support business	0.0730	meet sales	0.0450	drive_in employees	-0.1108	provide customer_service	-0.0840

We estimate equation (1) separately for each task, without any controls, and again with six-digit SOC f.e. We normalize the estimates by dividing by the standard deviation of the task. The table above presents the tasks with the steepest positive and negative gradients with respect to market size, as captured by $\hat{\beta}_{10}$, which reflects the difference between the 10th and 1st decile market size. All coefficients are statistically significant at the 1 percent level. The correlation between the task rankings, with and without SOC f.e., is 0.66.

Table 3: Technologies with the Steepest Gradient

All		**College**		**High School**	
Technology	$\hat{\beta}_{10}$	Technology	$\hat{\beta}_{10}$	Technology	$\hat{\beta}_{10}$
Microsoft Excel	0.1147	Python	0.1050	Microsoft Excel	0.0717
Python	0.0863	Geographic Information System (GIS)	0.1043	Microsoft Outlook	0.0536
Javascript	0.0853	Microsoft Excel	0.0924	Microsoft Word	0.0450
Microsoft Project	0.0805	Javascript	0.0875	Microsoft Office	0.0431
Linux	0.0803	Linux	0.0757	React	0.0297
Microsoft Word	0.0761	Microsoft Project	0.0743	Microsoft Access	0.0242
Microsoft Office	0.0742	SAS	0.0726	Microsoft Powerpoint	0.0237
SAP	0.0709	Git	0.0691	Objective C	0.0216
Microsoft Access	0.0697	Microsoft Access	0.0680	Tax Software	0.0212
Microsoft Powerpoint	0.0691	MySQL	0.0627	Facebook	0.0210
Microsoft Outlook	0.0645	Microsoft Powerpoint	0.0624	Youtube	0.0209
MySQL	0.0610	Unix	0.0587	Swift	0.0191
Unix	0.0605	Microsoft Office	0.0586	Python	0.0186
SAS	0.0592	Ruby	0.0579	Epic Systems	0.0174
Geographic Information System (GIS)	0.0584	Tax Software	0.0566	Yardi	0.0167

We estimate equation (1) where the dependent variable is a specific technology requirement, excluding controls. We estimate this regression separately for each O*NET technology. All coefficients are normalized by dividing by the standard deviation of the technology. We report the technologies with the steepest positive gradient with respect to market size, $\hat{\beta}_{10}$, which reflects the 10th decile technology intensity relative to the 1st decile. All estimates are statistically significant at the 5 percent level, with the following exceptions in the High School column: React ($p = 0.45$) and Swift ($p = 0.38$).

Table 4: Coefficients with Respect to Log Population

	All		BA or above		HS only	
	No SOC f.e.	SOC f.e.	No SOC f.e.	SOC f.e.	No SOC f.e.	SOC f.e.
Non-routine analytic	0.086	0.013	0.069	0.012	0.004	0.001
	(0.003)	(0.001)	(0.003)	(0.002)	(0.001)	(0.001)
Non-routine interactive	0.051	0.015	0.048	0.017	-0.004	-0.000
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
Non-routine manual	-0.010	-0.003	-0.024	-0.011	-0.001	0.005
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
Routine cognitive	0.012	-0.004	0.013	-0.001	-0.011	-0.017
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
Routine manual	-0.044	-0.021	-0.030	-0.022	-0.047	-0.027
	(0.002)	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)
O*NET Internal Interactive	0.048	0.015	0.020	0.003	0.006	0.009
	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)
O*NET External Interactive	0.059	0.019	0.059	0.014	0.015	0.012
	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)
Technologies	0.053	0.008	0.076	0.013	0.010	0.004
	(0.002)	(0.001)	(0.004)	(0.001)	(0.001)	(0.000)
Specialization (SOC-CZ)	0.238	0.248				
	(0.006)	(0.007)				
	Non-Tradable	Tradable				
Specialization (Firm-CZ)	0.174	0.164				
	(0.004)	(0.007)				

This table presents elasticities of tasks, technologies, and the degree of specialization with respect to log population. We adopt a two-step procedure, in which the first step is an ad-level regression of task intensity $t_{jn}^{(k)}$ (or technology intensity, or the degree of specialization) on controls (ad length and, where indicated, six-digit SOC fixed effects) and CZ indicators. In the second step, we regress the CZ fixed effects on log CZ population, weighting by the number of job ads in the CZ. We report the slope estimate in the second step along with the standard error (in parentheses). Each coefficient is a separate regression.

Table 5: Task Dissimilarity, Technologies, Interactive Tasks, and Wages

	All			White-collar		Blue-collar	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Interactive tasks	0.125***	0.032***	0.007**	0.047***	0.006	0.026***	0.021***
	(0.007)	(0.006)	(0.003)	(0.010)	(0.005)	(0.005)	(0.004)
Technology requirements	0.381***	0.328***	0.108***	0.353***	0.106***	0.017	0.004
	(0.013)	(0.040)	(0.018)	(0.045)	(0.021)	(0.023)	(0.022)
Task dissimilarity	0.026***	0.031***	0.018***	0.056***	0.033***	0.003	0.000
	(0.003)	(0.003)	(0.002)	(0.005)	(0.003)	(0.003)	(0.003)
BA or above			1.452***		1.476***		0.988***
			(0.087)		(0.088)		(0.135)
SOC f.e.	No	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	45,889	45,889	45,889	24,720	24,720	11,465	11,465
R^2	0.261	0.883	0.927	0.845	0.918	0.724	0.745
Mean of dependent var.	10.793	10.793	10.793	10.989	10.989	10.585	10.585
Mean task dissimilarity	0.000	0.000	0.000	0.152	0.152	-0.179	-0.179
Mean technology requirements	0.157	0.157	0.157	0.224	0.224	0.043	0.043
Mean interactive tasks	0.000	0.000	0.000	0.435	0.435	-0.919	-0.919
Mean BA or above	0.363	0.363	0.363	0.518	0.518	0.075	0.075

The unit of observation is the occupation-market. The dependent variable is log wages, regressed on the sum of external and internal tasks (normalized to have mean zero and standard deviation one across jobs), mean number of technologies, occupation-market task dissimilarity (normalized to have mean zero and standard deviation one across jobs), the fraction of workers with a BA or above, a control for log total ad words, and, where indicated, four-digit SOC fixed effects. Regressions are weighted by employment. Standard errors are clustered at the CZ level. Occupations are classified into blue-collar and white-collar by two-digit SOC as follows. Blue-collar: farming, fishing and forestry (45); construction and extraction (47); installation, maintenance and repair (49); production (51); and transportation and material moving (53). White-collar: management, business, and finance (11–13); professional (15–29); sales (41); and office and administrative support (43). *** indicates a p-value less than 1%, ** a p-value between 1% and 5%, and * a p-value between 5% and 10%.