The Geography of Job Tasks

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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% of task and technology variation between large and small commuting zones exists within occupations. Furthermore, 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.

I. Introduction

Geographic inequality is pervasive in the US 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

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labor markets foster distinct types of work. For example, managerial, financial, and computer occupations are overrepresented in large labor markets, and maintenance, production, and material moving occupations are overrepresented 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 Lincoln, Nebraska, may perform fundamentally different tasks compared with 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—that is, how far apart workers are in task space, within firms or occupations.

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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 higher intensity of nonroutine analytic tasks and 0.24 standard deviations higher intensity of nonroutine interactive tasks. In addition, these jobs have 0.18 standard deviations lower intensity of routine manual tasks. Even after conditioning on narrowly defined occupation (six-digit Standard Occupational Classification [SOC]) categories, about 16% of the gradient between largest and smallest CZs for nonroutine analytic tasks, 26% of the gradient for nonroutine interactive tasks, and 53% of the gradient for routine manual tasks remain. 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% 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, 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

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

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 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% (5.5 log points out of a total of 27.4) of the difference in wages between workers in top- and bottom-population-decile CZs and 22% (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 2013b; 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, Blum, and Strange 2009b; Michaels, Rauch, and Redding 2018; Rossi-Hansberg, Sarte, and Schwartzman 2019). Prior research also shows that new patents and occupational titles are more likely to appear in cities (Carlino, Chatterjee, and Hunt 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 (2013a) 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.

II. 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 (Deming and Kahn 2018; Hershbein and Kahn 2018; Modestino, Shoag, and Ballance 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% 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 North American Industry Classification System [NAICS] code), the occupation code (six-digit SOC code), and the job location (county Federal Information Processing Standard [FIPS] code). We map FIPS codes to CZs following Autor, Dorn, and Hanson (2019). We adopt the CZ as our geographic unit of analysis and refer to CZs throughout this paper as local labor markets. Section A.1 of the appendix 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 section A.2 of the appendix, 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 2010–17 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 pretax wage and salary income ("wages" throughout the paper), which we

[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 sec. C.4 of the appendix (available online). 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.

adjust by the consumer price index for all urban consumers 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 contain wages extracted from job ads (see sec. C.5 of the appendix).

A. 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—nonroutine interactive, nonroutine analytic, nonroutine 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 section A.5 of the appendix 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 0 and standard deviation 1 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; 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

[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 (figs. A.1–A.11, B.1, B.2, C.1–C.17 are available online) investigates this relationship and finds little evidence for a systematic pattern.

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 (tables A.1–A.11, B.1–B.9, C.1–C.12 are available online), 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 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 sections C.1 and C.3 of the appendix 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 (sec. C.2 of the appendix).

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 that each element of the vector is a 0 or 1. 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. Section B.1 of the appendix 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.

[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”).

[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 trade-off between being able to vectorize all ads and reducing bias from potentially counting instances of verb-noun pairs 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.

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.

B. 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 sections A.3 and A.4 of the appendix. We first document that our 5% sample of ads span four-digit SOC-by-CZ cells representing 98.3% 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 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.

C. 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 we construct occupation-level tasks using job ads following the Spitz-Oener (2006)

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	.1230	Provide customer service	.2973	Providing care	.1564	Written communication	.1497
2	Build relationships	.0990	Assist store	.2082	Continuing education	.0858	Providing support	.0928
3	Written communication	.0940	Written communication	.1643	Written communication	.0682	Working team	.0665
4	Ensure compliance	.0933	Ensure stores	.1483	Provides quality	.0597	Meet requirements	.0580
5	Perform maintenance	.0787	Maintain store	.1435	Demonstrate knowledge	.0462	Provide service	.0517
6	Lift lbs	.0571	Driving sales	.1269	Working team	.0411	Writing skills	.0463
7	Work shift	.0518	Closes store	.1258	Provide service	.0408	Provide guidance	.0451
8	Preferred ability	.0429	Assisting customers	.1251	Develop planning	.0393	Ensure compliance	.0417
9	Lifting pounds	.0417	Maintaining inventory	.1243	Establish policies	.0358	Conducting research	.0365
10	Provides leadership	.0383	Lifting pounds	.1048	Making decisions	.0338	Meet deadlines	.0306
N		8,073		320,882		241,859		14,400

NOTE.—This table 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.

categorization described above. We then study the task gradient with market size using the two distinct occupation-level task measures (O*NET vs. job ads), where the variation in tasks across markets is due solely to variation in employment shares. We demonstrate in section A.5 of the appendix 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 section A.5 of the appendix 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 ads 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 section B.6 of the appendix 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.

III. The Geography of Tasks and Technologies

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

A. Job Tasks across Space

We begin with our first approach to task measurement and study how the five task categories (nonroutine interactive, nonroutine analytic, nonroutine 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 first decile serving as the reference group, and x_j represents a control for ad length and, in some

[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 sec. A.5 of the appendix, 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.

specifications, six-digit SOC fixed effects. The coefficients of interest, $\beta_n^{(k)}$, capture the task intensities relative to the first-decile market size. Standard errors are clustered at the CZ level.

Figure 1*A* plots the coefficients on market size decile, $\beta_n^{(k)}$. The primary takeaway is that nonroutine interactive and nonroutine analytic tasks increase in market size, while routine manual tasks decrease in market size. Jobs in population decile 10 have 0.24 standard deviations greater intensity of nonroutine interactive tasks, 0.30 standard deviations greater intensity of nonroutine analytic tasks, and 0.18 standard deviations lower intensity of

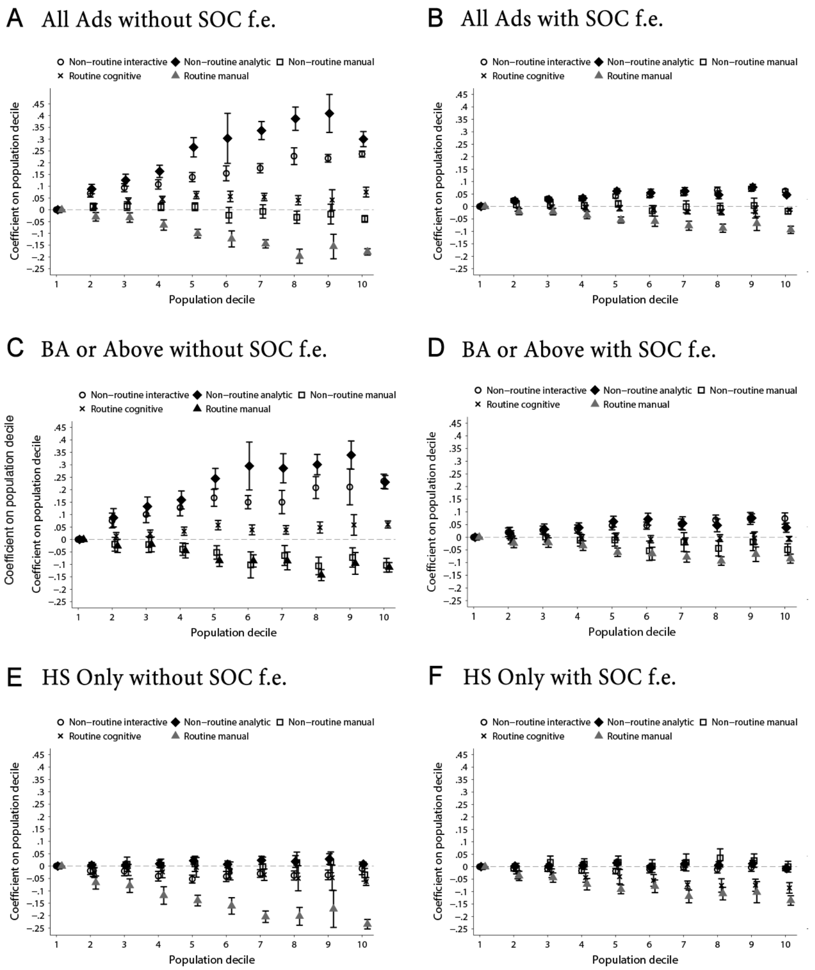

FIG. 1.—Tasks and market size. This figure presents estimates of equation (1). We control for log total ad words and, in *B*, *D*, and *F*, six-digit SOC fixed effects. The dependent variable is task intensity. Standard errors are clustered at the CZ level.

routine manual tasks relative to jobs in decile 1. Figure 1*B* 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, nonroutine interactive and analytic tasks are mentioned more frequently (by 0.06 and 0.05 standard deviations, respectively), and routine manual tasks are mentioned less frequently (by 0.09 standard deviations), 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 figure 1*B* relative to the estimate for decile 10 in figure 1*A*, about 16% of the gradient remains with six-digit SOC fixed effects for nonroutine analytic tasks and 26% remains for nonroutine interactive tasks. For routine manual tasks, about 53% 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, Blum, and Strange (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, Blum, and Strange (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, figure 1*C*–1*F* shows 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

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

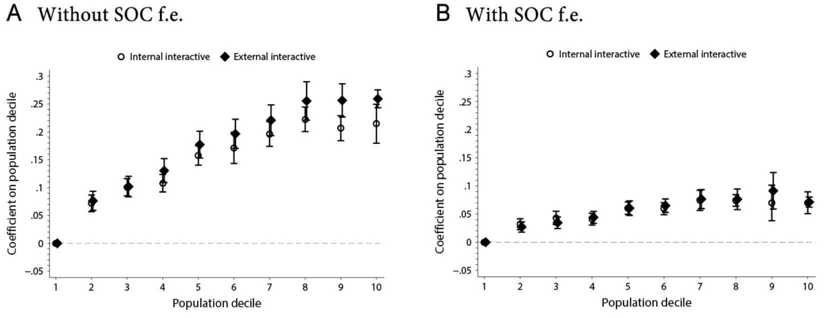

FIG. 2.—O*NET interactive tasks gradient. This figure presents estimates of equation (1). We control for log total ad words and, in *B*, six-digit SOC fixed effects. The dependent variable is task intensity. Standard errors are clustered at the CZ level.

qualitative findings hold within occupations. In sum, the increasing importance over time of 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 standard deviations) and external interactive tasks (by 0.26 standard deviations) more frequently. When we include six-digit SOC fixed effects, the gradients are 0.07 for both—about 30% as large.

[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 sec. A.5 of the appendix.

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 of 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, 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 mentions 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 fixed effects.

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 nonroutine 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

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

Positive Gradient				Negative Gradient			
No SOC Fixed Effects		SOC Fixed Effects		No SOC Fixed Effects		SOC Fixed Effects	
Task	$\hat{\beta}_{10}$	Task	$\hat{\beta}_{10}$	Task	$\hat{\beta}_{10}$	Task	$\hat{\beta}_{10}$
Written communication	.1619	Achieving sales	.0712	Maintain store	−.1767	Maximizes profitability	−.1607
Managing projects	.1170	Ensure safety	.0699	Maximizes profitability	−.1703	Protect company	−.1504
Meet deadlines	.1077	Written skills	.0585	Operating cash register	−.1654	Maintain store	−.1340
Providing support	.0973	Driving sales	.0579	Protect company	−.1646	Operating cash register	−.1252
Maintaining relationships	.0959	Stand walk	.0575	Make changes	−.1417	Make changes	−.1233
Written skills	.0931	Exceed sales	.0554	Provide customer service	−.1393	Greeting customers	−.1093
Problem-solving skills	.0893	Providing environment	.0536	Preventing trafficking	−.1383	Procedures cash	−.1077
Working relationships	.0864	Providing coaching	.0510	Greeting customers	−.1346	Skating carhop	−.1064
Develop business	.0834	Prioritize tasks	.0510	Skating carhop	−.1337	Ensure employees	−.1035
Developing strategies	.0759	Working relationships	.0506	Procedures cash	−.1260	Unloading trucks	−.1017
Identify opportunities	.0758	According company	.0503	Maintaining inventory	−.1235	Drive-in employees	−.0984
Prioritize tasks	.0751	Handle tasks	.0492	Assist store	−.1210	Maintaining inventory	−.0948
Develop relationship	.0737	Using eye	.0474	Unloading trucks	−.1206	Assigned store	−.0862
Make recommendations	.0733	Including nights	.0452	Ensure employees	−.1136	Working store	−.0856
Support business	.0730	Meet sales	.0450	Drive-in employees	−.1108	Provide customer service	−.0840

Note.—We estimate eq. (1) separately for each task, without any controls, and again with six-digit SOC fixed effects. We normalize the estimates by dividing by the standard deviation of the mentions of the task. This table 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 tenth- and first-decile market size. All coefficients are statistically significant at the 1% level. The correlation between the task rankings, with and without SOC fixed effects, is 0.66.

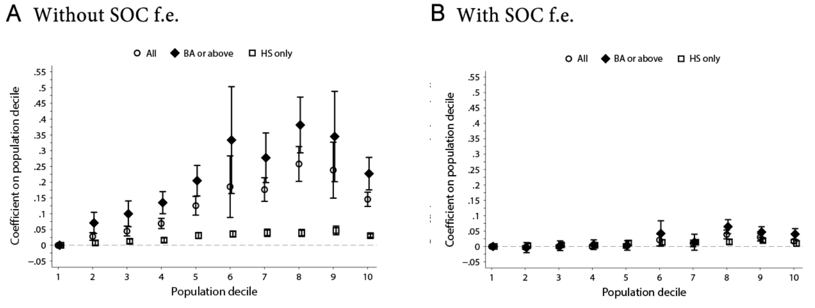

FIG. 3.—Technology gradient. The dependent variable is the number of O*NET hot technologies mentioned in the ad, which is regressed on a vector of deciles for CZ size. For reference, the first population decile mean is 0.09 across all job ads, 0.25 for BA or above, and 0.08 for high school (HS) only. We control for log total ad words. *B* includes six-digit SOC fixed effects. Standard errors are clustered at the CZ level.

fixed effects, and the patterns are similar. The correlation of task rankings with and without SOC fixed effects is 0.66.[12]

B. 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 are a job requirement on CZ size deciles, controlling for log ad length. Figure 3*A*, estimated without any occupational controls, shows that technological requirements

[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, Rauch, and Redding 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 sec. B.3 of the appendix. 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 sec. B.3 of the appendix. In sec. B.5 of the appendix, we reproduce our main results with R and C included in our list of technologies.

increase with labor market size. Figure 3*B* 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 noncollege 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% as large in figure 3*B* as in figure 3*A*, implying that 12% 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 Office 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, Chatterjee, and Hunt 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-educated and non-college-educated workers, one that widens with CZ size.[16] Hence, new technologies and education are complements, more so in large CZs.

[14] In sec. C.1 of the appendix, we show that our results are virtually unchanged if we estimate this regression using only the first or the second half of the sample period, which addresses the potential concern that gradients change over time because of 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 tasks. To the extent that analytic tasks are more intensive for college-educated workers (compared with non-college-educated workers), we uncover here that these complementarities are stronger with CZ size.

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	.1147	Python	.1050	Microsoft Excel	.0717
Python	.0863	GIS	.1043	Microsoft Outlook	.0536
JavaScript	.0853	Microsoft Excel	.0924	Microsoft Word	.0450
Microsoft Project	.0805	JavaScript	.0875	Microsoft Office	.0431
Linux	.0803	Linux	.0757	React	.0297
Microsoft Word	.0761	Microsoft Project	.0743	Microsoft Access	.0242
Microsoft Office	.0742	SAS	.0726	Microsoft PowerPoint	.0237
SAP	.0709	Git	.0691	Objective C	.0216
Microsoft Access	.0697	Microsoft Access	.0680	Tax software	.0212
Microsoft PowerPoint	.0691	MySQL	.0627	Facebook	.0210
Microsoft Outlook	.0645	Microsoft PowerPoint	.0624	YouTube	.0209
MySQL	.0610	Unix	.0587	Swift	.0191
Unix	.0605	Microsoft Office	.0586	Python	.0186
SAS	.0592	Ruby	.0579	Epic Systems	.0174
GIS	.0584	Tax software	.0566	Yardi	.0167

NOTE.—We estimate eq. (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 mentions of the technology. We report the technologies with the steepest positive gradient with respect to market size, $\hat{\beta}_{10}$, which reflects the tenth-decile technology intensity relative to the first decile. All estimates are statistically significant at the 5% level, with the following exceptions in the "High School" column: React ($p = .45$) and Swift ($p = .38$). GIS = geographic information system.

C. 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 1 if job ad j's description contains the corresponding task and 0 otherwise. We normalize the task vectors to have unit length: $V_j = T_j/\sqrt{T_j \cdot T_j}$. 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 0 and 1. Intuitively, if two jobs have perfect overlap in tasks, their similarity is 1, and if they have no tasks in common, their similarity is 0. We define the task dissimilarity between job ads j and j' as 1 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 $\times$ six-digit industry NAICS code.[17] Define $d_{jfm} = 1 - V_{jfm} \cdot \bar{V}_{(-j)fm}$, where $\bar{V}_{(-j)fm}$ 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 $d_{fm} = (1/n_{fm})\Sigma_{j\in fm} d_{jfm}$, where n_{fm} is the number of job ads in the firm-market.[18]

Note that we can define task dissimilarity more generally, $d_{jcm} = 1 - V_{jcm} \cdot \bar{V}_{(-j)cm}$, 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:

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

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. Figure 4*A* and 4*B* 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. Figure 4*C* and 4*D* 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 section C.2 of the appendix. 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 section, we apply three exercises to investigate whether the sampling of job postings may lead to measurement error in specialization

[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% of ads—and ads that are singletons in the firm-market cell, another 4%. In constructing the occupation-market sample, the respective numbers are 17% and 0.11%. The average number of job ads in a firm-market cell is 8.3, and the median is 5.

[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.

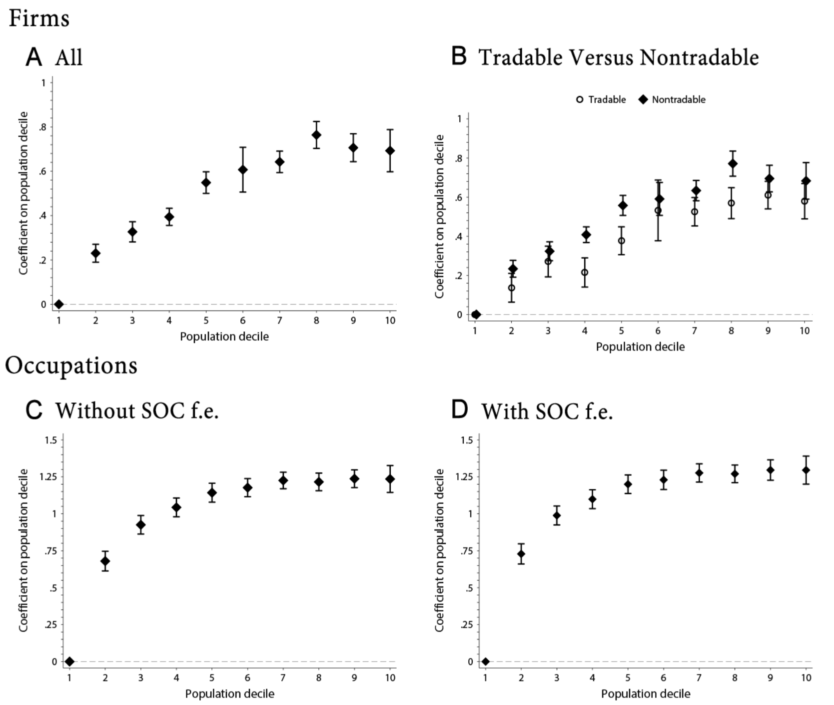

FIG. 4.—Specialization gradient: task dissimilarity within firms and occupations. This figure presents estimates of equation (2) and studies how task dissimilarity within the firm (*A*, *B*) and within the occupation (*C*, *D*) vary with market size. *A* and *B* use the firm-market sample, and the dependent variable is the mean task dissimilarity in the firm-market, while *C* and *D* use 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 the 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 first population decile mean for *A* is −0.52; for *B*, it is −0.55 for the nontradable sample and −0.06 for the tradable sample. The first population decile mean for *C* and *D* 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).

measures, since small markets may have fewer job ads in an occupation-market or firm-market cell.[20]

[20] First, we confirm that the patterns in fig. 4 are robust to controlling for the number of ads in the cell (fig. C.11). Second, we reproduce fig. 4*A* and 4*B* for firm-markets with above the median number of postings and for those with below the median number of postings (fig. 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

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 $d_{fim} = 1 - \bar{V}_{fim} \cdot \bar{V}_{(-f)im}$. In this equation, $\bar{V}_{fim}$ is the vector of average tasks for the firm-industry-market, and $\bar{V}_{(-f)im}$ 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 $d_{im} = (1/n_{im})\Sigma_{f,m} d_{fim}$; here, n_{im} is the number of firms in industry i and market m.

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, Blum, and Strange 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 III.E, these differences have implications for wages.

D. 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

flattened specialization gradient, as we might expect given the relative homogeneous organizational structure of national chains across space (see fig. C.13).

[21] In sec. C.2 of the appendix, 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 overrepresented in larger markets, reproducing the findings of Duranton and Jayet (2011) and Tian (2019) in our data.

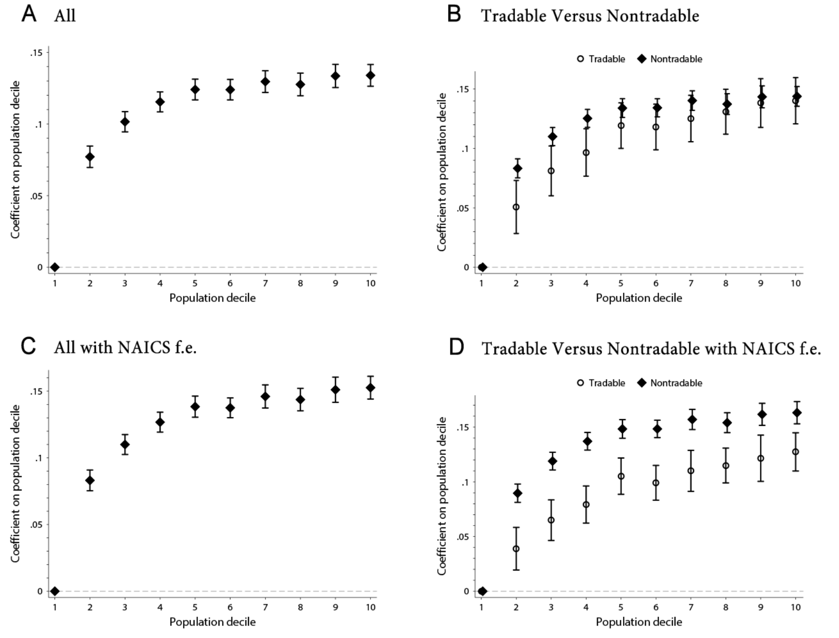

FIG. 5.—Specialization gradient: task dissimilarity across firms. This figure presents estimates of equation (3). All panels use the industry-market sample, and the dependent variable is the mean task dissimilarity in the industry-market. We control for log total ad words, which is averaged at the cell level. The industry-market regressions are weighted by the number of firms in the cell. Standard errors are clustered at the CZ level.

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

Table 4
Coefficients with Respect to Log Population

	All		BA or Above		High School Only	
	No SOC Fixed Effects	SOC Fixed Effects	No SOC Fixed Effects	SOC Fixed Effects	No SOC Fixed Effects	SOC Fixed Effects
Nonroutine analytic	.086	.013	.069	.012	.004	.001
	(.003)	(.001)	(.003)	(.002)	(.001)	(.001)
Nonroutine interactive	.051	.015	.048	.017	−.004	−.000
	(.001)	(.001)	(.002)	(.001)	(.001)	(.001)
Nonroutine manual	−.010	−.003	−.024	−.011	−.001	.005
	(.001)	(.001)	(.002)	(.002)	(.002)	(.002)
Routine cognitive	.012	−.004	.013	−.001	−.011	−.017
	(.001)	(.001)	(.001)	(.001)	(.002)	(.001)
Routine manual	−.044	−.021	−.030	−.022	−.047	−.027
	(.002)	(.001)	(.002)	(.001)	(.002)	(.001)
O*NET internal interactive	.048	.015	.020	.003	.006	.009
	(.001)	(.001)	(.002)	(.002)	(.001)	(.001)
O*NET external interactive	.059	.019	.059	.014	.015	.012
	(.001)	(.001)	(.002)	(.002)	(.001)	(.001)
Technologies	.053	.008	.076	.013	.010	.004
	(.002)	(.001)	(.004)	(.001)	(.001)	(.000)
Specialization (SOC-CZ)	.238	.248				
	(.006)	(.007)				
	Nontradable	Tradable				
Specialization (firm-CZ)	.174	.164				
	(.004)	(.007)				

NOTE.—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.

E. 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

[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.

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 0 and standard deviation 1 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 4-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 1 standard deviation increase in interactive tasks is associated with an increase in wages by approximately 12.5%, while a 0.1 increase in the number of technology mentions increases wages by 3.8%. A 1 standard deviation increase in task dissimilarity is associated with an increase in wages by 2.6%. Adding SOC fixed effects (in col. 2) and controls for education (in col. 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 reestimate equation (4) separately by occupational category. We classify workers into white-collar and blue-collar workers by

[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, sec. C.3 of the appendix 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.

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

	All			White Collar		Blue Collar	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Interactive tasks	.125***	.032***	.007**	.047***	.006	.026***	.021***
	(.007)	(.006)	(.003)	(.010)	(.005)	(.005)	(.004)
Technology requirements	.381***	.328***	.108***	.353***	.106***	.017	.004
	(.013)	(.040)	(.018)	(.045)	(.021)	(.023)	(.022)
Task dissimilarity	.026***	.031***	.018***	.056***	.033***	.003	.000
	(.003)	(.003)	(.002)	(.005)	(.003)	(.003)	(.003)
BA or above			1.452***		1.476***		.988***
			(.087)		(.088)		(.135)
SOC fixed effects	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	.261	.883	.927	.845	.918	.724	.745
Mean of dependent variable	10.793	10.793	10.793	10.989	10.989	10.585	10.585
Mean task dissimilarity	.000	.000	.000	.152	.152	−.179	−.179
Mean technology requirements	.157	.157	.157	.224	.224	.043	.043
Mean interactive tasks	.000	.000	.000	.435	.435	−.919	−.919
Mean BA or above	.363	.363	.363	.518	.518	.075	.075

NOTE.—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 0 and standard deviation 1 across jobs), mean number of technologies, occupation-market task dissimilarity (normalized to have mean 0 and standard deviation 1 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).
** Significant at the 5% level.
*** Significant at the 1% level.

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. Last, within occupation-CZ task

[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.

dissimilarity is associated with a wage premium for white-collar occupations but 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 ($\approx 0.15 \cdot 0.32$) 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 that in bottom-decile CZs (fig. 4*A*). Our specialization measure accounts for 4.0 ($\approx 1.30 \cdot 0.31$) log points of the difference in wages for workers living in top and bottom population deciles (table 5, col. 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*B*. Together, the three variables account for 20% ($\approx 5.5/27.4$) of the CZ size-wage premium. Furthermore, using the coefficient estimates from column 4, the three measures account for 22% (8.5 log points) of the 38.2 log point CZ size-wage premium in white-collar occupations.[26] In sum, our interactive 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]

IV. 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,

[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 sec. C.5 of the appendix. 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 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, cols. 3 and 5) imply that interactive tasks, technologies, and specialization measures account for 16.1% of the 16.7 log point conditional CZ size-wage premium and 16.6% of the 24.4 log point conditional CZ size-wage premium for white-collar 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, Rothstein, and Yi 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 United States, such as the Longitudinal Employer-Household Dynamics program used in Card, Rothstein, and Yi (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—for example, 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-noncollege 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-educated workers have a positive gradient for interactive tasks and the adoption of new technologies, these gradients are flat for non-college-educated workers. In addition, our wage regressions show that these three mechanisms are far more important for white-collar occupations than for blue-collar occupations.

Last, 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).

[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.

V. 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 CZs. 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.

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Appendix: The Geography of Job Tasks

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July 26, 2024

A Validating the Online Job Ads Data

This section presents supplementary information and validation of the job ads data. Appendix A.1 provides summary statistics on the CZ deciles. Appendix A.2 provides details on the construction and cleaning of the sample used in the paper. Appendix A.3 discusses the representativeness of online vacancies relative to total vacancies as measured in JOLTS. In Appendix A.4, we show that the educational requirements in the job ads data correlate strongly with the education of employed workers in the ACS in the same occupation-market, and that this relationship holds across large and small markets and within and between occupations. In Appendix A.5, we show that when we create occupation-level task measures from the job ad text that correspond to O*NET task categories, these measures are highly correlated with O*NET importance scales. Furthermore, drawing on a survey conducted as part of the Princeton Data Improvement Initiative, we validate our ad-based task measures using within-occupation variation. In Appendix A.6, we show that while there are trends in job ad length across space—larger markets have longer job ads—once we control for ad length, the gradient of job description keywords with respect to market size becomes economically insignificant.

A.1 CZ Decile Summary Statistics

There are 722 CZs in our analysis sample. Table A.1 presents summary statistics by CZ decile, including the total number of job ads in the decile, the median CZ population, and the name(s) of the median population CZ(s) within the decile. CZs are assigned to market size deciles using employment weights so that each decile n has approximately the same number of employed workers. Note that Table A.1 shows that the number of job ads in each decile differs somewhat due to the discreteness of assigning each CZ to one decile.

Table A.1: CZ Decile Summary Statistics

Decile	Total ads	Pct. urban	Density	Median CZ pop.	Median CZ name(s)
1	507.3	42.2	16.9	55.1	Norfolk & Madison Counties, NE; Tuscaloosa, AL
2	576.8	67.2	73.3	308.0	Bloomington, IN; Clarksville, TN
3	593.7	78.1	139.2	614.2	Wichita, KS; Lexington, KY
4	610.9	82.8	211.0	1,033.4	Tulsa, OK; Naples-Marco Island, FL
5	720.4	88.6	398.4	1,723.9	Fresno, CA
6	692.3	92.1	440.8	2,441.2	St. Louis, MO
7	705.1	94.9	461.1	3,453.2	Minneapolis-St. Paul, MN; Hartford-Bridgeport-Stamford-Norwalk, CT
8	858.4	96.0	666.5	5,056.6	Atlanta, GA; San Francisco-Oakland, CA
9	685.3	96.6	1,103.4	6,159.5	Newark-Trenton-White Plains NJ-NY; Houston, TX
10	385.4	98.5	920.7	15,273.6	New York, NY; Los Angeles, CA

The table above presents summary statistics by CZ decile, including the total number of job ads in the decile (expressed in 1,000s), the mean fraction of the population that is urban, the mean population density (persons per square kilometer), the median CZ population in the decile (in 1,000s), and the name(s) of the median population CZ(s) within the decile. In cases in which the median CZ population is the average of two CZs, we provide both names. Area and percent urban are provided by the U.S. Census's 2010 Percent Urban and Rural by County report, which we link to CZ and then report mean CZ statistics in the decile.

A.2 Details on Sample Construction

We use a 5 percent sample of the online job ads data we purchased from EMSI. The sample of our dataset covers January 2012 to March 2017. We exclude ads with fewer than the 1st percentile number of words and greater than the 95th percentile number of words. These restrictions ensure that the ads have enough content to measure tasks and also are not so long as to considerably slow processing time. This step limits the sample to ads with length between 11 and 841 words and reduces the sample to 7.0 million ads. We exclude Hawaii and Alaska from the analysis, which drops another 35,529 ads. We also exclude ads that do not contain a county FIPS code and therefore cannot be mapped to a CZ, eliminating another 503,051 ads. Finally, we drop 102,154 ads ads that have no SOC code. This leaves 6.3 million ads for our occupational analysis. Table A.2 presents the number of ads by year in the sample.

For the firm-level analysis sample, we impose a few additional restrictions. We drop ads placed by staffing or placement agencies, since they act as intermediaries between the worker and the firm hiring the worker. These ads are identified with a flag in the EMSI data. This step drops 596,578 ads. (We discuss ads placed by staffing agencies in the next paragraph.) We drop ads without a firm name, which is another 107,317 ads. Finally, we drop firms with no NAICS code—another 3,771 ads. These restrictions yield approximately 5.6 million ads for the sample used for the firm-level analysis.

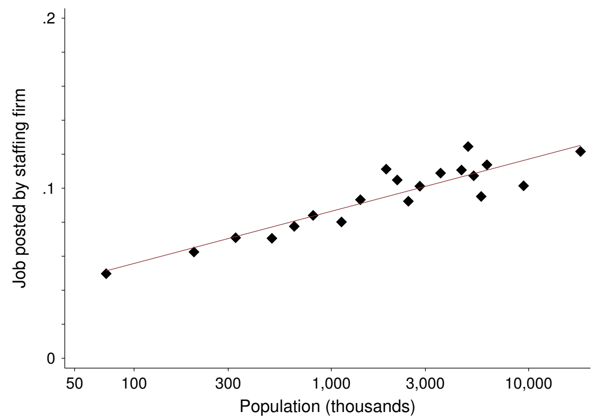
Jobs are more likely to be posted by a staffing agency in larger markets. This gradient can be seen in Figure A.1, which presents a binscatter of an indicator for the job ad's being posted by a staffing firm against the CZ population. To better understand these types of ads, we estimate a job ad-level regression of an indicator for a BA-requirement (or a HS-only requirement) on an indicator for the job being posted by a staffing agency, and estimate this regression for the sample of jobs with a non-missing education requirement. These results are reported in Table A.3. The main takeaway is a job ad posted by a staffing firm, on average, has a 20 percentage point higher likelihood of requiring a BA, which is mainly driven by occupational composition. Controlling for six-digit occupation fixed effects, the estimate is 4.4 percentage points. In our analysis, we find that higher-skilled jobs are more specialized; hence, the greater composition of staffing firm-posted vacancies in larger CZs is likely to lead us to understate the specialization gradient. We check the sensitivity of our specialization results by reproducing Figure 4, panel A and including the staffing firms; these results are in Figure A.2. The main takeaway that within-firm specialization is increasing in market size is unchanged.

Table A.2: Job Vacancy Counts by Year

Occupation-level dataset		Firm-level dataset	
Year	Count	Year	Count
2012	591,682	2012	504,618
2013	860,961	2013	751,387
2014	1,021,805	2014	904,882
2015	1,465,475	2015	1,327,579
2016	1,905,368	2016	1,709,801
2017	490,287	2017	429,645
Total	6,335,578	Total	5,627,912

The table above presents the number of job ads by year after applying the sample restrictions described in Appendix A.2.

Figure A.1: Job Posted by a Staffing Firm



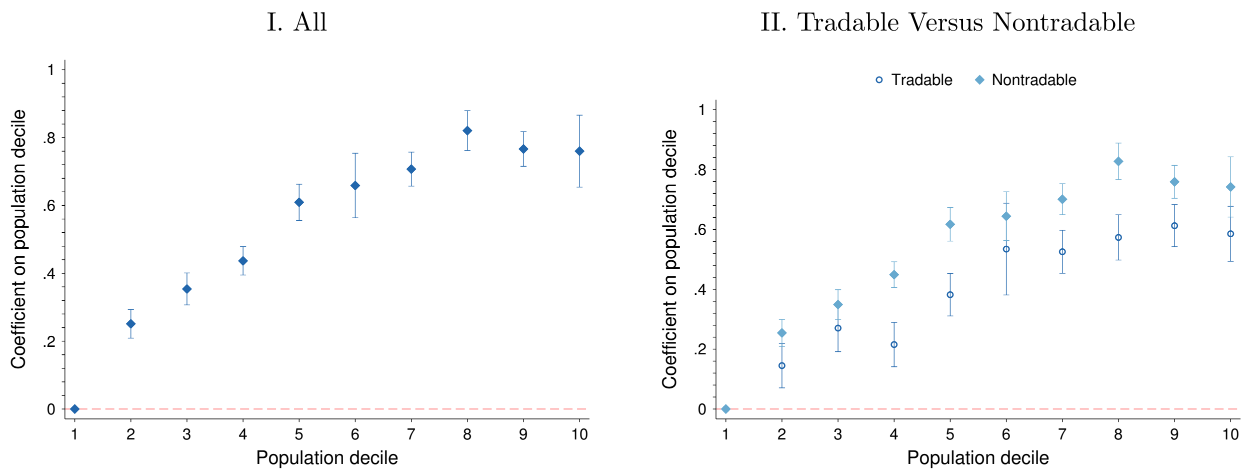
This figure presents a binned scatterplot of an indicator for the job ad's being posted by a staffing firm on log population at the CZ level.

Table A.3: Education Requirements and Staffing Firm-Posted Ads

	BA or above		HS only	
	(1)	(2)	(3)	(4)
Staffing firm	0.199***	0.044***	-0.175***	-0.032***
	(0.007)	(0.002)	(0.006)	(0.002)
SOC f.e.	No	Yes	No	Yes
Number of observations	3,209,292	3,209,292	3,209,292	3,209,292
R^2	0.012	0.555	0.010	0.542
Mean of dep. var.	0.51	0.51	0.35	0.35

The unit of analysis is the job ad and the regression sample includes all job ads with a posted education requirement. The dependent variable is an indicator for the job requiring a college degree (column 1-2), and an indicator for the job requiring a high school degree only (column 3-4). The right-hand side includes an indicator for the job being posted by a staffing firm and, in columns 2 and 4, six-digit SOC f.e. Standard errors are clustered at the CZ level.

Figure A.2: Specialization Gradient (Including Staffing Firms)



This figure reproduces panel A of Figure 4 but includes staffing firms in the sample.

A.3 Evaluating Online Vacancies: Representativeness and Selection

This section examines the coverage of job ads across SOC-CZ cells. It then compares the proportion of online job ads across industries to the proportion as measured in the Job Openings and Labor Turnover Survey (JOLTS).

We first characterize the coverage of job ads across SOC-CZ cells. We use the BLS 2010 version of the SOC classification, which are available in the IPUMS ACS. The IPUMS ACS has 111 four-digit SOCs that are non-aggregated, and there are 722 CZs.[1] Of the 80,142 potential cells, about 2.6 percent are missing from the ACS because rural commuting zones do not have employment in every occupation. Of the populated ACS four-digit SOC-CZ cells, the job ads data cover 68.1 percent of cells, which represent 98.3 percent of employment. The most common missing cells in the job ads data are those in the Military and those in Farm, Fishing, and Forestry occupations. Turning to two-digit SOCs, there are 722 CZs and 23 two-digit SOCs. Of the 16,606 possible cells, 0.04 percent are missing in the ACS. Our job ads data cover 90.3 percent of the remaining cells, which represent 99.8 percent of employment.

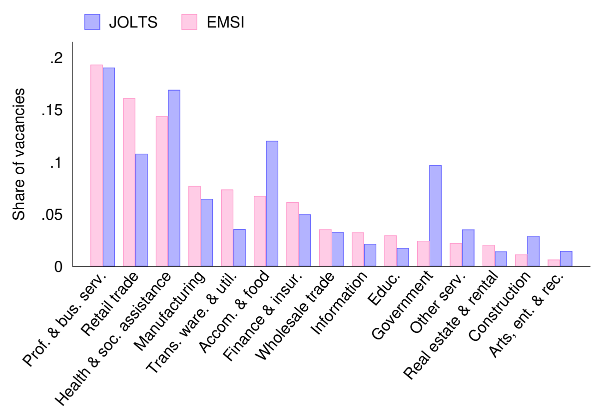
The standard resource for measuring job vacancies in the U.S. is JOLTS, conducted by the Bureau of Labor Statistics of the U.S. Department of Labor. The dataset consists of

[1]Some IPUMS occupation codes are aggregated because they lack an exact match to a Census occupation code or to preserve confidentiality because there are fewer than 10,000 individuals in the cell nationwide.

monthly job openings at the national level by major industry category.[2] JOLTS is based on a survey of a random subset of establishments covered by state or federal unemployment insurance laws.[3]

Figure A.3 plots the distribution of job ads by sector for JOLTS and EMSI. Certain industries, such as Manufacturing, Finance and Insurance, and Education, have higher representation in EMSI than in JOLTS, while others, such as Health and Social Assistance, Government, and Accommodation and Food, have higher representation in JOLTS. Overall, however, there is a high correspondence in industries' vacancy shares in the two datasets.

Figure A.3: Distribution of EMSI Job Ads Versus JOLTS



This figure plots the distribution of EMSI job ads and JOLTS job openings across major industries, from 2012-2017. Industries are sorted by their share of job ads in EMSI.

A.4 Additional Validation of Job Ads Data: Education Requirements in Job Ads Versus ACS Employment, and Worker Search Behavior

In this section, again with the aim of validating the EMSI dataset, we perform two exercises. First, we compare education levels in job ads versus ACS employed workers, across occupations and commuting zones. Second, we study the propensity of workers to search for jobs

[2]The JOLTS dataset also has vacancies at the census region level, but not at the region-by-industry level. JOLTS has no finer geographic unit than census region.

[3]JOLTS defines job openings as "positions that are open (not filled) on the last business day of the month. A job is 'open' only if it meets all three of the following conditions: (1) A specific position exists and there is work available for that position. The position can be full-time or part-time, and it can be permanent, short-term, or seasonal; (2) The job could start within 30 days, whether or not the establishment finds a suitable candidate during that time; (3) There is active recruiting for workers from outside the establishment location that has the opening." See https://www.bls.gov/help/def/jl.htm. Accessed February 23, 2021.

online, across large and small markets, for both college and non-college workers.

For each four-digit SOC $\times$ CZ, we compute the fraction of job ads requiring a college degree or above (in ads mentioning an educational requirement) and the fraction of employed workers, measured in the ACS, with a college degree or higher. Figure A.4 correlates these two measures, with weights for employment in the cell. There is a strong correlation, suggesting that job ads contain valuable information about the educational requirements of the occupation. The share of ads with a given educational requirement is somewhat greater than the corresponding share of workers with that level of educational attainment. This result is perhaps unsurprising, given that job vacancies represent the frontier of occupational change, and the supply of educated workers has increased over time. Figure A.5 plots the same regression by CZ population quartile, showing a strong correlation for both large and small labor markets.

Using the same data, Figure A.6 depicts the gradient of educational requirements across CZ population deciles for the job vacancy data, and, next to it, the gradient of educational attainment of employed workers in the ACS. The gradient looks remarkably similar, both within and across occupations, suggesting again that the job vacancy data are picking up meaningful variation in the educational requirements of jobs across geography.

A final potential concern is that firm recruiting strategies may differ between large and small markets, due to a larger pool of applicants in large markets, which may create selection into the types of jobs posted. We indirectly test this concern by studying the search behavior of workers, using the CPS Computer and Internet Use Supplement for 2011-2017. We regress an indicator for using the internet to search for jobs on CZ size decile indicators and present the results in Figure A.7. The two panels—with and without occupation fixed effects—show no evidence that using the internet for job search varies with CZ size. We perform this analysis separately for workers with a BA or above and for workers with a high school degree only. None of these analyses reveal worker search behavior differing with market size. These results provide at least suggestive evidence that selection of job postings online is not a major concern.

Figure A.4: Education of Workers in ACS Versus Education Requirements in Job Ads

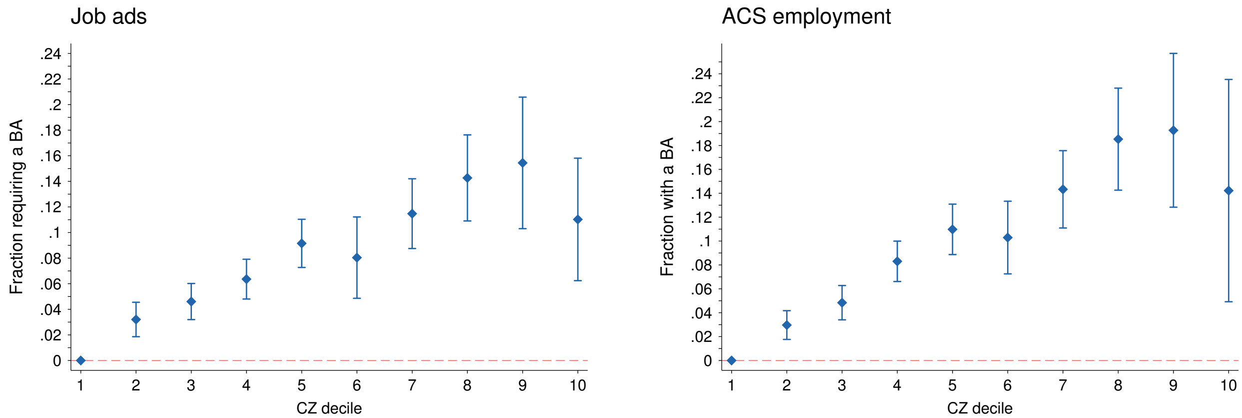
Each dot in the figure above corresponds to a four-digit SOC × market. The cells are weighted by employment. The y-axis corresponds to the fraction of workers in the ACS with at least a college degree. The x-axis corresponds to the fraction of job ads that require a BA degree or higher (among ads that mention any education requirement).

Figure A.5: Education of Workers in ACS Versus Education Requirements in Job Ads

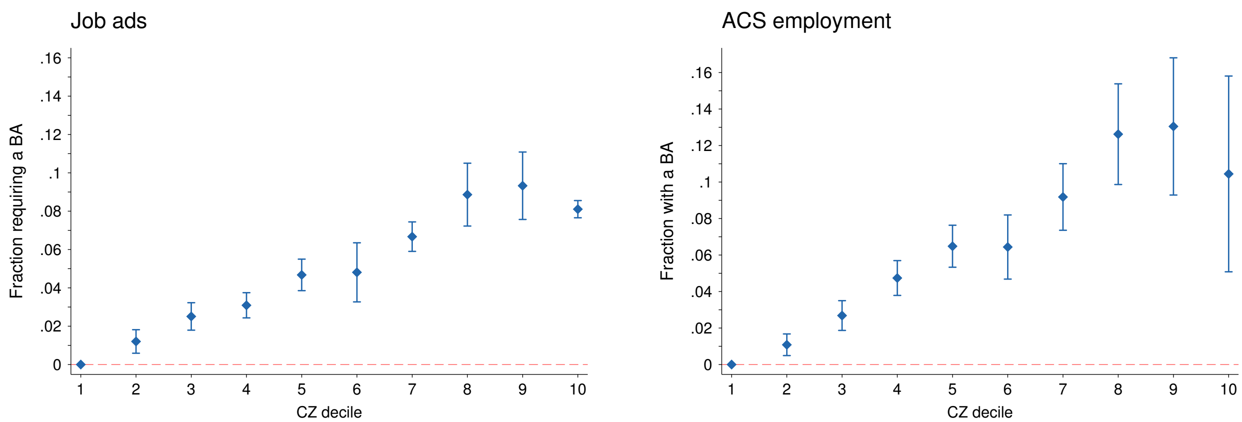
The figure above replicates Figure A.4 separately by CZ population quartile.

Figure A.6: Education Gradient with Market Size: Job Ads Versus ACS Employment

I. Without SOC f.e.

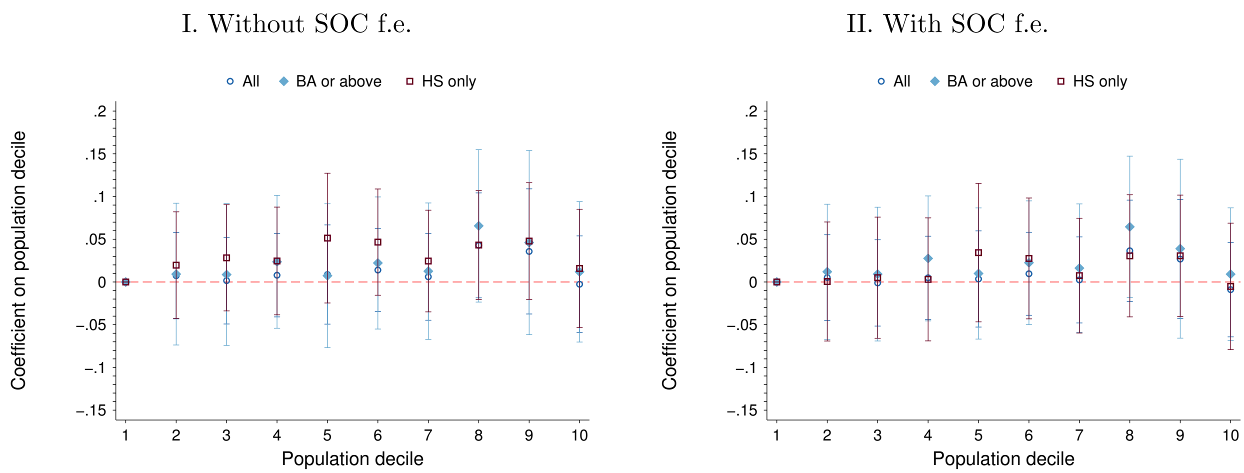


II. With SOC f.e.



Observations are four-digit SOC-CZ pairs. The top left panel plots the coefficients in a regression of the fraction of job ads having an education requirement of a BA or above (conditional on having an educational requirement) on dummies for CZ decile. The cells are weighted by employment, and standard errors are clustered at the CZ level. The top right panel plots the same regression except where the dependent variable is the fraction of employed workers with a BA or above using the ACS. The bottom two panels reproduce the top two panels with four-digit fixed effects.

Figure A.7: Worker Job Search Using the Internet



The table above uses the CPS Computer and Internet Use Supplement for 2011-2017. The dependent variable is an indicator for the worker using the internet to search for jobs, which is regressed on a vector of deciles for CZ. Panel II includes fixed effects for CPS OCC2010 codes. Standard errors are clustered at the CZ level.

A.5 Measuring Occupational Tasks

This section provides additional details on how we measure jobs' task content. These measures correspond to those used in past research: Spitz-Oener (2006) and the O*NET database. We then compare occupations' task content—according to these measures—using the EMSI dataset with measures directly observed in the O*NET database. These two sets of measures align, validating our use of the EMSI dataset. We also compare our data to within-occupation measures available from data collected by the Princeton Data Improvement Initiative (PDII) and find supportive evidence that our measures align with the PDII's within-occupation measures.

Mapping Words to Tasks

We map job description words to the five Spitz-Oener (2006) task categories: non-routine analytic, non-routine interactive, non-routine manual, routine cognitive, and routine manual. We use the word-to-task mappings we develop in Atalay et al. (2020). These mappings are available on our project website: https://occupationdata.github.io/. We use the continuous bag of words model list of word mappings, which is described in detail in the data documentation on the website.

Comparing Tasks from Job Ads to O*NET

A key limitation of O*NET is that it measures tasks only at the occupation level. Hence, O*NET is unable to speak to geographic variation in tasks aside from those arising from different employment shares across regions. Nevertheless, O*NET is valuable for testing the validity of our job ads for extracting occupation-level tasks. We construct occupation-level task content using the EMSI ads data and plot the correlation with O*NET's work activities.

The specific tasks we compare are O*NET's "Selling or Influencing Others," "Communicating with Persons Outside Organization," "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 adopt the mapping of words to O*NET work activities listed below.[4] Note that this mapping is by nature somewhat ad hoc. We count, for each ad, the total number of occurrences of any of the corresponding words. We then normalize the count so that it is expressed per 1,000 job ad words. The first two bullet points refer to interactive tasks that are external to the firm; the remaining five refer to internal interactive tasks.

- *Selling or Influencing Others*: sales marketing advertising advertise merchandising promoting telemarketing market plan
- *Communicating with Persons Outside Organization*: clients client vendor vendors public interface communicate communication communicating coordinating conferring public relation
- *Guiding, Directing, and Motivating Subordinates*: directing direction guidance leadership motivate motivating motivational subordinate supervise supervising
- *Developing and Building Teams*: team-building "team build" project leader
- *Coaching and Developing Others*: mentor mentoring coaching
- *Coordinating the Work and Activities of Others*: coordinate coordination coordinator
- *Communicating with Supervisors, Peers, or Subordinates*: peer subordinate subordinates supervisor supervisors manager managers interface communicate communication communicating coordinating conferring

[4]We count instances of each word separately; for example, "public" and "relations" are searched for separately rather than as the bigram "public relations." We make one exception for "team build" because in our judgment "build" on its own is likely to return false positives. In Atalay et al. (2020) and in the word mappings on our project website, some task-related words are bigrams.

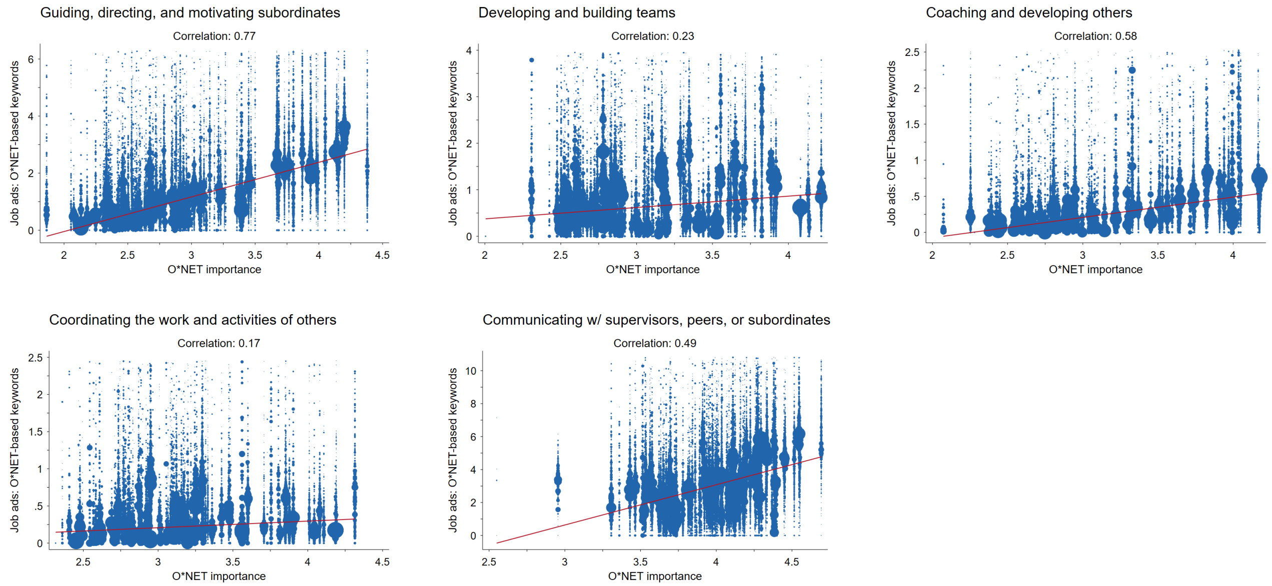
Figure A.8 demonstrates that our job ad-based task data have, for the most part, a high degree of correlation with O*NET tasks. We should not expect a perfect correlation, as O*NET itself has well-known limitations of small sample sizes, status quo bias, and subjective scales (Autor, 2013). However, these correlations indicate that the job description text provides meaningful information about the task content of occupations.

Comparing Occupation-Level Market Size Gradients: O*NET Versus Job Ads

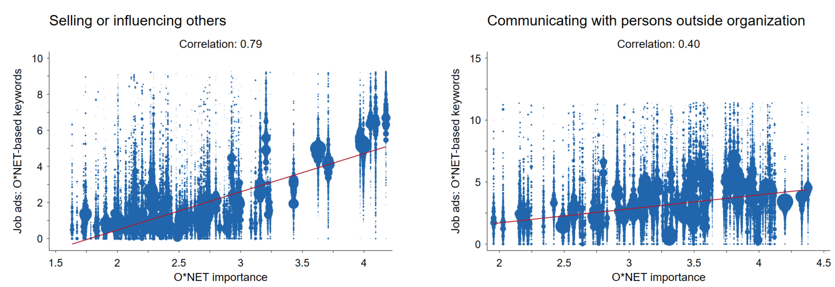
As additional evidence of the usefulness of job ads for studying job tasks in the labor market, we use occupation-level tasks extracted from job ads and compare these to widely-used occupation-level task measures from O*NET. We ask whether we would draw similar conclusions about the task gradients with market size using job ads as we would using O*NET, using a purely occupation-level analysis. To measure O*NET-based tasks, we adopt the O*NET items and categorization of Acemoglu and Autor (2011). We regress these tasks on CZ deciles, using ACS employment weights, and plot them in Figure A.9, panel I. We next construct our five task measures using job ads and applying the word mappings from Spitz-Oener. For this exercise, we constrain tasks to be fixed at the occupation level. We regress these tasks on CZ deciles using employment weights and plot them in Figure A.9, panel II. The task gradients are strikingly similar across data sources, particularly for the non-routine analytic, non-routine interactive, routine cognitive, and routine manual task categories, lending support to job ads data being useful for measuring tasks.

Figure A.8: Comparing Tasks from Job Ads with O*NET

I. Internal Interactive Tasks



II. External Interactive Tasks

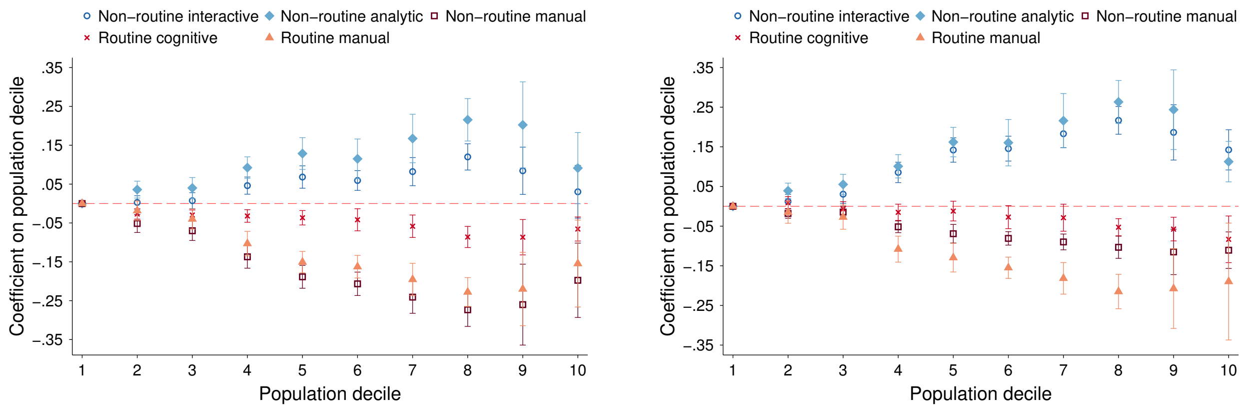


The figures above plot the correlations between occupation-level tasks extracted from the job ads to those based on O*NET. Each dot represents a four-digit SOC $\times$ CZ. The correlations are weighted by ACS employment. (The figures exclude task intensities over the 99th percentile in both the reported correlations and the scatterplots.)

Figure A.9: Comparing Job Ads-based Tasks to O*NET-based Tasks

I. O*NET

II. Job Ads



The left panel adopts the O*NET-based task measures and categories of Autor and Acemoglu (2011). O*NET items are averaged at the four-digit occupation level before being standardized to have mean zero and standard deviation 1 in the labor market. The job ads-based tasks are from the Spitz-Oener task categories that are first averaged at the four-digit occupation-level and then standardized to have mean zero and standard deviation 1 in the labor market. ACS employment in four-digit occupation-CZ cells are merged to the occupation-level task measures. Each task intensity measure is regressed on CZ deciles, with ACS employment weights, and with standard errors clustered at the CZ level.

Comparing Task Measures from EMSI to those in the Princeton Data Improvement Initiative

While useful, the preceding validation of our measurement of job task content relied solely on between-occupation task variation. In this section, we employ data from the Princeton Data Improvement Initiative (PDII)[5] to examine whether our measures align — looking within occupations as well — with those derived from existing datasets.[6]

[5]These data are described in Hallock (2013) and are used by Autor and Handel (2013) and Blau and Kahn (2013), among others.

[6]For our purposes, there are at least three advantages of EMSI over the PDII when measuring differences in job content between small versus large commuting zones. First, the PDII is drawn from a much smaller sample, with correspondingly large sampling error. Second, the geographic information available in the PDII include only the state of the survey respondent and whether the respondent was located in a metropolitan statistical area or not. Thus, with the PDII we cannot estimate CZ-size task gradients. Finally, the EMSI

As part of the Princeton Data Improvement Initiative, 2,513 adults were asked a wide array of questions about the types of skills required and tasks performed in their jobs. From these questions, we construct indices of non-routine analytic tasks, non-routine interactive tasks, routine cognitive tasks, and manual tasks.[7] To compare the indices based on the PDII data to those based on EMSI job ads, we take the average values from each of the two datasets by four-digit SOC code and geography. The finest level of geography available in both datasets is the interaction of state and whether the individual resides in a metropolitan statistical area (MSA).

First, in Table A.4, we regress PDII-task measures on an indicator of whether the observation (a four-digit occupation-by-state-by-metropolitan status) is in a metropolitan area. The first four columns of this table present coefficient estimates from regressions without four-digit SOC fixed effects; the final four columns present results from specifications where these fixed effects are included. Overall, we find that individuals report spending more time on non-routine analytic tasks—and less time on routine cognitive tasks and manual tasks—in metro areas. These results align, for the most part, with those in Figure 1. There, we also report greater mentions of non-routine analytic tasks in larger CZs and fewer mentions of routine manual and non-routine manual tasks in larger CZs. The one (partial) discrepancy relates to routine cognitive tasks. In Figure 1, in specifications without fixed effects, there is a greater propensity for firms to mention routine cognitive tasks in larger CZs; this relationship disappears in specifications with SOC fixed effects. By contrast, in the PDII data, there is a lower intensity of routine cognitive tasks in metro areas.

data permit measurement of individual tasks and technologies at a granular level across a wide variety of tasks and technologies, something that the PDII does not seek to measure. Nevertheless, the PDII provide the opportunity to validate our measurement of task categories using an existing, well-known dataset.

[7]We consider (i) the frequency with which the individual takes 30 minutes to solve a problem, (ii) the frequency with which the individual uses math to solve problems, and (iii) the longest document typically read for a job as measures of non-routine analytic tasks; (i) the frequency of managing/supervising, and (ii) how much face-to-face contact with others as measures of non-routine interactive tasks; the frequency of short/repetitive tasks as our measure of routine cognitive skills; and the frequency of physical tasks as our measure of manual tasks. We could not find separate measures of routine manual and non-routine manual tasks. Before constructing each of these four indices, we standardize questions from each individual survey question. We then take the mean of these standardized values and, finally, standardize the resulting indices.

Table A.4: Relationship Between PDII Task Measures and Metropolitan Status

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Metro	0.197***	-0.008	-0.215***	-0.327***	0.080	0.005	-0.096**	-0.158***
	(0.057)	(0.061)	(0.047)	(0.057)	(0.052)	(0.058)	(0.048)	(0.044)
Dependent variable	NR-Analytic	NR-Interactive	R-Cognitive	Manual	NR-Analytic	NR-Interactive	R-Cognitive	Manual
R^2	0.009	0.000	0.011	0.024	0.371	0.307	0.334	0.535
Number of observations	1602	1609	1598	1607	1602	1609	1598	1607
SOC f.e.	No	No	No	No	Yes	Yes	Yes	Yes

An observation is an occupation-state-metro status triple. Observations are weighted equally. The dependent variable in each regression is the standardized index of task measures, using questions from the PDII. Standard errors are clustered at the four-digit SOC level.

In Tables A.5 and A.6, we regress measures PDII measures of task intensity against corresponding measures from our EMSI dataset. In Table A.5, occupation by state by MSA status observations are weighted equally, while in Table A.6 we weight observations according to the number of EMSI job ads in the occupation by state by MSA status triple. In unweighted specifications, we find that the PDII and EMSI data are correlated with each other, but that these correlations disappear once we condition on four-digit SOC. In weighted specifications, the two datasets' measures align not only between but also within occupations.

Overall, we conclude that patterns identified from our job ads data align reasonably well with those constructed using the PDII.

Table A.5: Relationship Between PDII and EMSI Task Measures

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Non-routine Analytic	0.837***				-0.006			
	(0.089)				(0.109)			
Non-routine Interactive		0.285***				0.166		
		(0.091)				(0.127)		
Routine Cognitive			0.145*				-0.021	
			(0.075)				(0.111)	
Routine Manual				0.432***				-0.007
				(0.078)				(0.058)
Non-routine Manual				0.221***				-0.036
				(0.074)				(0.073)
Dependent variable	NR-Analytic	NR-Interactive	R-Cognitive	Manual	NR-Analytic	NR-Interactive	R-Cognitive	Manual
R^2	0.159	0.021	0.005	0.123	0.370	0.308	0.332	0.530
Number of observations	1602	1609	1598	1607	1602	1609	1598	1607
SOC f.e.	No	No	No	No	Yes	Yes	Yes	Yes

An observation is an occupation-state-metro status triple. Observations are weighted equally. The dependent variable in each regression is the standardized index of task measures, using questions from the PDII. Standard errors are clustered at the four-digit SOC level.

Table A.6: Relationship Between PDII and EMSI Task Measures

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Non-routine Analytic	0.977***				0.799***			
	(0.098)				(0.220)			
Non-routine Interactive		0.359***				0.464**		
		(0.118)				(0.231)		
Routine Cognitive			0.343***				0.612**	
			(0.095)				(0.282)	
Routine Manual				0.506***				0.062
				(0.102)				(0.145)
Non-routine Manual				0.230**				-0.081
				(0.093)				(0.175)
Dependent variable	NR-Analytic	NR-Interactive	R-Cognitive	Manual	NR-Analytic	NR-Interactive	R-Cognitive	Manual
R^2	0.223	0.035	0.024	0.151	0.467	0.402	0.429	0.571
Number of observations	1602	1609	1598	1607	1602	1609	1598	1607
SOC f.e.	No	No	No	No	Yes	Yes	Yes	Yes

An observation is an occupation-state-metro status triple. Observations are weighted according to the number of ads in the EMSI data in the occupation-state-metro status triple. The dependent variable in each regression is the standardized index of task measures, using questions from the PDII. Standard errors are clustered at the four-digit SOC level.

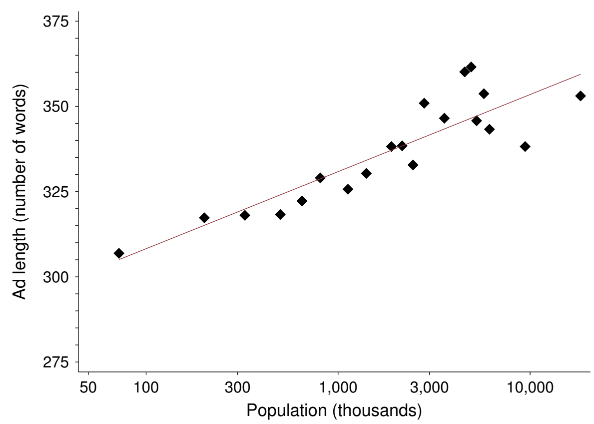
A.6 Job Ad Length and Description Keywords Across Space

We next consider the content of the job ads and how it differs across geography. First, we plot a binned scatterplot of job ad length (i.e., the number of words) against the log CZ population (Figure A.10). This exercise shows that larger markets have longer job ads on average. Motivated by this pattern, we control for job ad length throughout our analysis and standardize our task measures to be per 1,000 ad words. We also normalize our granular task measures so that each task vector has unit length.

As described in Section II, the first step of our approach to extracting job tasks from the text is to identify the part of the text corresponding to the job description. We use a set of keywords to identify this portion of the ad: "duties," "summary," "description," and "tasks." Figure A.11 examines the gradient of the job ad containing one of these keywords with market size, after controlling for ad length. The left panel shows a negligible relationship between market size and the presence of a keyword.

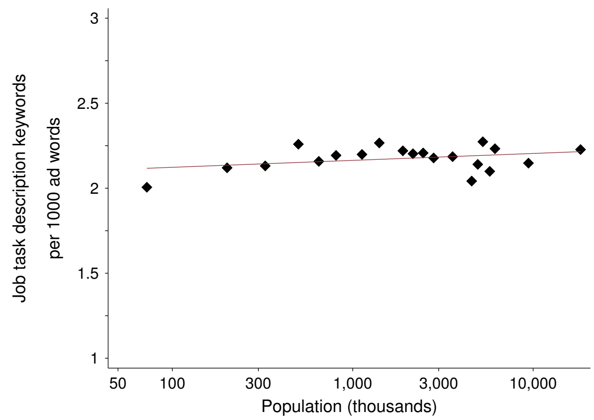
Lastly, we show that our novel task-extraction methodology—using job descriptions and parts of speech to let the text define the job tasks—passes a simple validation check. We calculate the average of the cosine similarity between each job and the occupation-market average. This exercise reveals that similarity is higher for more narrowly defined occupational categories. Specifically, the cosine similarity is 0.052 for two-digit SOCs, 0.072 for four-digit SOCs, 0.104 for six-digit SOCs, and 0.166 for job titles. Thus, the text-based tasks of occupations are more similar within more narrowly defined occupational categories. It is perhaps unsurprising that narrower occupational categories share more job ad words, but this finding is reassuring and suggests that the text contains valuable information about occupational characteristics that is reflected in standard occupational classifications.

Figure A.10: Job Ad Text Across Geography



The figure above presents a binned scatterplot of job ad length (number of words) on log population at the CZ-level. Cells are weighted by the number of job ads in the cell.

Figure A.11: Job Description Keywords Across Geography



The figure above presents a binned scatterplot of an indicator of the job ad's having a keyword in our task-extraction algorithm—"responsibilities," "duties," "summary," and "tasks"—normalized per 1,000 ad words and against log CZ population.

B Task Extraction and Validation

This section outlines our approach to measuring job tasks. We illustrate the algorithm and present the most common tasks, the list of excluded tasks, and a scatterplot of the number of granular tasks and market size (Appendix B.1); present a validation exercise using multi-establishment firms (B.2); present the most common technologies (Appendix B.3); evaluate the relationships among tasks, technologies, and market size (Appendices B.4 and B.5); and show that these tasks account for variation in wages across geography, above and beyond what is captured by occupational codes (Appendix B.6).

B.1 Task List

We first present two sample ads and the granular tasks extracted by the algorithm in Table B.1.

Table B.1: Illustrating the Algorithm to Extract Verb-Noun Tasks

Job Title	Job Ad Text	Tasks Extracted
Electrician	licensed electrician electronic control systems is seeking a full_time licensed electrician to **perform** commercial , residential , and industrial electrical **maintenance** and repair . candidates would be **assisting clients** in dade , bro ward and palm beach counties . candidate must be organized and motivated as we are looking for a person with skills and good working habits . specific responsibilities include , but are not limited to : assembling , installing , testing and maintaining electrical or electronic wiring , equipment , appliances , apparatus and fixtures **using hand** tools and power tools . diagnosing malfunctioning systems and components connecting wires to circuit breakers , transformers or other components . inspecting electrical systems , equipment and components to identify hazards , defects and the need for adjustment or repair , and to **ensure compliance** with codes . maintaining current electrician 's license or identification card to meet governmental regulations . . licensed electrician active journeyman electrician must be licensed 5 years of experience minimum (residential , commercial & industrial) proficient knowledge of local codes and safety regulations must speak fluent english work in dade , bro ward and palm beach counties must_have valid drivers_license and dependable transportation	perform maintenance, assisting clients, use hands, ensure compliance
Assistant Store Manager	general_summary : as a family dollar assistant store manager you will responsible for **providing** exceptional **service** to our customers . a key priority includes assisting the store manager in the daily operation of the store . under the direction of the store manager , you will also be responsible for **maintaining inventories** , **store** appearance and completing daily paperwork . principal duties & responsibilities : greets and **assists customers** in a positive , approachable manner . answers questions and resolves customer inquiries and concerns . maintains a presence in the store by **providing** excellent **customer_service** . **ensures** a clean , well_stocked **store** for customers . at the direction of the store manager , supervises , trains , and develops store team members on family dollar operating practices and procedures . assists in unloading all merchandise from delivery truck , organizes merchandise , and transfers merchandise from stockroom to store . **assists store** manager in ordering merchandise and record_keeping to include payroll , scheduling and cash_register deposits and receipts . supports store manager in loss_prevention efforts . assumes certain management responsibilities in absence of store manager . **follows** all **company** policies and procedures . bach f6f5fe bets arc setter maintaining store store .	provide service, maintaining inventory, maintain store, assisting customers, provide customer_service, ensure stores, assist store, following company

The table above presents the full text of two sample job ads and highlights in bold the verb-noun tasks extracted by our algorithm. Note that not all verb-noun pairs in the job ad text are highlighted as tasks because we define the set of tasks as the 500 most common verb-noun pairs.

Next, we list the 399 tasks we extract from the job ad text as verb-noun pairs along with the fraction of ads with each task (× 100). For readability, instead of listing the word stems, we present the verb-noun pairs as they appear in their first occurrence, which leads to variations in noun forms and verb conjugations in the table (e.g., "provide service" versus "providing support").

Table B.2: Tasks Extracted from Verb-Noun Pairs

written communication	13.0257	developed sales	0.8352	damaged merchandise	0.3108
working team	7.4251	communicate information	0.8348	move trays	0.3104
provide customer_service	6.6934	closes store	0.8229	needed customer_satisfaction	0.3092
provide service	5.3395	developing strategies	0.8218	increase customer_satisfaction	0.3044
lifting pounds	4.6136	working sales	0.8212	following pogs	0.3041
providing support	4.4229	writing skills	0.8198	responsibilities duties	0.3031
build relationships	3.8635	answering phones	0.8154	document counts	0.3024
ensure compliance	3.5870	increase sales	0.8052	assigned skills	0.3022
assisting customers	3.2288	maintaining environments	0.8014	may store	0.2908
provide customer	3.1077	handle tasks	0.7909	leads customers	0.2905
maintaining relationships	3.0468	support business	0.7870	maintaining program	0.2901
problem_solving skills	2.9784	ensure adherence	0.7739	executes store	0.2866
making decisions	2.9349	require walking	0.7711	supporting activities	0.2829
ensure customer	2.8990	ensure employees	0.7655	lead store	0.2827
lift lbs	2.8608	working variety	0.7644	serving quality	0.2689
provides quality	2.8342	assume responsibilities	0.7592	include staff	0.2668
provides leadership	2.5047	ensure completion	0.7577	maintain pharmacy	0.2627
develop relationship	2.5011	maintain productivity	0.7455	remove items	0.2540
perform job	2.4971	identifies problems	0.7329	requiring security	0.2536
leading team	2.3856	asking questions	0.7320	required paperwork	0.2522
achieve goals	2.2844	include service	0.7303	include hand	0.2513
working relationships	2.2757	providing environment	0.7301	seek customer	0.2444
continuing education	2.1940	writing reports	0.7265	lifting merchandise	0.2430
serving customers	2.1819	managing operations	0.7249	promote shopping	0.2401
following company	2.1392	including training	0.7245	merchandising product	0.2349
providing care	2.0627	providing expertise	0.7104	scheduling activities	0.2295
make recommendations	2.0457	ensure client	0.7027	set displays	0.2265
meet requirements	2.0141	assigned store	0.6921	has client	0.2240
meet deadlines	1.9775	maintain communication	0.6920	stored areas	0.2206
provides training	1.9577	assist development	0.6902	maintain card	0.2199

provided information	1.8973	generate sales	0.6839	training sessions	0.2183
will customers	1.8947	working departments	0.6815	conducting employee	0.2130
resolve issue	1.8601	using knowledge	0.6813	evaluates employees	0.2116
work flexible_schedule	1.8575	include development	0.6663	include shelves	0.2112
demonstrate knowledge	1.8571	answering telephone	0.6570	using phone	0.2054
taking actions	1.8503	develop productivity	0.6569	vacuum face	0.2037
provide feedback	1.8131	developing implement	0.6548	assigns directs	0.2007
provide assistance	1.8073	established guidelines	0.6539	using greet	0.1836
providing solutions	1.8068	maintain work_environment	0.6482	discontinued items	0.1835
driving sales	1.7791	preparing foods	0.6481	using orders	0.1808
ensure quality	1.7532	existing clients	0.6366	outdated merchandise	0.1800
helping customer	1.7479	ensure guests	0.6231	prepare returns	0.1797
works custom	1.7189	including work	0.6221	greeting card	0.1794
communicate customer	1.6945	maximizes profitability	0.6159	work stock	0.1765
follow instructions	1.6791	required driver	0.6138	securing company	0.1763
managing projects	1.6743	provide client	0.6136	crews customer_service	0.1761
maintain store	1.6554	meet clients	0.6114	recalled merchandise	0.1759
greeting customers	1.6384	set goals	0.6112	crew directing	0.1758
work shift	1.6339	including business	0.6068	change bulbs	0.1738
will teams	1.6264	are compliance	0.6046	labeling prescriptions	0.1735
answer questions	1.6252	move store	0.6043	maximizing customer_satisfaction	0.1723
ensure product	1.6196	provide technical_support	0.6015	needed in_store	0.1708
provide guidance	1.6020	provide recommendations	0.5896	reset departments	0.1703
detail ability	1.5925	opens store	0.5815	return system	0.1703
maintaining inventory	1.5885	obtain information	0.5811	signing maintain	0.1701
include sales	1.5879	ensuring team	0.5669	preventing trafficking	0.1699
written skills	1.5729	assigned supervisor	0.5577	windows ceilings	0.1698
work schedule	1.5256	requires merchandise	0.5567	windows removal	0.1690
achieving sales	1.5248	managing sales	0.5564	sweeping stock	0.1688
resolve problems	1.5085	include design	0.5528	signing shelves	0.1688
stand periods	1.4931	hiring training	0.5491	dump baskets	0.1688
maintaining standards	1.4602	ensure projects	0.5474	photofinishing orders	0.1688
assist store	1.4362	conducting research	0.5416	regarding cash_register	0.1688
meets customer	1.4272	assisting clients	0.5355	bags counter_tops	0.1687
work others	1.4230	assisted sales	0.5328	measuring drugs	0.1684
requires travel	1.4230	maintain awareness	0.5270	putting drug	0.1682

work week_ends	1.4150	include knowledge	0.5175	seal trays	0.1682
written instructions	1.3752	reaching pulling	0.5157	capping vials	0.1679
operating cash_register	1.3735	traveling store	0.5122	closing duties	0.1672
resolving customer	1.3628	unloading trucks	0.5120	make offer	0.1641
develop business	1.3594	move merchandise	0.5054	ensures quality_assurance	0.1606
maintain working	1.3569	develop test	0.5026	following reports	0.1567
maintain knowledge	1.3533	including performance	0.4901	communicating field	0.1554
providing direction	1.3523	including maintenance	0.4849	execute cash	0.1530
establish relationships	1.3468	supervising store	0.4845	returned check	0.1492
perform variety	1.3458	guided values	0.4785	following vendor	0.1492
ensure safety	1.3232	ensuring food	0.4728	execute display	0.1459
handling customer	1.3140	handle merchandise	0.4725	request help	0.1459
interact customers	1.3129	build customer	0.4707	including translation	0.1426
exceed sales	1.3000	make adjustments	0.4695	appropriate use	0.1422
ensure stores	1.2915	include merchandising	0.4597	perform register	0.1418
developing team	1.2807	manages business	0.4588	opening duties	0.1410
develop solutions	1.2723	taking orders	0.4545	executing set	0.1401
preferred ability	1.2457	ensuring communications	0.4525	sustained work	0.1397
using computer	1.2323	including systems	0.4524	pay policy	0.1393
maintain appearance	1.2284	meets standards	0.4505	securing door	0.1390
identify opportunities	1.2281	manage relationships	0.4499	execute completion	0.1379
weighing pounds	1.2267	including preparation	0.4490	pay vendors	0.1377
growing business	1.2217	ensure policies	0.4467	checking employee	0.1375
make changes	1.2214	comply state	0.4383	check_in merchandise	0.1374
maintain custom	1.2155	include program	0.4380	check acceptance	0.1371
existing customers	1.1991	ensure restaurant	0.4377	skating carhop	0.1368
on_going training	1.1942	may merchandise	0.4361	maintain prescription	0.1365
including nights	1.1743	may floor	0.4279	sustained periods	0.1365
work projects	1.1730	put customer	0.4249	pulls deposits	0.1360
develop planning	1.1620	scheduling appointments	0.4193	apprehend company	0.1358
stand walk	1.1526	assisting team	0.4184	document cash	0.1356
maximize sale	1.1489	providing coaching	0.4137	adapting store	0.1355
sells products	1.1478	have merchandise	0.4125	secure change	0.1352
written oral_communication	1.1286	including support	0.4115	identify shoplifters	0.1350
ensure customer_satisfaction	1.1274	causing discomfort	0.4102	react program	0.1350
operate equipment	1.1250	provides performance	0.4035	in_store repairs	0.1350

meet goals	1.1221	processing transactions	0.4030	resolve rejections	0.1350
use hands	1.1209	offer products	0.3978	organized pharmacy	0.1348
analyzing data	1.1207	include client	0.3976	signing crew	0.1348
meet sales	1.1067	containing materials	0.3974	react shoplifters	0.1347
prepare reports	1.1062	may slippery	0.3958	using enhancements	0.1346
assigned management	1.1047	maintain area	0.3946	execute walk_through	0.1346
according company	1.0815	receives service	0.3945	intern communication	0.1344
including management	1.0743	transforming delivery	0.3921	according hipaa	0.1344
engage customers	1.0722	maintain files	0.3918	locking setting	0.1340
provides input	1.0682	become slippery	0.3917	sweep room	0.1339
perform maintenance	1.0614	causing walking	0.3916	adjust facings	0.1335
prioritize tasks	1.0197	causing drafts	0.3916	trash rest	0.1335
managing teams	1.0034	appear floor	0.3915	dcr photofinishing	0.1335
ensure accuracy	1.0017	floors work	0.3912	bulletins action	0.1335
improving quality	1.0000	passing emit	0.3910	maintain pull	0.1335
team members	0.9907	include customer_service	0.3894	comply cvs	0.1332
establish policies	0.9903	focus team_work	0.3883	pharmacist communicate	0.1331
assisting management	0.9799	as_needed assist	0.3864	needed inventory_management	0.1330
maintain records	0.9741	retrieving information	0.3735	according cvs	0.1330
ensure delivery	0.9489	assist staff	0.3715	cvs workflow	0.1330
working store	0.9374	maintaining business	0.3691	greeting operations	0.1274
meet business	0.9364	include order	0.3660	sorting merchandise	0.1226
using equipment	0.9115	generating business	0.3639	delegated photo	0.1214
protect company	0.8972	staffing needs	0.3632	merchandising directives	0.1102
carry pounds	0.8943	establish priorities	0.3496	preventing terrorists	0.1075
ensuring merchandising	0.8941	bagging merchandise	0.3460	supervisor team	0.0957
following policies	0.8890	handling cash	0.3437	driving culture	0.0908
ensure operation	0.8781	procedures cash	0.3257	drive_in employees	0.0902
responding customer	0.8579	using eye	0.3249	identifying conditions	0.0699
ensure service	0.8539	taking vehicle	0.3210	assigned reading	0.0413
including cash	0.8443	maintained times	0.3133	customer_service culture	0.0241

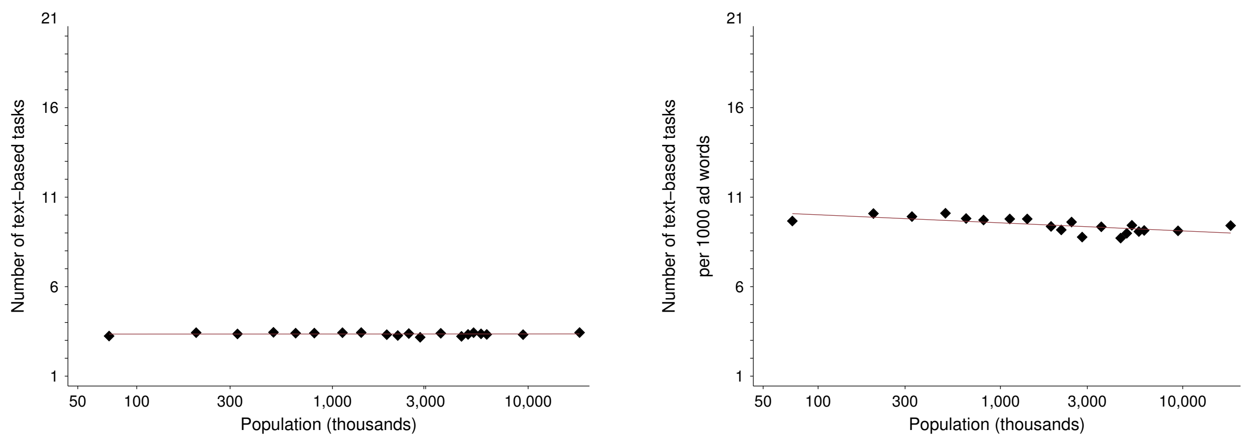
As described in the text, we exclude 101 tasks from the original list of 500 most common verb-noun pairs, using our judgment to select pairs that do not correspond to tasks. These excluded verb-noun pairs are presented below and describe worker skills (e.g., "high school diploma," "ged years," "required bachelor"); firm attributes (e.g., "is company," "is equal_opportunity"); aspects of the job search process ("pass drug"); or are simply uninformative ("meet needs," "be duties").

Table B.2 (continued): Verb-Noun Pair Drop List

be years	be doors	is job
is equal_opportunity	can doors	be company
arc bach	are business	perform duties
must years	requested react	be part
high_school diploma	are store	work environment
demonstrated ability	including evenings	perform functions
required employee	is law	required knowledge
bachelor degree	is customer	have experience
meet needs	earned degree	are position
required ability	is ability	have years
required years	send resume	required qualifications
required skills	s journal	is service
according state	eas program	includes ability
include customers	is delivery	committed diverse
work hours	are company	are sales
are customers	ged years	knowledge skills
be customer	include duties	working business
preferred years	required position	desired skills
required experience	be duties	providing product
s degree	pass drug	be lbs
arc setter	required bachelor	are manages
end caps	are accordance	are duties
preferred experience	sporting goods	is walks
including products	have ability	will career
is position	based business	are reporting
work part	ensuring aspects	according needs
are time	assigned job	permitted law
ensure execution	be ability	performing tasks
bach bets	may duties	playing role
be team	are fast_growing	preferred knowledge
travel travel	requires state	achieve results
is experience	must_have driver	completing tasks
may materials	will business	performing work
are drafts	s level	

Figure B.1 presents the frequency of text-extracted job tasks per ad. The left panel is a binscatter of number of tasks at the ad level on CZ size, while the right panel presents the same figure but first normalizes the number of tasks per 1,000 ad words. There are about four tasks per ad on average (out of 399 total tasks), and when we normalize by ad length, as in the right panel, the number of tasks decreases with market size.

Figure B.1: Number of Tasks and Market Size



The left panel above presents a binned scatterplot of number of tasks against log CZ population. The right panel presents the same figure, except the dependent variable is normalized per 1,000 ad words.

B.2 Comparing Tasks in a Firm's Headquarters Versus Other Establishments

In this section, we compare the intensity of tasks in a firm's headquarters relative to its other establishments. We find that systematic differences align with our priors about the tasks that take place in headquarters. As a result, we conclude that the EMSI data and our extraction of granular tasks provide a useful new characterization of differences in work activities between geographies.

For this exercise, we limit ourselves to the 10 largest firms, measured by total job postings, and exclude chains and postings by government agencies. We identify the headquarters location for each firm as the CZ with the largest number of the firm's postings and then validate this list against public records. The list of firms used for this validation exercise, along with the location of their headquarters, is: Amazon (Seattle, WA), Genesis HealthCare (Kennett Square, PA), UnitedHealth Group (Minnetonka, MI), IBM (Armonk, NY), HCA Healthcare (Nashville, TN), Lockheed Martin Corporation (Bethesda, MD), Aramark Corporation

(Philadelphia, PA), Providence Health and Services (Renton, WA), Citigroup Incorporated (New York, NY), and Parallon (Nashville, TN). This subsample includes 136,324 ads. We run a regression at the job ad level for each task. We regress task intensity on an indicator for the job being in the firm headquarters, along with six-digit SOC fixed effects and with the standard errors clustered at the CZ-level. In Table B.3, we report the tasks with the largest positive and negative coefficient estimates on headquarters (after standardizing by dividing by the task standard deviation). The list of largest positive and negative gradients are presented. A clear pattern emerges, which is that the locations of the headquarters require management, teamwork, or span of control: managing projects, communication (both written and oral), analyzing data, and identifying opportunities are all tasks that reflect these types of work activities. The tasks with the largest negative gaps—i.e., tasks that are common in non-headquarters' locations relative to the locations of the headquarters—involve training and working with or assisting clients. Overall, we view these intuitive differences as an additional validation of our approach.

Table B.3: Tasks with Largest Gap Between Headquarters' and Non-Headquarters' Locations

Positive gradient		Negative gradient	
Task	$\hat{\beta}_{hq}$	Task	$\hat{\beta}_{hq}$
written communication	0.2714	on_going training	-0.3949
managing projects	0.2041	provides training	-0.3694
growing business	0.1910	work projects	-0.3409
written oral_communication	0.1717	requires travel	-0.2930
detail ability	0.1603	existing clients	-0.1394
will teams	0.1359	include client	-0.1310
analyzing data	0.1292	work others	-0.1098
support business	0.1243	assisting clients	-0.1039
working team	0.1235	meet clients	-0.1011
sells products	0.1106	provide assistance	-0.0897
identify opportunities	0.0923	stand walk	-0.0800
provides quality	0.0910	written skills	-0.0785
meet deadlines	0.0857	assume responsibilities	-0.0772
serving customers	0.0851	providing solutions	-0.0593
seek customer	0.0847	increase sales	-0.0591

The table above is based on a subsample of 136,324 ads from the following multi-establishment firms: Amazon, Genesis HealthCare, UnitedHealth Group, IBM, HCA Healthcare, Lockheed Martin Corporation, Aramark Corporation, Providence Health and Services, Citigroup Incorporated, and Parallon. We run a regression at the job-ad level for each of the 399 tasks. We regress the task intensity on an indicator for the job being in the firm headquarters, along with six-digit SOC fixed effects, and with the standard errors clustered at the CZ-level. We report the tasks with the largest positive and negative coefficient estimates on headquarters (after standardizing by dividing by the task standard deviation). The list of the 15 largest positive and negative gradients is presented. All estimates are significant at the 5 percent level.

B.3 Technology List

The table below lists the O*NET Hot Technologies that we identify in the job ads text along with the fraction of ads with each technology ($\times$ 100). To be counted as a technology appearance, all words in the technology name must appear in the vacancy text, although we do not require that the words appear in order.

For the three social media technologies in the list (Facebook, YouTube, and LinkedIn), we explicitly search for and exclude false positives in our analysis. To identify false positives, we search for phrases that strongly suggest the ad is directing the reader to visit or follow the firm on social media. For example, any of the following bracketed phrases along with the mention of "facebook" would be flagged as a false positive for the Facebook technology: "[fan us][visit us][like us][connect with us][follow us][check us out][for more information][please visit][share this job][how did you hear][look for us][learn more about] ... facebook." We perform the analogous exercise to create false positive flags for YouTube and LinkedIn. We conducted robustness to our method of identifying false positives, such as creating a "true positive" flag that explicitly identifies the phrase "social media" along with other words, such as "knowledge," "experience," or "proficiency" in the ad, and the results are unchanged.

Table B.4: Technologies Extracted from Job Vacancy Data (with Frequency per 100)

microsoft excel	2.0566	apache hive	0.0135
sap	1.4853	geographic information system gis software	0.0134
linux	1.4065	microsoft dynamics gp	0.0133
microsoft project	1.3218	transact-sql	0.0132
microsoft word	1.1720	unified modeling language uml	0.0125
javascript	1.1669	apache cassandra	0.0119
unix	1.0452	apache pig	0.0097
microsoft office	1.0363	extensible markup language xml	0.0077
microsoft access	0.8903	cascading style sheets css	0.0077
microsoft windows	0.8149	oracle business intelligence enterprise edition	0.0076
react	0.7996	apache kafka	0.0071
microsoft outlook	0.7230	spring boot	0.0071
python	0.7208	integrated development environment ide software	0.0068
c++	0.7007	delphi technology	0.0065
microsoft powerpoint	0.6548	apache groovy	0.0060
microsoft sql server	0.5013	adobe systems adobe creative cloud	0.0057
oracle java	0.4844	enterprise resource planning erp software	0.0054
chef	0.4732	atlassian bamboo	0.0053
sas	0.4551	virtual private networking vpn software	0.0046
ruby	0.4071	node.js	0.0045
tax software	0.3962	ibm spss statistics	0.0045
ajax	0.3503	google angularjs	0.0037
mysql	0.3412	hypertext markup language html	0.0036
git	0.2910	job control language jcl	0.0030
swift	0.2735	apache subversion svn	0.0019
microsoft sharepoint	0.2653	oracle hyperion	0.0015
citrix	0.1815	backbone.js	0.0014
microsoft visio	0.1793	customer information control system cics	0.0013
facebook	0.1707	oracle primavera enterprise project portfolio management	0.0013

nosql	0.1579	adobe systems adobe aftereffects	0.0009
tableau	0.1526	microsoft asp.net	0.0007
linkedin	0.1426	practical extraction and reporting language perl	0.0007
bash	0.1416	ca erwin data modeler	0.0006
microsoft visual studio	0.1412	microsoft active server pages asp	0.0002
microsoft dynamics	0.1411	common business oriented language cobol	0.0001
relational database management software	0.1397	salesforce software	0.0001
microsoft exchange server	0.1342	google analytics	0.0001
google drive	0.1230	computer aided design cad software	0.0001
epic systems	0.1166	qlik tech qlikview	0.0000
objective c	0.1140	ibm websphere	0.0000
microsoft sql server reporting services	0.1110	junit	0.0000
selenium	0.1097	oracle peoplesoft	0.0000
puppet	0.1069	microsoft .net framework	0.0000
spring framework	0.1022	microsoft asp.net core mvc	0.0000
apache tomcat	0.1010	yardi	0.0000
data entry software	0.0952	oracle taleo	0.0000
microsoft visual basic	0.0860	national instruments labview	0.0000
symantec	0.0858	oracle pl/sql	0.0000
mongodb	0.0846	splunk enterprise	0.0000
youtube	0.0825	marketo marketing automation	0.0000
red hat enterprise linux	0.0769	healthcare common procedure coding system hcpcs	0.0000
ruby on rails	0.0690	adobe systems adobe indesign	0.0000
postgresql	0.0617	microsoft powershell	0.0000
microsoft azure	0.0549	c#	0.0000
shell script	0.0532	the mathworks matlab	0.0000
scala	0.0508	aws redshift	0.0000
teradata database	0.0492	microstrategy	0.0000
drupal	0.0486	handheld computer device software	0.0000
nagios	0.0476	google adwords	0.0000
confluence	0.0466	minitab	0.0000
verilog	0.0458	netsuite erp	0.0000
adobe systems adobe acrobat	0.0457	autodesk autocad civil d	0.0000
mcafee	0.0448	oracle weblogic server	0.0000
docker	0.0442	medical procedure coding software	0.0000
oracle jdbc	0.0439	apple macos	0.0000

adobe systems adobe photoshop	0.0438	microsoft visual basic scripting edition vbscript	0.0000
intuit quickbooks	0.0433	smugmug flickr	0.0000
eclipse ide	0.0408	oracle jd edwards enterpriseone	0.0000
fund accounting software	0.0348	enterprise javabeans	0.0000
apache hadoop	0.0337	dassault systemes catia	0.0000
adobe systems adobe illustrator	0.0325	apache solr	0.0000
oracle fusion applications	0.0322	trimble sketchup pro	0.0000
google docs	0.0314	wireshark	0.0000
ubuntu	0.0307	red hat wildfly	0.0000
apache maven	0.0298	ibm infosphere datastage	0.0000
django	0.0282	adobe systems adobe dreamweaver	0.0000
structured query language sql	0.0282	github	0.0000
apache http server	0.0250	medical condition coding software	0.0000
hibernate orm	0.0245	javascript object notation json	0.0000
meditech software	0.0237	elasticsearch	0.0000
apache ant	0.0231	oracle javaserver pages jsp	0.0000
ansible software	0.0229	php: hypertext preprocessor	0.0000
autodesk autocad	0.0219	supervisory control and data acquisition scada software	0.0000
ibm notes	0.0186	advanced business application programming abap	0.0000
atlassian jira	0.0182	oracle solaris	0.0000
adp workforce now	0.0178	blackbaud the raiser's edge	0.0000
apache struts	0.0156	bentley microstation	0.0000
sap crystal reports	0.0148	dassault systemes solidworks	0.0000
esri arcgis software	0.0146	autodesk revit	0.0000
jquery	0.0140	ibm cognos impromptu	0.0000

B.4 Tasks and Market Size

Tables B.5 and B.6 reproduce Tables 2 and 3, respectively, except with a continuous measure of market size on the right-hand side—log population—rather than market size decile indicators. The tasks with the largest positive and negative gradients are similar to those presented in Section III. Table B.7 re-estimates equation (1) using a predetermined list of verbs from Michaels et al. (2018) instead of our task list extracted from the text itself. The takeaway is quite similar. Using only the Michaels et al. (2018) verb list, more abstract or non-routine verbs, such as "design," "project," "research," and "manage," have the steepest positive gradient, while more routine verbs, such as "store," "clean," and "count," and manual verbs, such as "fuel" and "rotate," have the steepest negative gradient.

Table B.5: Tasks with the Steepest Gradient in Log Population

Positive Gradient				Negative Gradient			
No SOC f.e.		SOC f.e.		No SOC f.e.		SOC f.e.	
Task-Population	$\hat{\beta}$	Task	$\hat{\beta}$	Task-Population	$\hat{\beta}$	Task	$\hat{\beta}$
written communication	0.0451	written skills	0.0134	maintain store	-0.0414	maximizes profitability	-0.0303
managing projects	0.0367	achieving sales	0.0121	operating cash_register	-0.0393	protect company	-0.0288
providing support	0.0294	ensure safety	0.0115	provide customer_service	-0.0380	maintain store	-0.0272
develop solutions	0.0269	stand walk	0.0113	protect company	-0.0357	operating cash_register	-0.0256
problem_solving skills	0.0268	prioritize tasks	0.0111	maximizes profitability	-0.0350	make changes	-0.0236
meet deadlines	0.0263	providing coaching	0.0106	greeting customers	-0.0321	greeting customers	-0.0217
work projects	0.0234	driving sales	0.0105	assist store	-0.0313	procedures cash	-0.0215
support business	0.0230	supervising store	0.0104	make changes	-0.0298	skating carhop	-0.0198
written skills	0.0219	providing environment	0.0102	maintaining inventory	-0.0274	unloading trucks	-0.0186
developing strategies	0.0217	meet deadlines	0.0101	procedures cash	-0.0273	ensure employees	-0.0185
provide guidance	0.0212	written communication	0.0100	following company	-0.0264	drive_in employees	-0.0177
identify opportunities	0.0207	identify opportunities	0.0099	preventing trafficking	-0.0264	assigned store	-0.0176
develop business	0.0205	exceed sales	0.0097	unloading trucks	-0.0257	maintaining inventory	-0.0175
will teams	0.0200	provide feedback	0.0097	skating carhop	-0.0255	provide customer_service	-0.0173
working team	0.0198	managing projects	0.0096	assigned store	-0.0251	working store	-0.0161

The table above reproduces Table 2, but it replaces the right-hand side market size decile indicators with a continuous log population measure. The coefficients above present the tasks with the steepest positive and negative gradients with respect to market size, as captured by $\hat{\beta}$ on the continuous population measure. All coefficients are statistically significant at the 1 percent level, except "supervising store" in column 3 ($p = 0.091$).

Table B.6: Technologies with the Steepest Gradient in Log Population

All		**College**		**High School**	
Technology	$\hat{\beta}$	Technology	$\hat{\beta}$	Technology	$\hat{\beta}$
Linux	0.0361	Python	0.0352	Microsoft Excel	0.0174
JavaScript	0.0324	Linux	0.0327	Microsoft Outlook	0.0127
Python	0.0319	JavaScript	0.0317	Microsoft Office	0.0108
Unix	0.0309	Unix	0.0283	Microsoft Word	0.0102
Microsoft Excel	0.0288	Ruby	0.0249	Chef	0.0097
Microsoft Project	0.0272	C++	0.0246	Microsoft Powerpoint	0.0088
C++	0.0256	SAS	0.0222	Microsoft Access	0.0086
Oracle Java	0.0220	Microsoft Project	0.0219	Linux	0.0068
SAP	0.0215	Oracle Java	0.0215	Epic Systems	0.0065
Microsoft Access	0.0209	Microsoft Excel	0.0203	Swift	0.0061
SAS	0.0205	Git	0.0198	Citrix	0.0060
MySQL	0.0202	Ajax	0.0198	Tax Software	0.0056
Git	0.0199	MySQL	0.0196	Facebook	0.0056
Microsoft Office	0.0196	Tableau	0.0195	Microsoft Sharepoint	0.0056
Microsoft Powerpoint	0.0193	NoSQL	0.0187	Python	0.0054

We reproduce Table 3 by re-estimating equation 1 except replacing the right-hand side market size decile indicators with a continuous log population measure. All estimates are statistically significant at the 1 percent level, with the following exceptions: C++ in the college column ($p = 0.025$) and Swift in the high school column ($p = 0.017$).

Table B.7: Verbs with the Steepest Gradient

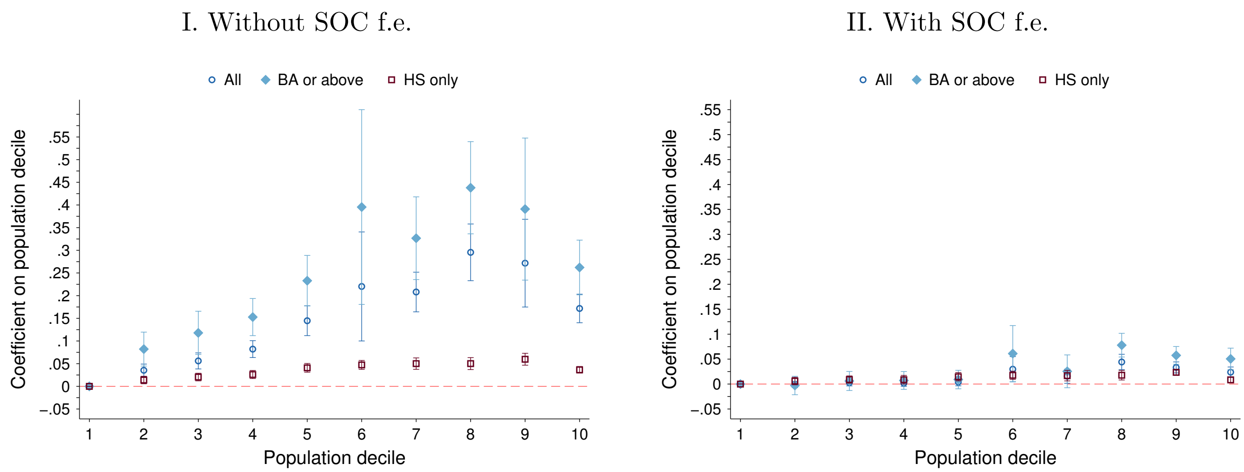
Positive gradient		Negative gradient	
Task	$\hat{\beta}_{10}$	Task	$\hat{\beta}_{10}$
experience	0.2698	truck	-0.3079
design	0.2559	pay	-0.2785
project	0.2533	earn	-0.2413
beach	0.2490	fuel	-0.2351
research	0.2187	get	-0.2278
develop	0.2086	authorize	-0.2053
manage	0.1966	clean	-0.1948
analyze	0.1914	store	-0.1849
resume	0.1899	rotate	-0.1821
create	0.1839	count	-0.1702
process	0.1803	drop	-0.1569
finance	0.1657	trash	-0.1545
content	0.1642	haul	-0.1507
equal	0.1623	lease	-0.1492
web	0.1614	average	-0.1442

The table above reproduces Table 2 using the list of verbs from Michaels et al. (2018). This exercise is conducted on a 1 percent sample of all job ads, rather than 5 percent, for computational speed, since the verb list includes 1,665 verbs. All estimates are statistically significant at the 1 percent level.

B.5 Technology Requirements and Market Size

We check the sensitivity of our result on the market size gradient of technologies with respect to our decision to exclude R and C from the technology list. Figure B.2 reproduces Figure 3 but includes the technologies R and C, which are potentially susceptible to false positives in processing the job vacancy text. Our main result is largely unaffected.

Figure B.2: The Technology Gradient (including R and C)



The figure above reproduces Figure 3 but includes the technologies R and C.

B.6 Wages and Tasks Across Space

This section demonstrates that tasks extracted from job vacancy ads account for variation in wages across geography, above and beyond what is captured by occupational codes.

For this analysis, we construct occupation-education-market average tasks from the job ads data. We then merge mean wages at the occupation-education-market level from the IPUMS-ACS. Finally, we regress log wages on tasks with different sets of controls. All regressions are weighted by employment in the cell.

Note that these regressions probably understate the explanatory power of job tasks in accounting for wage variation, since we do not observe ad-level wages and these are regressions of mean wages on mean tasks using variation across geography-education cells. While it is tempting to interpret these estimates as hedonic regressions that are delivering "task prices," we should avoid this interpretation because tasks are endogenous to unobserved worker sorting or job characteristics.

Table B.8 first shows that task variation across geography accounts for variation in wages above and beyond what is captured by occupation fixed effects. This result can be seen by the statistically significant coefficients on tasks in columns 3-6. Note that the slight increase in R^2 between columns 2 and 3 indicates that the five task categories capture only 0.1 percent of wage variation beyond occupation categories. Column 4 adds the granular task measures averaged to the occupation-education-market cell to the regression. The granular task measures account for an additional 1.7 percent of wage variation, as seen by comparing R^2 between columns 3 and 4. Thus, the granular tasks extracted from job descriptions capture meaningful information about job tasks that are reflected in wages. Note that for jobs requiring a four-year college degree, non-routine analytic tasks have a stronger relationship with wages than for jobs requiring a high school diploma only.

Table B.9 presents regressions of log wages on log population, tasks, and tasks interacted with population. In the coefficient on log-population, we confirm the finding in the literature that the relationship between population and wages is stronger for higher educated workers. We also see that the interaction terms between population and tasks appears important. For example, column 2 shows that an increase in interactive tasks in larger labor markets accounts for higher wages of jobs requiring a four-year college degree, while an increase in interactive tasks for jobs requiring a high school diploma has a weaker correlation with wages. Note that this table uses *within-occupation* variation in tasks across geography in accounting for higher wages. Overall, Tables B.8 and B.9 show that task variation across space accounts for variation in wages above and beyond occupation codes.

Table B.8: Wages and Tasks

	Baseline				HS only	BA or above
	(1)	(2)	(3)	(4)	(5)	(6)
Non-routine analytic	0.225***		0.041***	0.039***	0.013**	0.049***
	(0.013)		(0.009)	(0.010)	(0.005)	(0.014)
Non-routine interactive	0.091***		-0.002	-0.011**	0.007	-0.005
	(0.012)		(0.005)	(0.004)	(0.007)	(0.007)
Routine cognitive	-0.008**		-0.017***	-0.000	-0.021***	-0.012
	(0.004)		(0.003)	(0.003)	(0.004)	(0.010)
Routine manual	0.060***		-0.015***	-0.006*	-0.015***	-0.049***
	(0.004)		(0.004)	(0.004)	(0.004)	(0.009)
Non-routine manual	0.040***		0.009**	-0.001	0.002	-0.051***
	(0.007)		(0.004)	(0.004)	(0.004)	(0.011)
SOC f.e.	No	Yes	Yes	Yes	Yes	Yes
Text-based tasks	No	No	No	Yes	No	No
Number of observations	62,014	62,014	62,014	62,014	36,078	25,936
R^2	0.551	0.882	0.883	0.900	0.758	0.821
Adjusted R^2		0.882	0.883	0.899	0.757	0.820
Mean of dep. var.	10.70	10.70	10.70	10.70	10.49	10.99

The unit of observation is the occupation-education-market. The dependent variable is log wages, regressed on Spitz-Oener (2006) task-related keywords per 1,000 ad words, which are standardized to have mean zero and standard deviation one across ads before averaging to the cell. Column 4 includes the verb-noun tasks averaged to the occupation-education-market cell. Education category dummies are included in columns 1-4. Regressions are weighted by employment. Standard errors are clustered at the CZ level.

Table B.9: Wages and Task-Population Gradient

	HS only	BA or above
	(1)	(2)
Log pop.	0.039***	0.016***
× non-routine analytic	(0.003)	(0.004)
Log pop.	0.013***	0.021***
× non-routine interactive	(0.004)	(0.007)
Log pop.	0.004***	0.007
× routine cognitive	(0.001)	(0.005)
Log pop.	-0.016***	-0.013***
× routine manual	(0.002)	(0.004)
Log pop.	0.000	-0.012*
× non-routine manual	(0.002)	(0.007)
Log population	0.065***	0.071***
	(0.007)	(0.007)
SOC f.e.	Yes	Yes
Number of observations	36,078	25,936
R^2	0.800	0.888
Mean of dep. var.	10.49	10.99

The unit of observation is the occupation-education-market. The dependent variable is log wages, which is regressed on four-digit SOC f.e., tasks, log population, and log population interacted with tasks. Tasks are standardized to have mean zero and standard deviation one across ads before averaging to the cell. Regressions are weighted by employment. Task coefficients are not reported above. Standard errors are clustered at the market level. Tasks correspond to the classification in Spitz-Oener (2006).

C Analysis Appendix

This section presents tables and figures to supplement the main analysis.

C.1 Appendix to Sections III.A and III.B

In this appendix, we present additional tables and figures on the relationships among job tasks and population.

Within-Between Decompositions

To further evaluate how much of the variation in occupational tasks across geography is due to within- versus between-occupation variation in task content, we perform a simple decomposition. Denote the average task k content in market size quartile q as, $t_{kq} = \sum_{o \in \mathcal{O}} t_{koq} s_{oq}$, where the average task content of each occupation o in quartile q, t_{koq}, is multiplied by occupation o's share of quartile q's employment, s_{oq}. We express the difference in task content between two quartiles, q and $\tilde{q}$, as

$$t_{kq} - t_{k\tilde{q}} = \sum_{o \in \mathcal{O}} (t_{koq} - t_{ko\tilde{q}}) \bar{s}_{oq\tilde{q}} + \sum_{o \in \mathcal{O}} \bar{t}_{koq\tilde{q}} (s_{oq} - s_{o\tilde{q}}), \tag{C.1}$$

where $\bar{s}_{oq\tilde{q}} = (s_{oq} + s_{o\tilde{q}})/2$ and $\bar{t}_{koq\tilde{q}} = (t_{koq} + t_{ko\tilde{q}})/2$. The first term on the right-hand side of equation (C.1) represents the within component, and the second term represents the between component. Dividing both sides by $(t_{kq} - t_{k\tilde{q}})$ yields the within and between shares.

Table C.1 presents the results of this decomposition. For non-routine analytic tasks, 14 percent of the variation between 1st quartile and 4th quartile CZs is within occupation. For non-routine interactive tasks, the corresponding figure is 22 percent. This result implies that standard data sources fail to capture much of the variation in tasks between small and large labor markets.

We perform the decomposition on each of our granular task measures to understand how much of the variation in these tasks across markets occurs within occupations versus between occupations. We calculate the decomposition shares for each of the granular tasks and report the median. We find that 18 percent of the variation from smallest to largest quartile CZs occurs within occupations. Applying the equation (C.1) decomposition to the number of technologies, we find that about 79 percent of the variation in technologies between 1st quartile CZs and 4th quartile CZs occurs between occupations and about 21 percent within occupations.

Table C.2 examines the sensitivity of our within-between decomposition of Table C.1 to measurement error. To do so, we randomly assign ads to population quartiles, in proportion to the actual distribution of six-digit SOCs across quartiles. We then reproduce the within-between decomposition exercise of Table C.1. Since we randomize ads to quartiles, the within shares should be close to or exactly zero. Table C.2 shows that most of the within shares are close to zero and most of the between shares are close to one, as we would expect if measurement error were not a major concern. This pattern notably holds for the Q4-Q1 decompositions. There are a couple of exceptions to this pattern, such as the routine cognitive decompositions for the Q4-Q3 and Q3-Q2 differences. However, in those cases the within shares are less meaningful, as the differences in average tasks (the denominators in the decompositions) are nearly zero. Overall, the main takeaway from Table C.2 is that our within-between decompositions are robust to measurement error.

Evidence for Jobs Being Jointly Intensive in Interactive and Analytic Tasks

We consider whether jobs that are jointly intensive in interactive and analytic tasks appear predominantly in large markets. We place each job into one of four groups based on whether it is above or below the median non-routine interactive task content and above or below the median non-routine analytic task content. We then plot, for each CZ population decile, the difference between the proportion of jobs in each of the four groups relative to the proportion of jobs in the same group in the first CZ decile. This plot is presented as the left panel of Figure C.1. We find that 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, while jobs that are only interactive but not analytical make up a smaller share of total jobs in the highest decile markets, relative to smallest decile markets. This finding holds even after removing the mean task content at the six-digit SOC level before categorizing into the four groups, as seen in the right panel of Figure C.1.

Internal and External Interactive Tasks by Education

In Figure C.2, we explore whether the gradients presented in Figure 2 differ according to the jobs' educational requirements. For the most part, gradients are steeper for jobs requiring a college degree. However, in specifications with six-digit SOC fixed effects, the difference between these gradients is minor.

Sensitivity to Time Period

In Figure C.3, we explore whether the key tasks and technologies gradients of Figures 1 and 3 might be sensitive to the time period studied. Specifically, a potential concern is that a rapidly changing labor market in large versus small CZs might generate changing gradients over time. To explore this issue, we divide the sample period into two approximately equal periods, 2012-2014 and 2015-2017, and re-estimate panel I of each of the two figures. The results are highly stable across the two time periods.

Market Density and Tasks and Technologies

We next assess whether the task and technology patterns with respect to CZ population size, observed in Figures 1-4, also hold with respect to CZ population density. We construct CZ population density deciles. Then, we reproduce Figures 1-4 using population density deciles, as opposed to population size deciles, as the explanatory variables of interest. The coefficient estimates are presented in Figures C.4-C.7.

Table C.1: Task Decomposition Across Markets

	NR-Analytic		NR-Interactive		NR-Manual		R-Cognitive		R-Manual		Granular Tasks		Technologies	
Q1	5.28		5.66		0.81		0.71		2.74				0.12	
Q2	6.42		6.10		0.82		0.78		2.49				0.20	
Q3	7.51		6.49		0.77		0.78		2.20				0.32	
Q4	7.78		6.84		0.74		0.76		2.09				0.34	
	Between and Within Occupational Decomposition													
	Between	Within	Between	Within	Between	Within	Between	Within	Between	Within	Between	Within	Between	Within
Q2-Q1	0.80	0.20	0.78	0.22	0.97	0.03	1.08	-0.08	0.49	0.51	0.63	0.37	0.84	0.16
Q3-Q2	0.93	0.07	0.83	0.17	0.51	0.49	-4.25	5.25	0.59	0.41	0.61	0.39	0.79	0.21
Q4-Q3	1.01	-0.01	0.70	0.30	0.72	0.28	0.07	0.93	0.72	0.28	0.04	0.96	0.36	0.64
Q4-Q1	0.86	0.14	0.78	0.22	0.53	0.47	1.71	-0.71	0.57	0.43	0.82	0.18	0.79	0.21

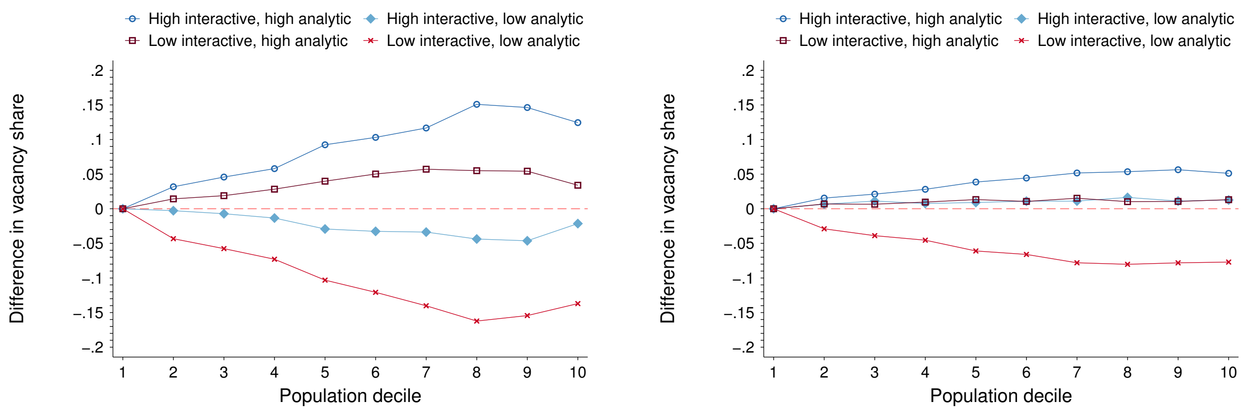
This table presents the results of the decomposition of equation (C.1) for each of the five task categories (non-routine analytic, non-routine interactive, non-routine manual, routine cognitive, and routine manual), each granular task (reporting the median), and the number of technologies. The top panel reports the average task content and the average number of technologies in each of four market size quartiles. Tasks in the top panel are expressed as number of task-word mentions per 1,000 ad words, and technologies are expressed as the average number of technologies mentioned per ad. The bottom panel presents the within and between shares of the total difference between population quartiles. The decomposition for granular tasks is constructed by first calculating the decomposition for each of the 399 tasks separately and then taking the median of the within and between shares.

Table C.2: Task Decomposition Across Markets: Sensitivity to Measurement Error

	NR-Analytic		NR-Interactive		NR-Manual		R-Cognitive		R-Manual		Granular Tasks		Technologies	
Q1	5.49		5.78		0.80		0.69		2.58				0.13	
Q2	6.43		6.15		0.81		0.77		2.45				0.21	
Q3	7.41		6.46		0.78		0.79		2.27				0.31	
Q4	7.70		6.71		0.75		0.79		2.19				0.32	
	Between and Within Occupational Decomposition													
	Between	Within	Between	Within	Between	Within	Between	Within	Between	Within	Between	Within	Between	Within
Q2-Q1	1.00	0.00	0.99	0.01	0.93	0.07	1.00	-0.00	0.99	0.01	0.99	0.01	1.00	-0.00
Q3-Q2	1.01	-0.01	1.03	-0.03	0.94	0.06	0.85	0.15	0.97	0.03	0.99	0.01	1.00	0.00
Q4-Q3	0.96	0.04	0.98	0.02	1.02	-0.02	0.13	0.87	1.04	-0.04	0.86	0.14	0.99	0.01
Q4-Q1	1.00	0.00	1.00	-0.00	0.98	0.02	0.98	0.02	1.00	0.00	0.99	0.01	1.00	0.00

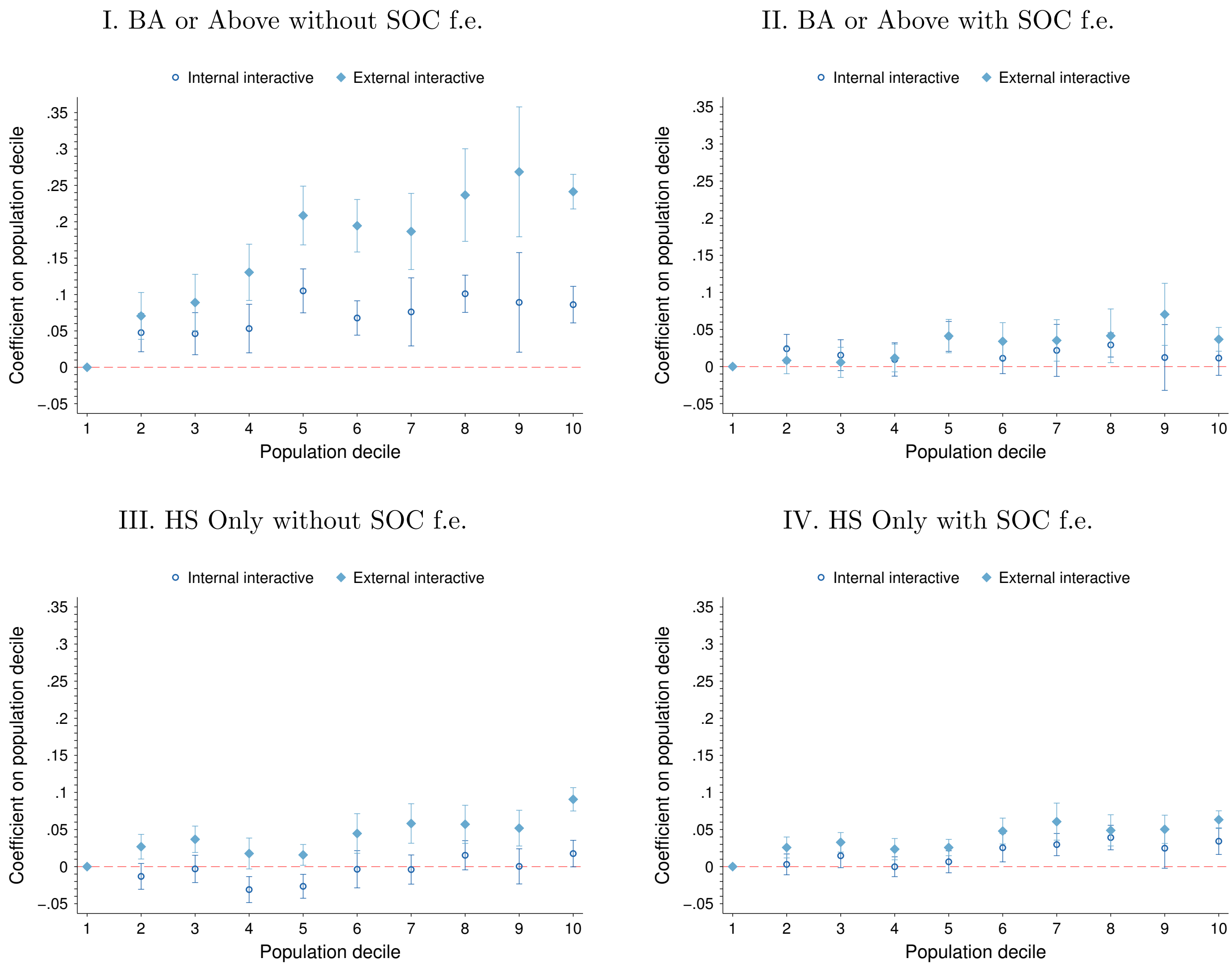
This table checks the sensitivity of Table C.1 to measurement error. To do so, we randomize job ads to population quartiles, based on the actual distribution of six-digit SOCs across quartiles. We then reproduce the decomposition of Table C.1. Since ads are randomized to quartiles, the within shares should be approximately zero.

Figure C.1: Interactive and Analytic Tasks and Market Size



The panels above depict the distribution of jobs across space. To construct the left panel, we first place job ads into one of four mutually exclusive groups, based on whether they are above or below the median non-routine interactive task content and non-routine analytic task content. We then plot the difference between the proportion of jobs in each of the four categories (high or low analytic or interactive) relative to the proportion of jobs in the same category in the first CZ decile. The right panel is constructed in the same way, except we first subtract the SOC mean task content from each job before placing jobs into groups. Hence, the right panel reflects within-occupation changes in task content across space.

Figure C.2: O*NET Interactive Tasks Gradient

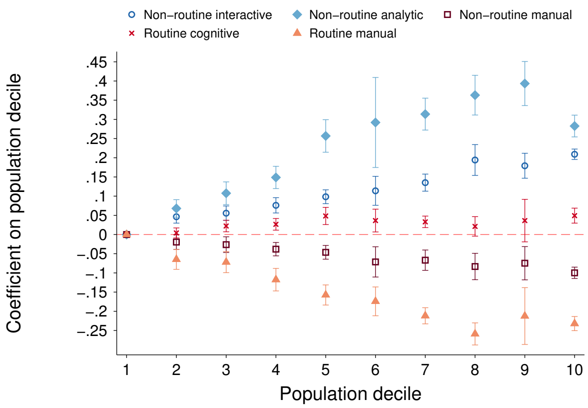


This figure reproduces Figure 2 separately by the educational requirement of the job. Panels I and II restrict the sample to ads requiring a BA or above, while panels III and IV restrict the sample to ads requiring high school only.

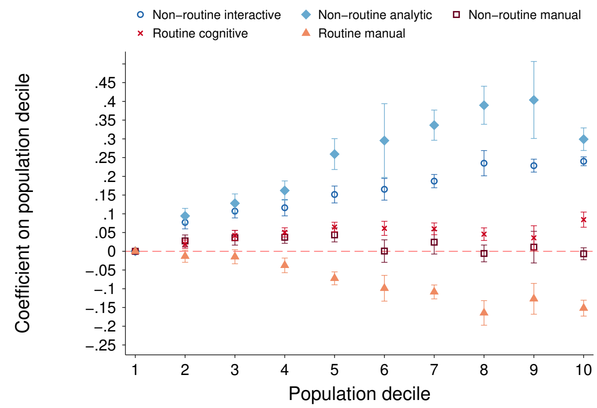
Figure C.3: Tasks and Technologies Gradient by Sample Period

A. Tasks

I. 2012-2014

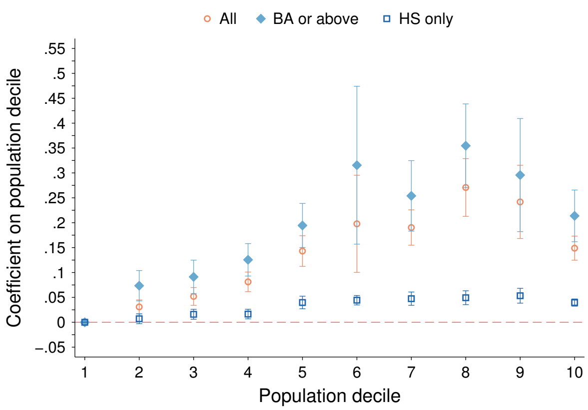


II. 2015-2017

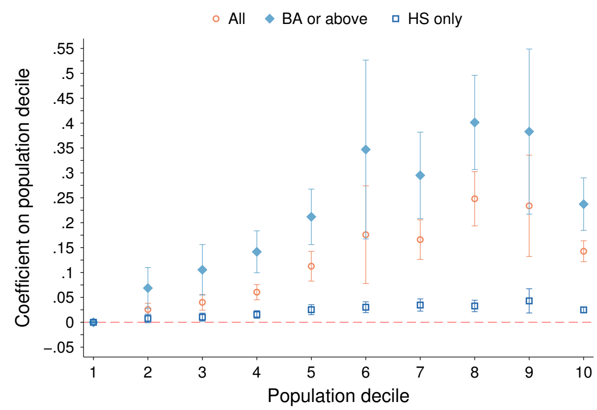


B. Technologies

III. 2012-2014

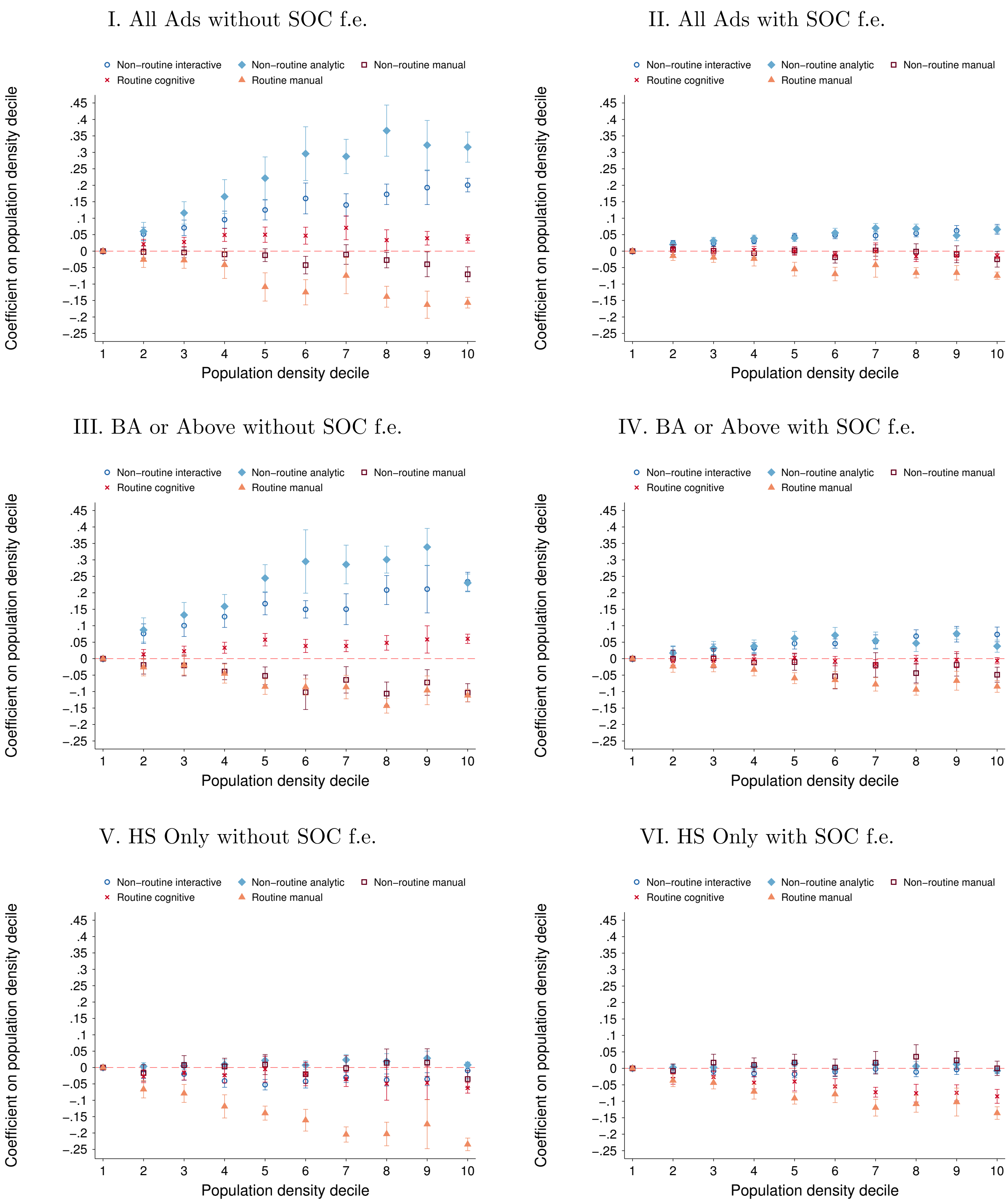


IV. 2015-2017



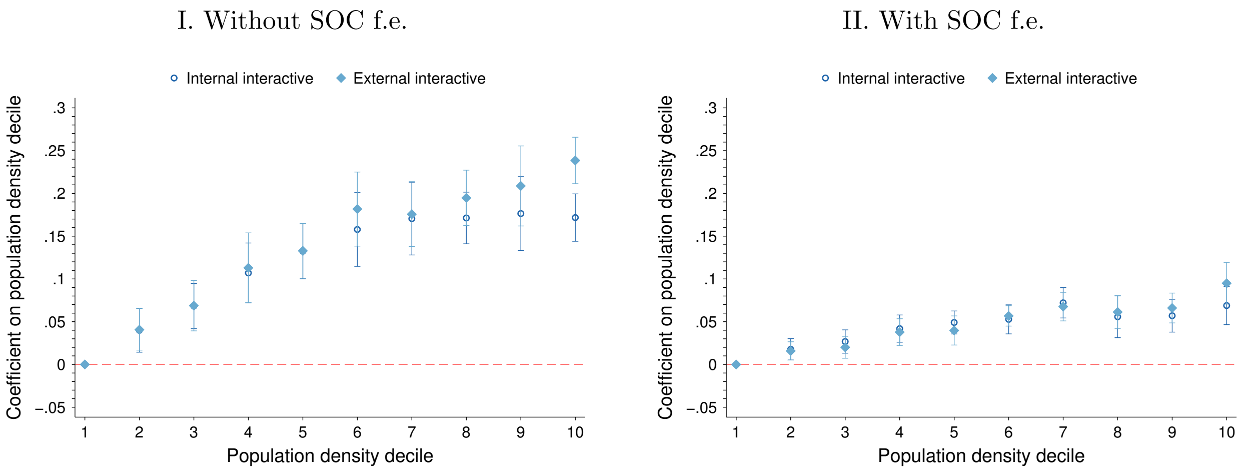
This figure presents estimates of Figure 1, panel I and Figure 3, panel I by time period. We divide the sample period into 2012-2014 and 2015-2017.

Figure C.4: Tasks and Market Density



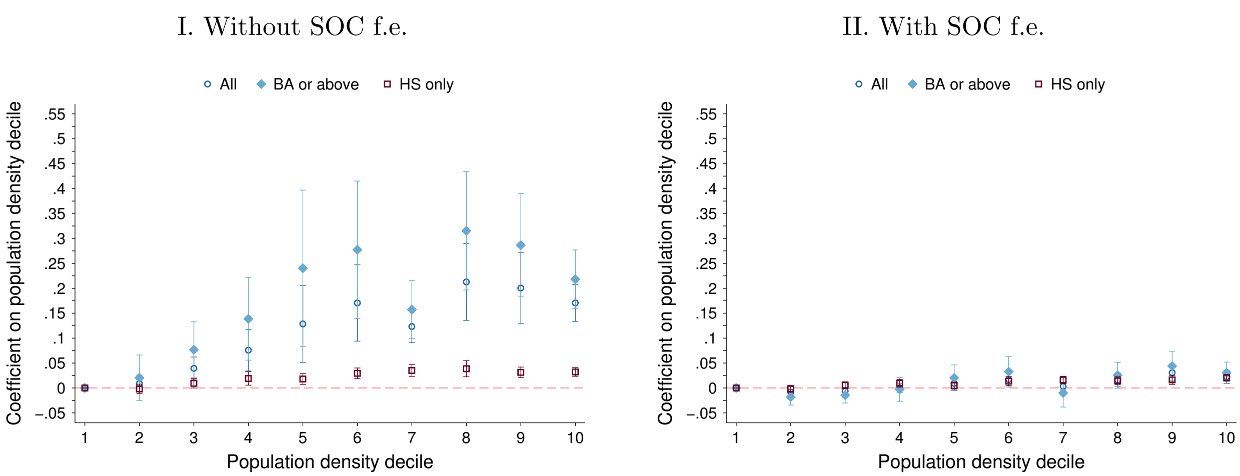
This figure reproduces Figure 1 but substitutes CZ population density deciles for CZ population deciles.

Figure C.5: O*NET Interactive Tasks and Market Density



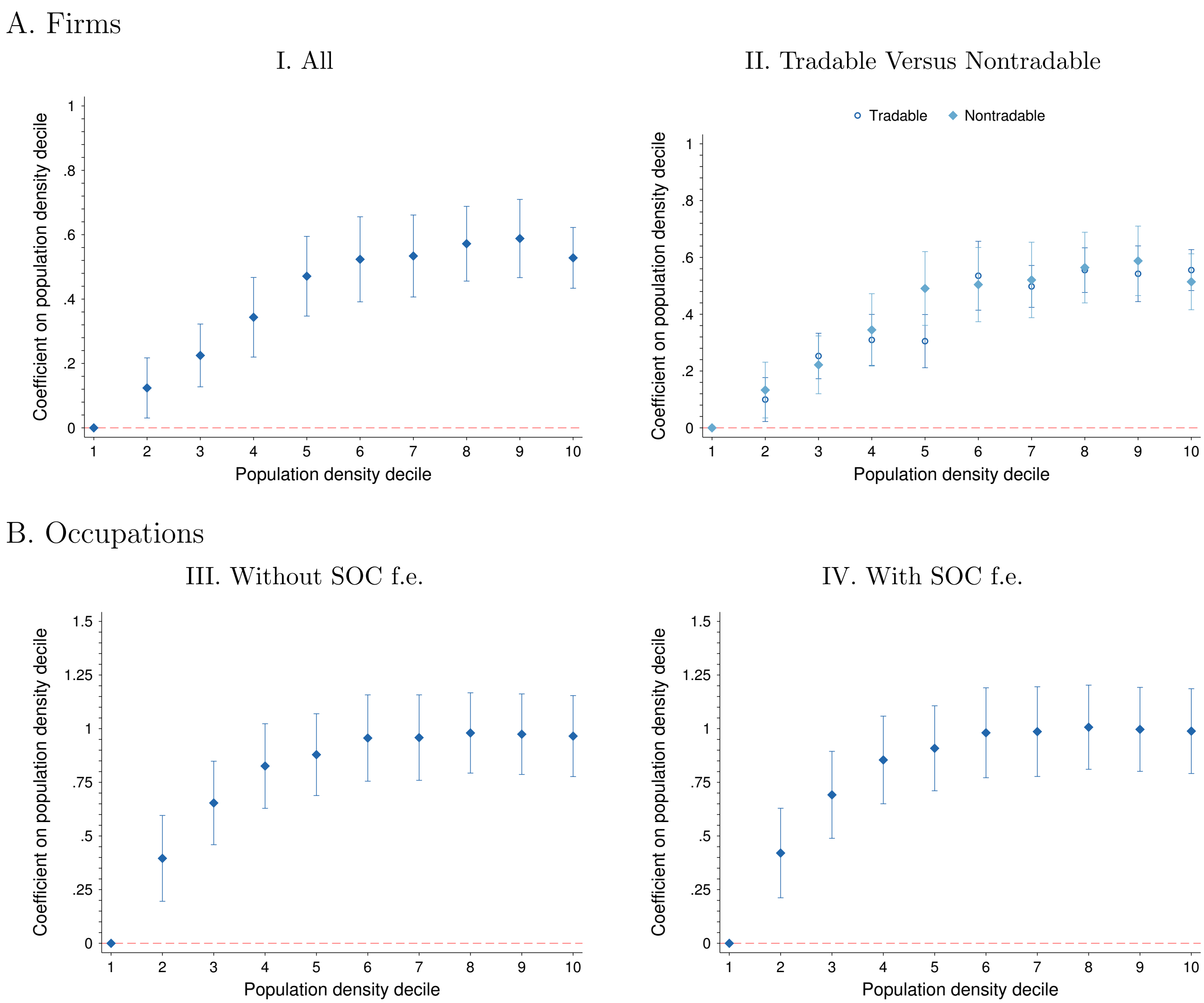
This figure reproduces Figure 2 but substitutes CZ population density deciles for CZ population deciles.

Figure C.6: The Technology Gradient with Market Density



This figure reproduces Figure 3 but substitutes CZ population density deciles for CZ population deciles.

Figure C.7: Specialization Gradient and Market Density



This figure reproduces Figure 4 but substitutes CZ population density deciles for CZ population deciles.

C.2 Specialization and Market Size

This section provides supplemental evidence on the relationship between specialization within and between firms and market size.

Robustness to the Number of Tasks

Our measurement approach requires setting a threshold for the number of tasks (verb-noun pairs) we use to study specialization. In the paper, we use a task list of 500 verb-noun pairs, which we winnow down to 399 by excluding those that, according to our judgment, do not reflect job tasks.

In this section, we increase the number of tasks to 2,000—a higher resolution—and reproduce Figure 4, the main figure using these granular task measures to study the relationship between specialization and market size. Figure C.8 shows that the results are not sensitive to increasing the number of tasks to 2,000. Figure C.9 reproduces Figure 4 where the specialization measures are based on a task vector of 300—i.e., keeping the most common 300 of our main specification's 399 tasks. Figure C.9 shows that the results are not sensitive to reducing the number of tasks to 300.

We lastly check the sensitivity of our specialization results to aggregating granular tasks that have similar meanings. The task extraction algorithm produces some distinct tasks that are similar, such as "provide feedback" and "provide recommendations." Rather than rely on our judgment to determine the similarity of different tasks, we use a natural language processing approach that uses word contexts (from a separate corpus) to aggregate similar tasks. To group our verb-noun tasks into a smaller number of clusters, we follow two steps. In the first step, we convert our list of tasks into a vector representation, using the Word2Vec implementation in the Gensim library for Python. Specifically, we use one of Gensim's pre-trained models, which was trained on the Google News data set. Using this model, we recover each task's underlying representation as a 100-element vector.[8] We next add the vector representation of the verb to that of the noun, so as to obtain a single vector for each task. In the second step, we cluster tasks in this vector space, using Stata's implementation of k-means clustering. The algorithm requires specifying the number of clusters ex-ante, and we experiment with 50, 75, and 100, all of which entail a substantial dimensionality reduction relative to our original list of tasks. We choose 75 task clusters for the exercise presented here, but we note that we examined the sensitivity to this choice to using 50 or 100 task clusters and it has little effect on the results.

Tables C.3-C.4 illustrate how the aggregation works. The tables show the original list of 399 tasks and the corresponding 75 task clusters. The first task cluster the algorithm creates is "identifies problems," "resolve issue," and "resolve problems." The second task cluster includes intuitively similar tasks such as "provide feedback," "provide recommendations," "provide guidance," and "provide leadership," but also includes tasks we may not a priori view as similar, such as "offer products" or "make offer." We believe the clustering method does a reasonably good job of aggregating similar tasks in a way that minimizes bias from excess reliance on researcher discretion. Using the 75 task clusters, we calculate

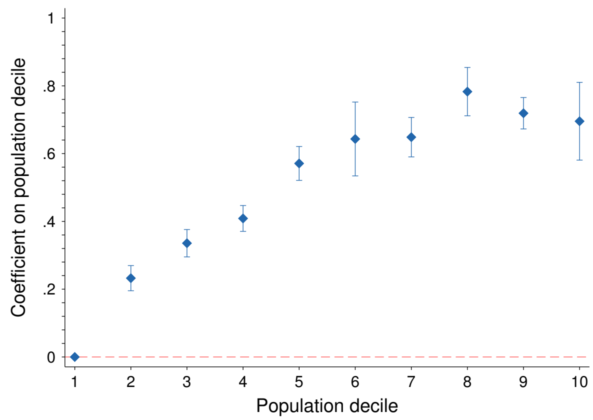
[8]This library can be found at https://radimrehurek.com/gensim/index.html. The library's documentation states that the Google News model was trained on "about 3 million words and phrases." We adopt Gensim's default for the size of vector representation.

task cluster dissimilarities in firm-market and occupation-market cells and reproduce the key specialization gradients in the paper. Figure C.10 shows the results of this exercise. This figure shows a similar specialization gradient as Figure 4, reinforcing the finding of increased specialization in larger markets.

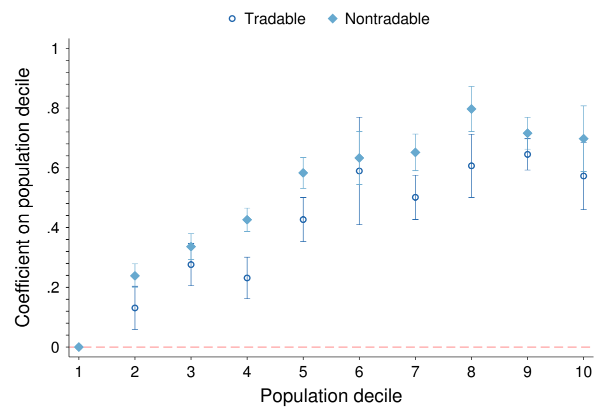
Figure C.8: Specialization Gradient: Task Dissimilarity Within Firms and Occupations (with 2,000 Tasks)

A. Firms

I. All

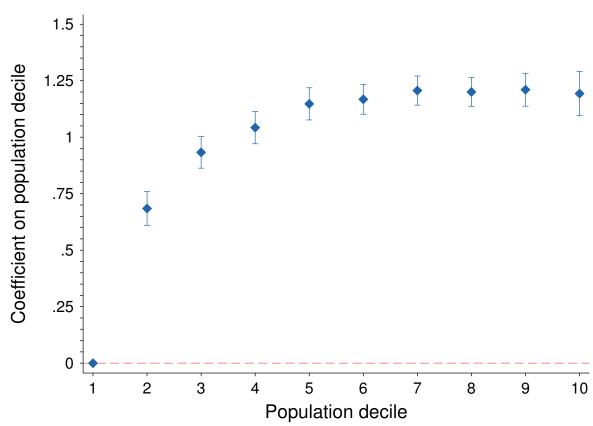


II. Tradable Versus Nontradable

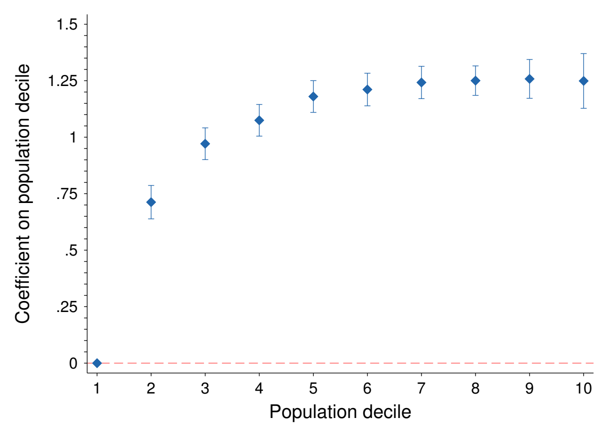


B. Occupations

III. Without SOC f.e.

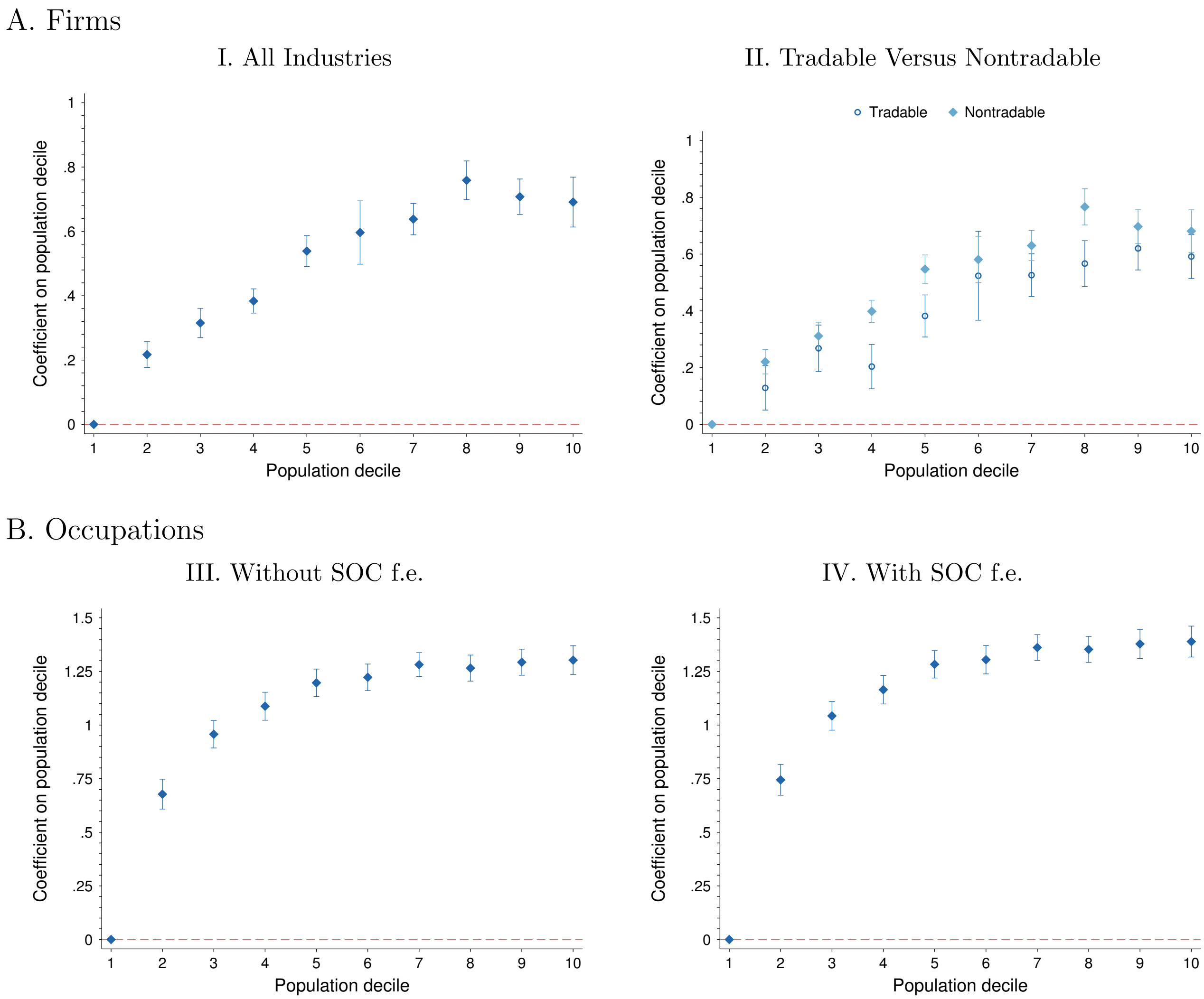


IV. With SOC f.e.



The figure above reproduces Figure 4, except the task dissimilarity measures in the occupation-CZ are constructed based on extracting 2,000 tasks, a higher resolution vector of verb-noun tasks per job ad. For reference, the 1st population decile mean for the top left panel is -0.51, and for the top right panel, it is -0.54 for the nontradable sample and -0.07 for the tradable sample. The 1st population decile mean for the bottom two panels is -1.01.

Figure C.9: Specialization Gradient: Task Dissimilarity Within Firms and Occupations (300 Tasks)



This figure reproduces Figure 4 using a task list of 300 verb-noun pairs. For reference, the 1st population decile mean for the top left panel is -0.52, and for the top right panel, it is -0.54 for the nontradable sample and -0.07 for the tradable sample. The 1st population decile mean for the bottom two panels is -1.07.

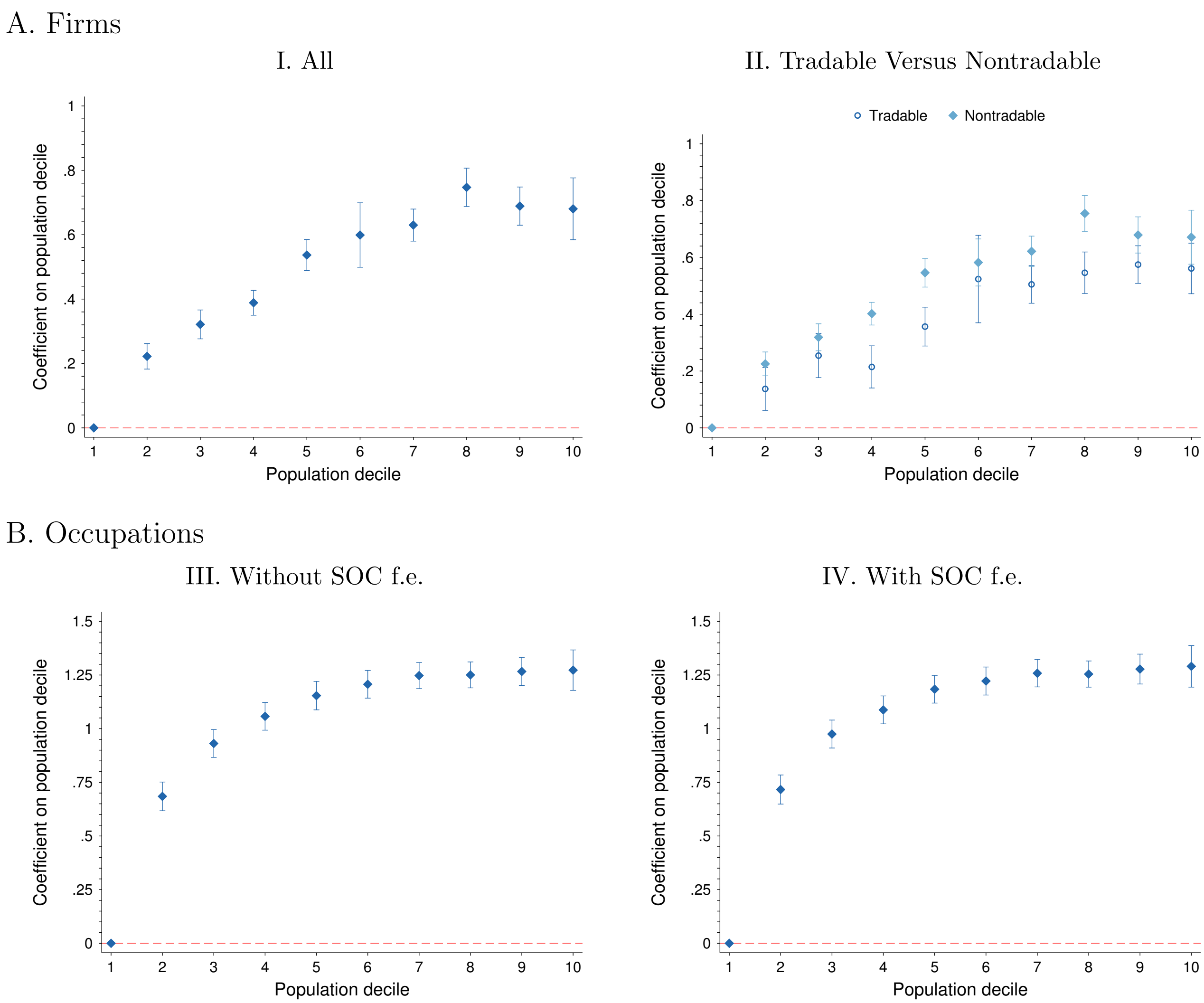
Table C.3: Task Clusters: Part I

identifies problems	1	assist store	8	sustained work	14	written skills	24	existing customers	29
resolve issue	1	bags counter tops	8	reaching pulling	15	assigned management	25	interact customers	29
resolve problems	1	dump baskets	8	assume responsibilities	16	assigned reading	25	leads customers	29
make offer	2	in store repairs	8	closing duties	16	assigned store	25	meet clients	29
offer products	2	lead store	8	opening duties	16	assigned supervisor	25	serving customers	29
provide client	2	maintain store	8	responsibilities duties	16	assigns directs	25	will customers	29
provide feedback	2	may store	8	analyzing data	17	executes store	26	answer questions	30
provide guidance	2	move store	8	conducting research	17	continuing education	27	asking questions	30
provide recommendations	2	needed in store	8	reset departments	18	generating business	27	according company	31
provide technical support	2	signing shelves	8	build relationships	19	growing business	27	following company	31
provided information	2	supervising store	8	maintaining relationships	19	has client	27	following pogs	31
provides input	2	traveling store	8	manage relationships	19	including business	27	following policies	31
provides leadership	2	working store	8	working relationships	19	manages business	27	following vendor	31
provides performance	2	improving quality	9	ensure delivery	20	managing operations	27	pay vendors	31
provides quality	2	maintaining business	9	ensure quality	20	managing projects	27	including nights	32
providing care	2	maintaining environments	9	ensures quality assurance	20	meet business	27	including performance	32
providing direction	2	maintaining inventory	9	ensuring communications	20	processing transactions	27	sweep room	32
providing expertise	2	maintaining program	9	ensuring food	20	securing company	27	ensuring merchandising	33
providing solutions	2	maintaining standards	9	assisting management	21	staffing needs	27	include merchandising	33
providing support	2	providing environment	9	assisting team	21	support business	27	merchandising directives	33
preparing foods	3	achieve goals	10	communicating field	21	supporting activities	27	merchandising product	33
crews customer service	4	resolve rejections	11	crew directing	21	ensure accuracy	28	execute completion	34
preventing terrorists	5	include client	12	developing team	21	ensure adherence	28	execute display	34
preventing trafficking	6	include design	12	ensuring team	21	ensure client	28	execute walk through	34
containing materials	7	include development	12	focus team work	21	ensure completion	28	executing set	34
discontinued items	7	include hand	12	leading team	21	ensure compliance	28	according cvs	35
measuring drugs	7	include knowledge	12	managing teams	21	ensure employees	28	appear floor	35
operate equipment	7	include order	12	providing coaching	21	ensure guests	28	are compliance	35
remove items	7	include program	12	signing crew	21	ensure operation	28	capping vials	35
retrieving information	7	include sales	12	supervisor team	21	ensure policies	28	check acceptance	35
stored areas	7	include service	12	team members	21	ensure product	28	comply cvs	35
taking orders	7	include shelves	12	will teams	21	ensure projects	28	comply state	35
taking vehicle	7	include staff	12	working team	21	ensure restaurant	28	delegated photo	35
unloading trucks	7	closes store	13	as needed assist	22	ensure safety	28	detail ability	35
using computer	7	opens store	13	assist development	22	ensure service	28	document counts	35
using enhancements	7	causing discomfort	14	assist staff	22	ensure stores	28	drive in employees	35
using equipment	7	causing drafts	14	provide assistance	22	assisting clients	29	driving culture	35
using knowledge	7	causing walking	14	request help	22	assisting customers	29	floors work	35
using orders	7	required driver	14	written oral communication	23	engage customers	29	follow instructions	35
adapting store	8	returned check	14	writing skills	24	existing clients	29	including work	35

Table C.4: Task Clusters: Part II

make recommendations	35	adjust facings	41	working variety	49	answering telephone	56	maintain pull	66
making decisions	35	guided values	41	meet deadlines	50	using phone	56	maintain records	66
may floor	35	locking setting	41	meet goals	50	trash rest	57	maintain work environment	66
pay policy	35	set displays	41	set goals	50	develop relationship	58	maintain working	66
perform job	35	build customer	42	labeling prescriptions	51	establish relationships	58	maintained times	66
perform maintenance	35	communicate customer	42	maintain pharmacy	51	stand periods	59	signing maintain	66
perform register	35	ensure customer	42	maintain prescription	51	sustained periods	59	document cash	67
pulls deposits	35	handling customer	42	organized pharmacy	51	ensure customer satisfaction	60	operating cash register	67
putting drug	35	helping customer	42	pharmacist communicate	51	increase customer satisfaction	60	procedures cash	67
react program	35	meets customer	42	requires merchandise	52	maximizing customer satisfaction	60	required paperwork	67
require walking	35	put customer	42	requires travel	52	needed customer satisfaction	60	exceed sales	68
return system	35	resolving customer	42	windows ceilings	53	checking employee	61	generate sales	68
scheduling activities	35	responding customer	42	windows removal	53	conducting employee	61	increase sales	68
scheduling appointments	35	seek customer	42	apprehend company	54	evaluates employees	61	intern communication	69
securing door	35	meet requirements	43	communicate information	54	carry pounds	62	written communication	69
skating carhop	35	meets standards	43	demonstrate knowledge	54	lift lbs	62	written instructions	69
stand walk	35	appropriate use	44	develop business	54	lifting pounds	62	make adjustments	70
taking actions	35	move trays	44	develop planning	54	weighing pounds	62	make changes	70
work others	35	passing emit	44	develop productivity	54	prioritize tasks	63	secure change	70
work projects	35	preferred ability	44	develop solutions	54	bagging merchandise	64	work flexible schedule	70
work schedule	35	seal trays	44	develop test	54	check in merchandise	64	work shift	70
work week ends	35	use hands	44	developing implement	54	damaged merchandise	64	sweeping stock	71
working departments	35	using eye	44	developing strategies	54	handle merchandise	64	work stock	71
works custom	35	vacuum face	44	establish policies	54	have merchandise	64	prepare returns	72
outdated merchandise	36	change bulbs	45	establish priorities	54	lifting merchandise	64	become slippery	73
customer service culture	37	assigned skills	46	established guidelines	54	may merchandise	64	may slippery	73
include customer service	37	on going training	47	identify opportunities	54	move merchandise	64	hiring training	74
provide customer	37	achieving sales	48	identify shoplifters	54	react shoplifters	64	including maintenance	74
provide customer service	37	assisted sales	48	identifying conditions	54	recalled merchandise	64	including management	74
provide service	37	dcr photofinishing	48	maximize sale	54	sorting merchandise	64	including preparation	74
receives service	37	developed sales	48	maximizes profitability	54	problem solving skills	65	including support	74
execute cash	38	driving sales	48	obtain information	54	maintain appearance	66	including systems	74
handling cash	38	managing sales	48	promote shopping	54	maintain area	66	including training	74
including cash	38	meet sales	48	protect company	54	maintain awareness	66	including translation	74
regarding cash register	38	needed inventory management	48	transforming delivery	54	maintain card	66	provides training	74
handle tasks	39	photofinishing orders	48	greeting card	55	maintain communication	66	requiring security	74
bulletins action	40	sells products	48	greeting customers	55	maintain custom	66	training sessions	74
following reports	40	working sales	48	greeting operations	55	maintain files	66	cvs workflow	75
prepare reports	40	perform variety	49	using greet	55	maintain knowledge	66		
writing reports	40	serving quality	49	answering phones	56	maintain productivity	66		

Figure C.10: Specialization Gradient: 75 Task Clusters



The figure above reproduces Figure 4, except the task dissimilarity measures in the firm-market and occupation-market cells are constructed using 75 task clusters. These task groupings are constructed from the original 399 tasks, which are reduced to 75 task clusters using a natural language processing approach described in the text. The 1st population decile mean for the top left panel is -0.51, and for the top right panel, it is -0.53 for the nontradable sample and -0.05 for the tradable sample. The 1st population decile mean for the bottom two panels is -1.02.

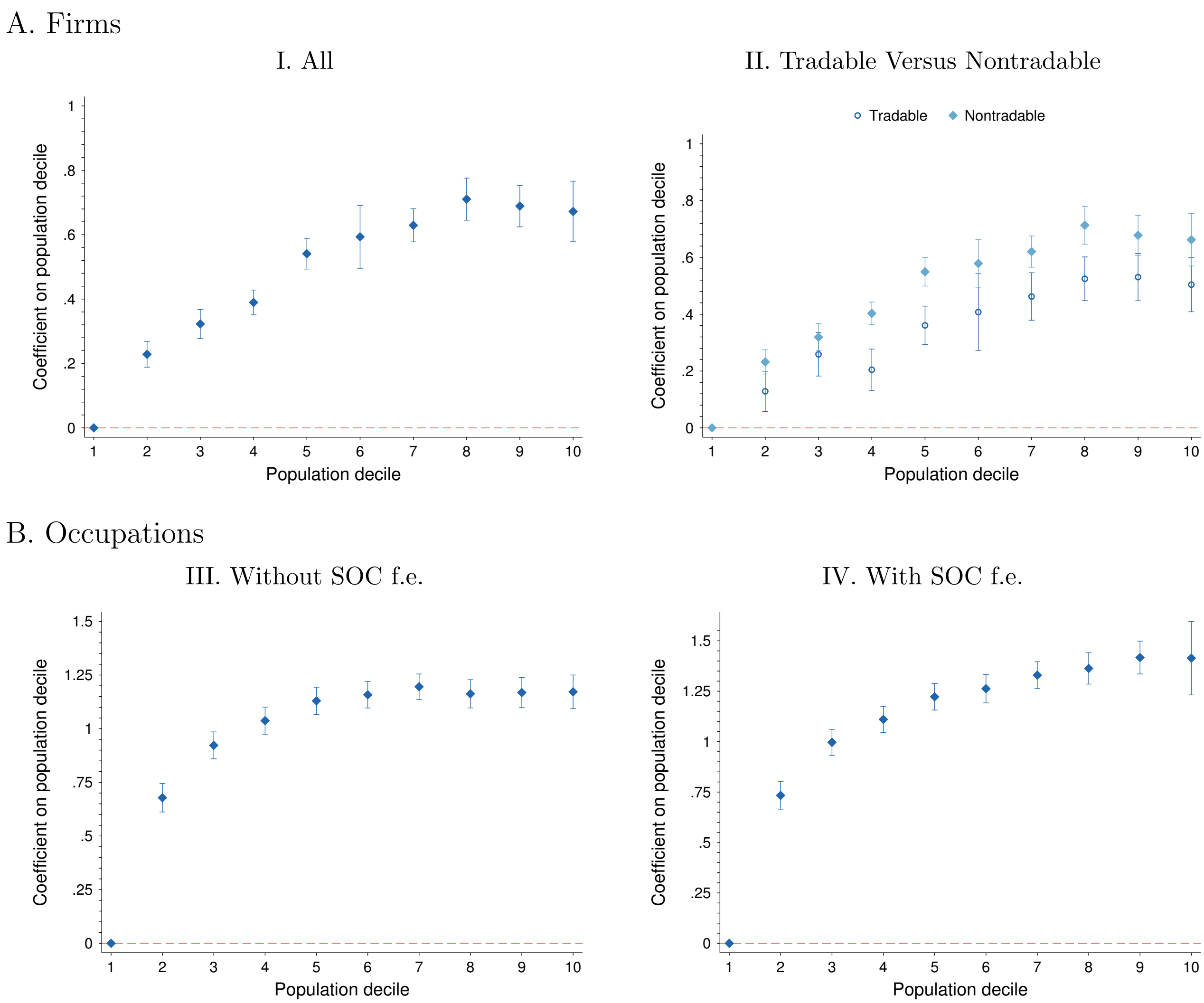
Measurement Error and Robustness to Controls

Small markets have fewer job ads per occupation-market (or firm-market) cell. Since the resulting within-cell sampling error may systematically vary with market size, one may worry that sampling error may lead us to spuriously conclude that job dissimilarity is increasing in market size. To assess the validity of this concern, we reproduce the key specialization figure in the analysis (Figure 4) with an additional control for the number of ads in the cell. Reassuringly, the estimates of this exercise, reported in Figure C.11 below, are virtually identical to Figure 4. We also check the sensitivity of the specialization gradients to measurement error by reproducing panel A of Figure C.12 for firm-market cells with strictly more than the median number of job ads, which is 5, and below or including the median number of job ads.

Placebo-Type Exercise: Analysis of National Chains

We also perform a placebo-type analysis of our specialization gradients for a subset of firms: national chains. To come up with a list of these national chains, we first identify the top 20 company names that have the most job postings. From this list, we identify the chains, which include: Advance Auto Parts, CVS Caremark, Dollar General, Family Dollar, Harbor Freight, Home Depot, Lowes, Macys, McDonalds, Pizza Hut, Sears, Taco Bell, and Wells Fargo. We reproduce panel A of Figure 4 for these retailers (which are all in non-tradable industries) and compare it to all other non-tradable sector firms, presented in Figure C.13. The results show a flattened specialization gradient, as we might expect, given the relative homogeneous types of organizational structure of these chains across space. Note that we would not expect the specialization gradient to flatten entirely, since even the workforce of national chains may become more specialized in large markets. Nevertheless, it is reassuring to see a flattened gradient for these national chains.

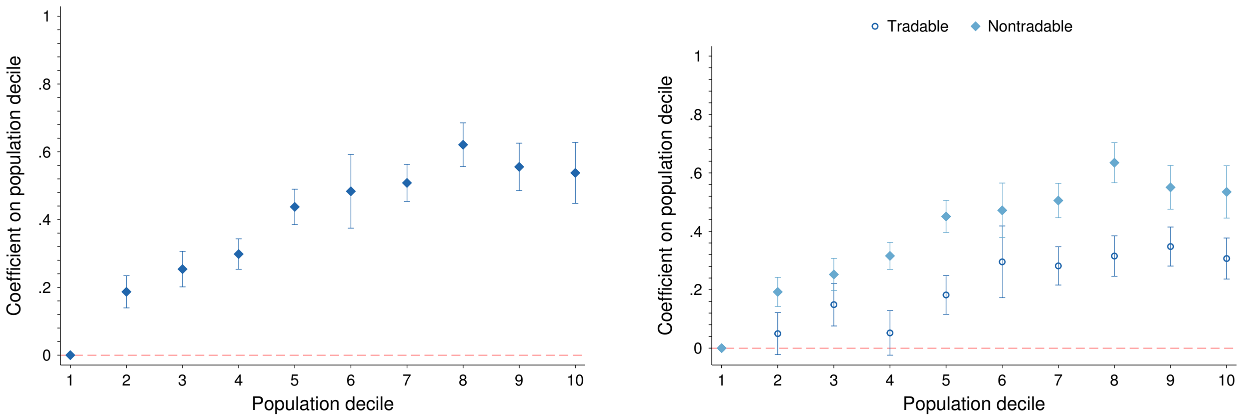
Figure C.11: Specialization Gradient: Task Dissimilarity Within Firms and Occupations



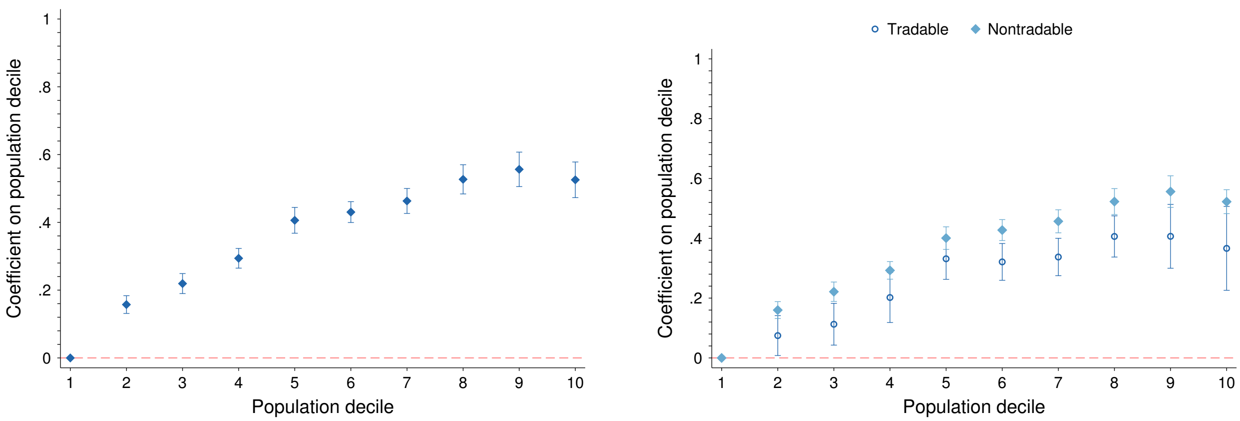
The figures above reproduce Figure 4 with an additional control for the number of ads in the cell.

Figure C.12: Specialization Gradient: Above Versus Below Median Firm Size

I. Above Median

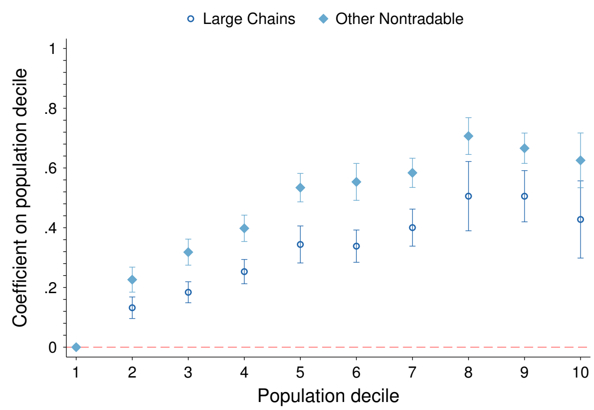


II. Below Median



The figures above reproduce panel A of Figure 4 separately for firm-markets with strictly more than the median number of postings (5) and below or including the median number of postings.

Figure C.13: Specialization Gradient: Large Chains Versus Other Non-Tradable

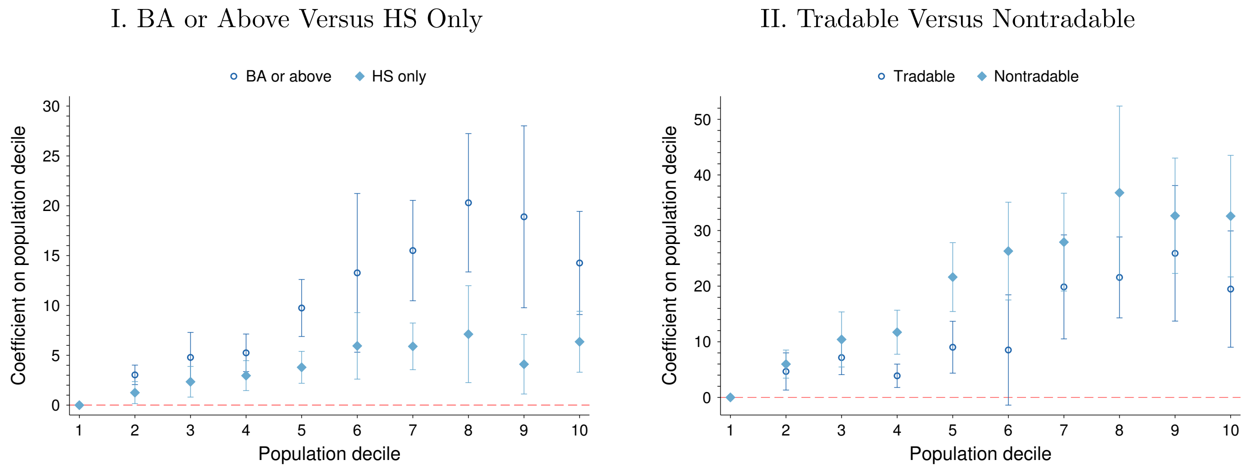


The figures above reproduce panel A.I of Figure 4 separately for large chains (which are all in non-tradable industries) and other non-tradable firms. We control for both log ad words in the cell and two-digit NAICS fixed effects.

Number of Job Titles

Prior research—notably, Tian (2019)—examines evidence for specialization by counting the number of distinct occupation codes in a firm-market. The idea behind this exercise is that a greater number of distinct occupations implies greater specialization in production. We examine this relationship in Figure C.14, using our job vacancy data to count distinct job titles within a firm name $\times$ six-digit industry NAICS $\times$ CZ. We produce these market size gradients separately for high- and low-education-level job titles, and for tradable and nontradable sector firms. The key takeaway is that we do see a positive relationship between market size and the degree of worker specialization, and this relationship is stronger for workers with a BA degree or above and for nontradable sector firms.

Figure C.14: Specialization Gradient: Number of Job Titles



The unit of observation is the firm-market (CZ). We regress the number of distinct job titles on market size deciles, controlling for the total number of ads placed by the firm in the CZ, two-digit NAICS code, and the average log ad length. The left panel depicts two regressions. In the first, the dependent variable is the number of job titles requiring a high school diploma, and in the second, the dependent variable is the number of distinct job titles requiring a college degree. In the right panel, the dependent variable is the number of distinct job titles, and the regression is estimated separately on tradable and nontradable sector firms. All regressions are weighted by the number of ads in the firm-market. Standard errors are clustered at the CZ level. The figure plots the coefficients on the CZ size deciles. For reference, in the left panel, the 1st population decile mean for BA or above is 2.48 and for HS only is 3.14. In the right panel, the 1st population decile mean for tradable is 9.69 and for nontradable is 10.57.

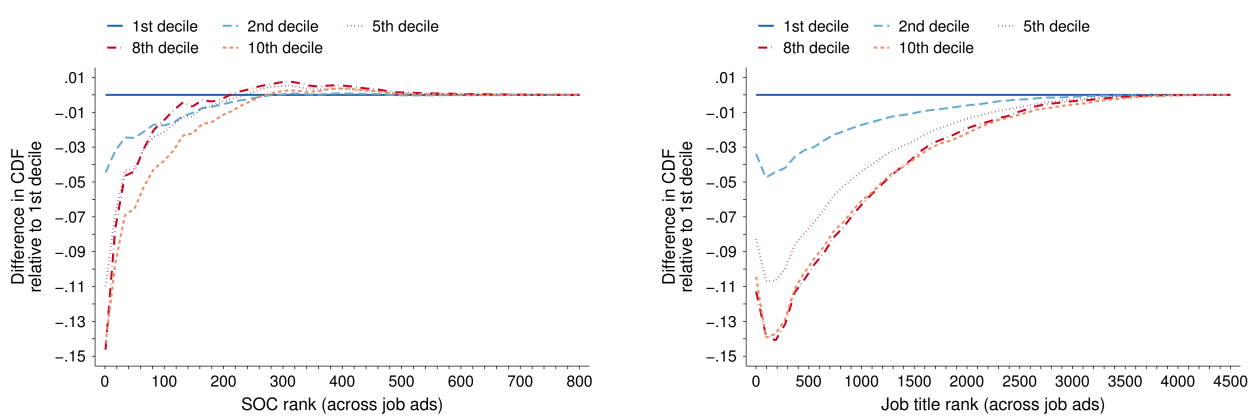
The Distribution of Common and Rare Occupations

As another robustness exercise, we measure the degree of specialization by examining the distribution of common and rare occupations across space.

We rank six-digit SOCs based on their share of all ads in the full sample. The x-axis presents SOCs in descending order based on their overall rank in the sample. We then compute the share of each SOC in each market size decile and plot the difference relative to the share in the 1st population decile. The left panel of Figure C.15 shows that the most common occupations are overrepresented in small markets, while more rare occupations are overrepresented in large markets. For example, of the 10 most common occupations economy-wide, the 10th decile market has an 11-13 percentage points lower share of these occupations compared with the 1st population decile. For the 300-400 most common occupations, the 10th decile market has about a 0.3 percentage point greater share relative to the 1st population decile.

This finding—that rare jobs represent a larger share of total jobs in larger markets—is even more pronounced when we perform the analysis at the job title level. Note that the job title is not observed in standard datasets such as the ACS or the CPS and hence represents an additional advantage of the job ads data used here. The right panel presents the analysis at the job title level, showing even more dramatically that common jobs are overrepresented in smaller markets (as a share of total jobs).

Figure C.15: Common and Rare Occupations and Job Titles



The left panel is constructed as follows. We first generate the empirical cdf of occupational shares for each CZ decile. On the x-axis, the six-digit SOCs are ranked in descending order of their shares of all job ads in the sample. The left panel presents the difference between each CZ decile cdf and the 1st decile CZ's cdf. The right panel is constructed analogously, except the unit of analysis is the job title rather than the six-digit SOC. A local polynomial smoother is applied to both panels.

C.3 Robustness of Wage Regressions

This section evaluates the sensitivity of the wage regressions presented in Table 5. We then examine the sensitivity of the wage regression table to two-way clustering of the standard errors, by CZ and four-digit SOC. We then examine the sensitivity of Table 5 to using an alternative task dissimilarity measure—one in which dissimilarity is based on a task vector with 2,000 tasks, a higher resolution of tasks per job ad. Lastly, we examine the sensitivity to including CZ fixed effects.

Table C.5 reproduces Table 5, the main wage regression table, except uses two-way clustering of the standard errors, by CZ and four-digit SOC. The estimated coefficient on task dissimilarity in column 1—the full sample excluding SOC fixed effects—and columns 6 and 7—the sample of blue-collar occupations—lose statistical significance, but the overall takeaways of Table 5 are unchanged.

Table C.6 reproduces Table 5 except the task dissimilarity measures in the occupation-CZ are constructed based on a task vector with 2,000 tasks, a higher resolution of tasks per job ad. The results are nearly identical to those in Table 5. Note that the number of observations is slightly higher compared to Table 5. One difference, since longer task vectors are more likely to have a non-zero element, is that there are slightly more occupation-CZ cells with more than 2 job ads that have non-zero task vectors, which is required for the task dissimilarity to be defined and for the occupation-CZ cell to enter the regression. Table C.7 reproduces Table 5 with task dissimilarity measures in the occupation-CZ based on 300 tasks, a lower resolution, and shows similar results.

Table C.8 reproduces Table 5 with CZ fixed effects. The goal is to understand whether specialization and technologies have an effect on wages after controlling for CZ size and other unobserved features of the labor market. Table C.8 shows that with CZ f.e., the coefficient on specialization diminishes. This result is precisely what Smith's theory would predict: It is *through* market size that specialization affects productivity; after controlling for CZ size, the link between specialization and productivity is muted. Nevertheless, the specialization coefficient remains significant with CZ and SOC fixed effects for white-collar occupations in column 5. The interactive tasks coefficient is also diminished once we control for CZ f.e., which is consistent with market size enhancing the relationship between worker interactions and productivity. The technologies coefficient remains statistically significant even with CZ f.e. for the full sample and for white collar occupations.

Table C.5: Task Dissimilarity, Technologies, Interactive Tasks, and Wages (with Two-Way Clustering)

	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**
	(0.043)	(0.013)	(0.008)	(0.023)	(0.012)	(0.009)	(0.008)
Technology requirements	0.381***	0.328***	0.108***	0.353***	0.106***	0.017	0.004
	(0.072)	(0.073)	(0.028)	(0.076)	(0.030)	(0.037)	(0.033)
Task dissimilarity	0.026	0.031***	0.018***	0.056***	0.033***	0.003	0.000
	(0.021)	(0.006)	(0.004)	(0.010)	(0.005)	(0.004)	(0.003)
BA or above			1.452***		1.476***		0.988***
			(0.121)		(0.129)		(0.219)
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

This table reproduces Table 5, except uses two-way clustering by CZ and four-digit SOC.

Table C.6: Task Dissimilarity, Technologies, Interactive Tasks, and Wages (with 2,000 Tasks)

	All			White-collar		Blue-collar	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Interactive tasks	0.119***	0.033***	0.008***	0.046***	0.006	0.026***	0.021***
	(0.006)	(0.006)	(0.003)	(0.010)	(0.005)	(0.005)	(0.004)
Technology requirements	0.370***	0.324***	0.107***	0.347***	0.104***	0.018	0.004
	(0.013)	(0.040)	(0.018)	(0.044)	(0.021)	(0.023)	(0.022)
Task dissimilarity	0.048***	0.032***	0.018***	0.061***	0.033***	0.003	0.001
	(0.003)	(0.003)	(0.002)	(0.006)	(0.003)	(0.002)	(0.002)
BA or above			1.447***		1.468***		0.986***
			(0.087)		(0.089)		(0.136)
SOC f.e.	No	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	46,572	46,572	46,572	25,047	25,047	11,706	11,706
R^2	0.267	0.883	0.927	0.846	0.918	0.724	0.744
Mean of dependent var.	10.792	10.792	10.792	10.989	10.989	10.585	10.585
Mean task dissimilarity	0.000	0.000	0.000	0.177	0.177	-0.234	-0.234
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	0.434	0.434	-0.916	-0.916
Mean BA or above	0.363	0.363	0.363	0.518	0.518	0.075	0.075

This table reproduces Table 5, except the task dissimilarity measures in the occupation-CZ are constructed based on extracting 2,000 tasks, a higher resolution vector of verb-noun tasks per job ad.

Table C.7: Task Dissimilarity, Technologies, Interactive Tasks, and Wages (with 300 Tasks)

	All			White-collar		Blue-collar	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Interactive tasks	0.125***	0.032***	0.008**	0.048***	0.006	0.026***	0.021***
	(0.007)	(0.006)	(0.003)	(0.010)	(0.005)	(0.005)	(0.004)
Technology requirements	0.379***	0.329***	0.110***	0.354***	0.107***	0.018	0.004
	(0.013)	(0.040)	(0.018)	(0.045)	(0.021)	(0.023)	(0.022)
Task dissimilarity	0.035***	0.032***	0.018***	0.056***	0.033***	0.003	-0.000
	(0.004)	(0.004)	(0.002)	(0.005)	(0.003)	(0.003)	(0.003)
BA or above			1.448***		1.475***		0.991***
			(0.086)		(0.088)		(0.135)
SOC f.e.	No	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	45,303	45,303	45,303	24,628	24,628	11,304	11,304
R^2	0.264	0.884	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	0.141	0.141	-0.215	-0.215
Mean technology requirements	0.158	0.158	0.158	0.224	0.224	0.043	0.043
Mean interactive tasks	0.000	0.000	0.000	0.434	0.434	-0.923	-0.923
Mean BA or above	0.364	0.364	0.364	0.518	0.518	0.076	0.076

This table reproduces Table 5, except the task dissimilarity measures in the occupation-CZ are constructed based on extracting 300 tasks.

Table C.8: Task Dissimilarity, Technologies, Interactive Tasks, and Wages: Adding CZ Fixed Effects

	All			White-collar		Blue-collar	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Interactive tasks	0.124***	0.004	-0.000	-0.002	-0.005	0.005	0.005
	(0.006)	(0.003)	(0.003)	(0.005)	(0.005)	(0.004)	(0.004)
Technology requirements	0.336***	0.149***	0.078***	0.104***	0.054***	0.003	-0.004
	(0.010)	(0.018)	(0.010)	(0.016)	(0.010)	(0.015)	(0.015)
Task dissimilarity	0.003	-0.004***	0.002*	-0.001	0.007***	-0.001	0.000
	(0.003)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
BA or above			0.948***		0.845***		0.604***
			(0.042)		(0.040)		(0.057)
SOC f.e.	No	Yes	Yes	Yes	Yes	Yes	Yes
CZ f.e.	Yes	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	0.330	0.943	0.953	0.947	0.957	0.859	0.864
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

This table reproduces Table 5 with CZ fixed effects.

C.4 Robustness to Data Source

In this appendix, we reproduce some of our main empirical exercises using a sample of ads from Burning Glass. The EMSI dataset has its own advantages for our purpose. In particular, it contains the ads' raw text, allowing us to isolate the tasks that employers list. In contrast, Burning Glass commingles jobs' skills, technologies, and tasks. Nevertheless, since Burning Glass has been so commonly used in recent analyses of the labor market, we check the robustness of our results to this alternate data source.

We draw a random sample of 2.4 million ads from January 2012 to December 2017. For this sample, so that we can replicate Figure 2, we compute measures of internal-to-the-firm interactive tasks[9] and external-to-the-firm interactive tasks.[10] As in Section III.A, we

[9]We map the following Burning Glass elements to internal interactive tasks: "Agile coaching," "Communication Skills," "Employee Coaching," "Executive Coaching," "Leadership," "Leadership Development," "Leadership Training," "Mentoring," "Oral Communication," "Peer Review," "Personal Coaching," "Supervisory Skills," "Team Building," "Verbal / Oral Communication," and "Written Communication."

[10]We map the following Burning Glass elements to external interactive tasks: "Advertising," "Client Base Retention," "Client Care," "Client Needs Assessment," "Client Relationship Building and Management,"

compute the number of task mentions per 1000 ad words. Second, as in Section III.B, we compute whether each ad mentions individual O*NET Hot Technologies. So that we can compute specialization, as in Section III.C, for each job ad j, we define a 400-dimensional vector, T_j, with each element characterizing whether ad j mentions the individual Burning Glass element. As in Section III.C, we define the normalized task vectors $V_j = \frac{T_j}{\sqrt{T_j \cdot T_j}}$ and the distance between job j and other jobs in the occupation- (or firm-) market as $d_{jcm} = 1 - V_{jcm} \cdot \overline{V}_{(-j)cm}$.

First, Figure C.16 replicates Figure 2. As in Section III.A, external tasks increase in CZ size both within and between six-digit SOCs. However, potentially due to the smaller sample size, the relationship between CZ size and internal tasks is no longer statistically significant.

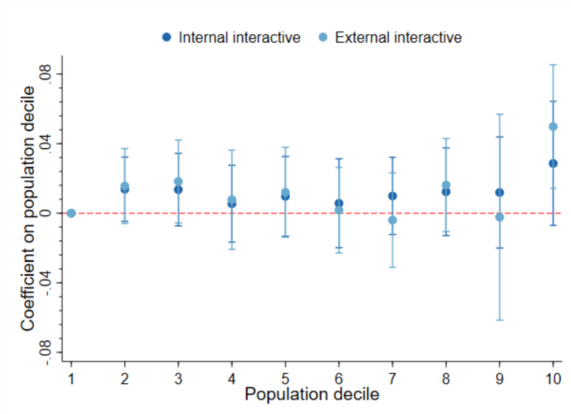
Second, we reproduce Figure 4. As in Figure 4, Figure C.17 indicates that within-occupation and within-firm specialization is greater in more populous commuting zones, with a steeper gradient for firms in nontradable industries than for firms in tradable industries (panel II).

Finally, we reproduce Table 5. As in Table 5, Table C.9 indicates that wages are higher in markets with greater specialization, with greater technology usage, and with a greater share of workers with a college degree. Furthermore, also as in Table 5, the relationships between wages and within-occupation × market specialization and technology intensity are each stronger in white-collar than in blue-collar occupations. In contrast to Table 5, the relationship between interactive tasks and wages is statistically significant only in the specification without SOC fixed effects.

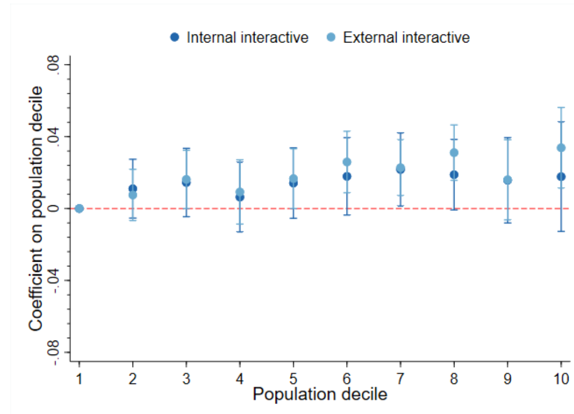
"Communication Skills," "Digital Marketing," "Market Planning," "Marketing," "Marketing Communications," "Marketing Programs," "Marketing Sales," "Marketing Strategy Development," "Merchandising," "Oral Communication," "Print Advertising," "Product Marketing," "Professional Services Marketing," "Prospective Clients," "Public Relations," "Public Relations Campaigns," "Public Relations Industry Knowledge," "Public Relations Strategy," "Sales," "Telemarketing," "Vendor Interaction," "Vendor Performance Monitoring," "Vendor Relations," "Verbal / Oral Communication," and "Written Communication."

Figure C.16: O*NET Interactive Tasks Gradient

I. Without SOC f.e.



II. With SOC f.e.

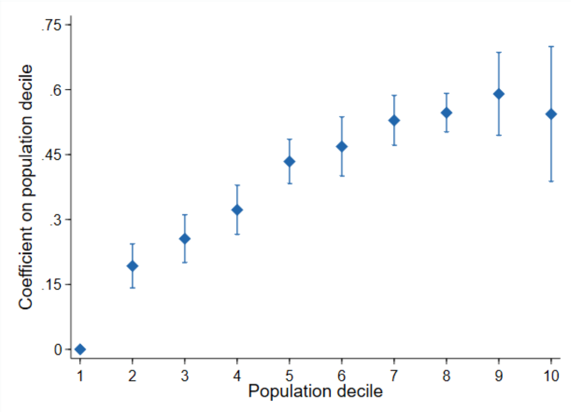


See the caption for Figure 2. In contrast, our task measures here come from Burning Glass data.

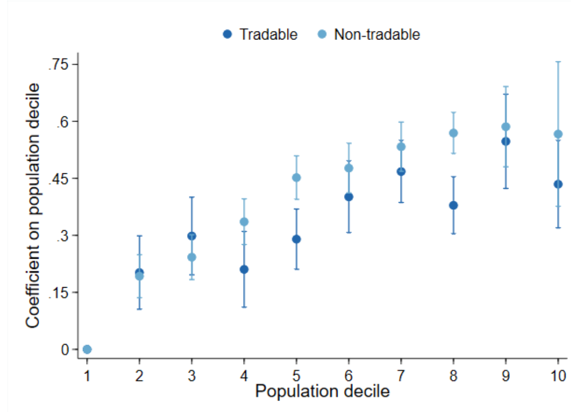
Figure C.17: Specialization Gradient: Task Dissimilarity Within Firms and Occupations

A. Firms

I. All

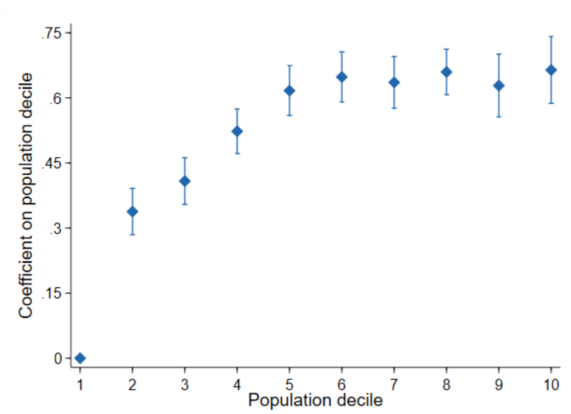


II. Tradable Versus Nontradable

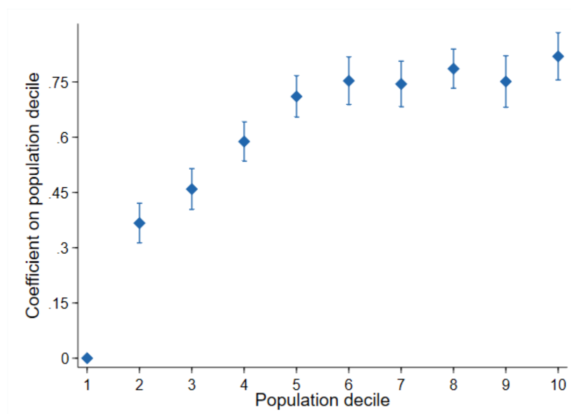


B. Occupations

III. Without SOC f.e.



IV. With SOC f.e.



See the caption for Figure 4. In contrast, the task dissimilarity and technology measures here come from Burning Glass data.

Table C.9: Task Dissimilarity, Technologies, and Wages

	All			White collar		Blue collar	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Task dissimilarity	0.066***	0.018***	0.013***	0.048***	0.038***	0.004**	0.003**
	(0.005)	(0.003)	(0.002)	(0.009)	(0.006)	(0.001)	(0.001)
Technology requirements	0.308***	0.183***	0.114***	0.231***	0.141***	0.024	0.013
	(0.007)	(0.023)	(0.014)	(0.039)	(0.020)	(0.016)	(0.014)
Interactive Tasks	0.030***	0.001	-0.000	-0.004	-0.007	0.001	0.001
	(0.004)	(0.003)	(0.003)	(0.004)	(0.005)	(0.003)	(0.003)
Education			0.547***		0.664***		0.138***
			(0.073)		(0.140)		(0.042)
SOC f.e.	No	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	36,408	36,408	36,408	22,123	22,123	8,109	8,109
R^2	0.206	0.885	0.896	0.847	0.869	0.724	0.726
Mean of dependent var.	10.802	10.802	10.802	10.990	10.990	10.588	10.588
Mean task dissimilarity	-0.000	-0.000	-0.000	0.079	0.079	-0.083	-0.083
Mean technology requirements	0.572	0.572	0.572	0.770	0.770	0.245	0.245
Mean interactive tasks	0.000	0.000	0.000	0.236	0.236	-0.600	-0.600
Mean BA or above	0.383	0.383	0.383	0.554	0.554	0.070	0.070

See the caption for Table 5. In contrast, the task dissimilarity and technology measures here come from Burning Glass data.

C.5 Robustness to Using Posted Wages

To close, we examine the sensitivity of our results to the use of wage data from the American Community Survey. Unfortunately, we are unable to extract information on ads' wages from our EMSI job ads data. Given this, we rely on data from Burning Glass for this sensitivity analysis.[11]

To begin, Tables C.10 and C.11 summarize the share of Burning Glass ads with a posted salary as well as the average (annual) posted salary in the American Community Survey. We find that the share of ads with a posted salary varies systematically by occupation—with 45 percent of Farming, Fishing, and Forestry jobs with a posted salary compared to 7 percent

[11] Another alternative source of wage data is the Occupational Employment Statistics Survey (OES). While the OES measures wages at the six-digit occupation level within certain metro areas, these data have their own disadvantages: (i) They do not cover non-metro areas; (ii) the level of detail varies according to the metro area size (i.e., for smaller metro areas they do not have wage information at the six-digit level or even at the four-digit level for very small metro areas); and (iii) there is no information on wages by worker education, which we control for in some of our specifications.

in Sales and Related Occupations—and by CZ population decile—with a larger share of ads with a posted salary in lower population CZs. Second, average wages in the two datasets are highly correlated with one another: Across the 23 two-digit SOCs presented in Table C.10, the raw (unweighted) correlation between log wages in the ACS and in Burning Glass equals 0.95. Across the 10 CZ population deciles, the analogous correlation equals 0.97.

Table C.10: Posted Wages by Occupation

Occupation	Share with Posted Salary	Log Salary	
		ACS	Burning Glass
Management (11)	0.13	11.31	11.14
Business and Financial Operations (13)	0.16	11.20	10.92
Computer and Mathematical (15)	0.11	11.31	11.22
Architecture and Engineering (17)	0.14	11.30	11.11
Life, Physical, and Social Science (19)	0.19	11.16	10.91
Community and Social Science (21)	0.20	10.73	10.72
Legal (23)	0.13	11.53	11.14
Educational Instruction and Library (25)	0.18	10.81	10.66
Arts, Design, and Entertainment (27)	0.13	10.90	10.71
Healthcare Practitioners and Technical (29)	0.10	11.18	11.01
Healthcare Support (31)	0.09	10.30	10.33
Protective Service (33)	0.36	10.87	10.59
Food Preparation and Serving (35)	0.09	10.09	10.24
Building, Grounds Cleaning and Maintenance (37)	0.18	10.18	10.27
Personal Care and Service (39)	0.16	10.01	10.33
Sales and Related (41)	0.07	10.87	10.71
Office and Administrative Support (43)	0.19	10.57	10.44
Farming, Fishing, and Forestry (45)	0.45	10.15	10.32
Construction and Extraction (47)	0.22	10.57	10.66
Installation, Maintenance, and Repair (49)	0.15	10.72	10.58
Production (51)	0.24	10.58	10.43
Transportation and Material Moving (53)	0.19	10.53	10.40
Military (55)	0.33	10.87	10.89

For each two-digit occupation, this table lists the share of Burning Glass ads with a posted salary, average annual (log) wages in the American Community Survey, and (for the subset of ads with a posted salary) average annual wages in the Burning Glass data.

Table C.11: Posted Wages by CZ Population Decile

CZ Population Decile	Share with Posted Salary	Log Salary	
		ACS	Burning Glass
1	0.19	10.58	10.49
2	0.18	10.65	10.54
3	0.17	10.68	10.57
4	0.17	10.72	10.61
5	0.16	10.78	10.65
6	0.16	10.80	10.70
7	0.15	10.87	10.73
8	0.14	10.97	10.82
9	0.12	10.98	10.84
10	0.15	10.88	10.84

For each CZ population decile, this table lists the share of Burning Glass ads with a posted salary, average annual (log) wages in the American Community Survey, and (for the subset of ads with a posted salary) average annual wages in the Burning Glass data.

Finally, Table C.12 reproduces Table 5, replacing ACS with Burning Glass as the source of (log) wages by occupation and commuting zone. (Since only a fraction—less than one-fifth—of ads have a posted wage, both the number of observations and the number of underlying ads represented in this regression table are smaller than in Table 5.) As in Table 5, we find that wages are increasing in task dissimilarity and technology usage, with greater slopes in white-collar occupations. Also as in Table 5, the relationship between wages and interactive task mentions is statistically significant only in certain specifications.

Table C.12: Task Dissimilarity, Technologies, Interactive Tasks, and Wages

	All			White collar		Blue collar	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Task dissimilarity	0.081***	0.020***	0.012***	0.039**	0.024	0.010	0.007
	(0.006)	(0.006)	(0.004)	(0.014)	(0.013)	(0.007)	(0.006)
Technology requirements	0.252***	0.233***	0.127***	0.244***	0.124***	0.195***	0.131***
	(0.005)	(0.026)	(0.016)	(0.043)	(0.025)	(0.039)	(0.028)
Interactive Tasks	0.019***	0.005	0.002	-0.002	-0.006	0.016***	0.013**
	(0.003)	(0.004)	(0.004)	(0.007)	(0.006)	(0.005)	(0.005)
Education			0.759***		0.806***		0.746***
			(0.062)		(0.086)		(0.103)
SOC f.e.	No	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	24,974	24,974	24,974	15,845	15,845	5,226	5,226
R^2	0.191	0.685	0.708	0.679	0.711	0.432	0.453
Mean of dependent var.	10.694	10.694	10.694	10.825	10.825	10.500	10.500
Mean task dissimilarity	0.062	0.062	0.062	0.113	0.113	0.030	0.030
Mean technology requirements	0.592	0.592	0.592	0.785	0.785	0.247	0.247
Mean interactive tasks	-0.006	-0.006	-0.006	0.227	0.227	-0.633	-0.633
Mean BA or above	0.394	0.394	0.394	0.556	0.556	0.066	0.066

See the caption for Table 5. In contrast, the cell-level average wages are computed as the average posted salary within Burning Glass among the subset of ads for which this salary exists.

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