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THE GEOGRAPHY OF JOB TASKS

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ABSTRACT

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

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1 Introduction

Geographic inequality is a pervasive feature of the U.S. labor market. Average wages, the college wage premium, and the wage gap between white-collar and blue-collar occupations all increase with the size of the labor market. Furthermore, different labor markets foster distinct types of work. For example, managerial, financial, and computer occupations are overrepresented in large labor markets, while maintenance, production, and material moving occupations employ a greater share of workers in small labor markets.

While economists have studied how jobs vary with market size, prior research has been limited in its ability to characterize spatial differences in the nature of work. Analyses of job content, applying 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, Michigan as in Dallas, Texas. But for other occupations, job tasks and technologies likely vary with the size of the labor market. For example, financial analysts in Hastings, Nebraska may perform fundamentally different tasks compared to those in New York City. Existing datasets are silent on these differences.

In this paper, we study the geography of job tasks and technology requirements in the United States. We do so using a novel approach to measurement applied to an increasingly utilized data source: the text of online job ads. We 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.

We leverage the job description text and tools from natural language processing to extract detailed information about job tasks and technologies. Our measures are not fixed at the occupation level, and capture differences in task content within and across regions. As we show in this paper, work is different 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 in job descriptions into routine and non-routine task categories. Our second approach uses tools from natural language processing to define tasks as verb-noun pairs that appear in job descriptions. This second approach is new to this paper and departs from prior research on tasks, in which it is common to select a subset of survey questions from data sources such as O*NET and then classify these items into economically meaningful task categories (Spitz-Oener, 2006; Autor, 2013). There are two key advantages to our more granular approach to task measurement.

First, it reduces the amount of researcher discretion in classifying tasks, and second, because of its high resolution, it allows us to measure how specialized jobs are—i.e., how far apart workers are in task space, within firms or occupations.

Our main empirical analysis introduces several facts regarding the geography of work in the United States. We first show that analytic and interactive tasks have a steep positive gradient in market size: Relative to jobs in the bottom population decile, jobs in the top population decile have 0.30 standard deviations (s.d.) higher intensity of non-routine analytic tasks and 0.24 s.d. higher intensity of interactive tasks. In addition, these jobs have 0.18 s.d. lower intensity of routine manual tasks. A large part of these gradients is due to occupational composition, but even after conditioning on narrowly defined occupation categories (six-digit SOC) about 16 percent of the gradient between largest and smallest CZs for non-routine analytic tasks, 27 percent of the gradient for non-routine interactive tasks, and 53 percent of the gradient for routine manual tasks remains. We further decompose interactive tasks into those that capture interactions outside the firm and those that capture interactions within the firm. The CZ size gradient is positive for both external and internal interactive tasks, and these relationships are more pronounced for jobs requiring a college degree.¹ Our subsequent analysis using the 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.

We next consider whether technological requirements—specifically the use of computer software—are more likely to be mentioned in job descriptions in larger markets, and how this gradient differs for college- and non-college-requiring jobs. Measuring technology requirements as the appearance of O*NET’s Hot Technologies in the job descriptions, we find that technology requirements increase steeply with market size, with approximately one-and-a-half times as many technology mentions in the largest CZs as in the smallest. About 11 percent of the gradient remains after conditioning on six-digit occupational categories. Moreover, the technology gradient is present only for jobs requiring a college degree, and vanishes for jobs requiring only high school. We also measure the specific types of technologies demanded by education level, and we find that technologies with the steepest gradient for college degree holders involve computer programming (e.g., Python, JavaScript, and Linux), while for high school diploma holders, they involve data entry and word processing (e.g.,

¹We also show that jobs that are jointly intensive in interactive and analytic tasks are overrepresented in large markets. Thus, the increasing aggregate importance of social and analytic tasks since the 1980s (Deming, 2017) is mirrored by the differential task content between small and large labor markets.

Microsoft Excel, Microsoft Outlook, Microsoft Word).²

Our paper also introduces a novel approach for measuring the degree of worker specialization using the content of job descriptions. We measure the degree of specialization between two jobs as the cosine dissimilarity between vectors representing their task contents. The motivation behind this measure is that jobs with less overlap in tasks are more dissimilar and therefore more specialized relative to one another. For this exercise, we represent a job’s task content as a vector of verb-noun pairs from the job description text. We show that task specialization is increasing in market size, and this relationship holds along a number of dimensions—within occupations, within firms, and between firms. These relationships are stronger for firms in the nontradable sector.

Workers in top population decile CZs earn 33.5 log points more than those residing in bottom population CZs. Even within occupations, this premium is 30.1 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 21 percent (6.2 log points out of a total of 30.1) of the difference in wages between workers in top and bottom population decile commuting zones, and 23 percent (9.3 log points out of a total of 40.8) when we subset to white-collar occupations. We interpret these regressions descriptively, since the premia on tasks and technologies may in part reflect worker sorting on unobservables correlated with job characteristics. Nevertheless, they show that jobs differ between large and small labor markets—even within occupations—in ways that have been previously unmeasured and are reflected in wages. In addition, our evidence suggests that worker sorting is driven in part by the particular job tasks and technologies that employers demand.

Our paper contributes to research on geographic inequality (Glaeser and Maré, 2001; Moretti, 2013a; Diamond, 2016; Frank et al., 2018) by using job postings data to study the geography of tasks and technologies.³ Worker interactions have long been pointed to as a source of productivity gains in cities (Marshall, 1890; Jacobs, 1969), and recent research studies worker interactions as a source of agglomeration, both theoretically (Davis and Dingel, 2019) and empirically (Bacolod et al., 2009b; Michaels et al., 2018; Rossi-Hansberg et al.,

²These results complement an expanding literature on the spatial distribution of technology adoption. Eckert et al. (2020) emphasize the impact of cheaper ICTs on services that agglomerate in large cities and that focus on the creation and communication of information. Bloom et al. (2020) examine where new technologies develop and how they diffuse. Eeckhout et al. (2021) find that IT investments have impacted job and wage polarization since the 1980s.

³Previous research exploits job vacancy postings across different labor markets, without seeking to explain the CZ size premium (Hershbein and Kahn, 2018; Deming and Kahn, 2018; Hemelt et al., 2020).

2019; Moretti, 2021). Prior research also shows that new patents and occupational titles are more likely to appear in cities (Carlino et al., 2007; Lin, 2011), suggesting that innovation and technology adoption is concentrated in larger CZs. Using the text of job vacancies, we allow for within-occupation heterogeneity in job tasks and technologies, and 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. These findings suggest there are limits to worker mobility, even within the same occupation.

We also contribute to the literature that relates productivity and the division of labor to the extent of the market (Young, 1928; Stigler, 1951; Kim, 1989; Becker and Murphy, 1992). Recent work finds greater occupational diversity in cities (Duranton and Jayet, 2011; Tian, 2019). Moretti (2013b) and Dauth et al. (2022) provide evidence for more efficient matching of workers and firms in cities. Our contribution is to measure the degree of specialization directly, by first extracting a high-dimensional vector of work content from job ads, and then measuring the distance between jobs in task space. We show that worker specialization increases in CZ size and that this increased specialization accounts for a substantial portion of the CZ size-wage premium.

2 Data and Measurement

Our data source is 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 Burning Glass Technologies (Burning Glass), which has been used in recent work to study the labor market (Hershbein and Kahn, 2018; Deming and Kahn, 2018; Modestino et al., 2020). Like Burning Glass, EMSI data are proprietary and assembled using web crawlers that extract job vacancy postings from all major online job boards; EMSI also removes duplicate postings that appear across boards. An advantage of the EMSI data for our purposes is that it contains all of the original job ad text. To reduce computational time, we use a 5 percent random sample of the data (7.2 million ads).⁴

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

In addition to the full text content of each ad, EMSI provides fields for the educational requirement of the job, the firm name (which we use to create firm identifiers), the firm’s industry (six-digit NAICS), the occupation code (six-digit SOC), and the job location (county FIPS code). We map FIPS codes to commuting zones (CZs) following [Autor et al. \(2019\)](#). We adopt the CZ as our geographic unit of analysis and refer to CZs throughout as local labor markets. Appendix [A.1](#) provides descriptive statistics for the CZs in the sample, including population and number of ads by CZ decile. We exclude ads with fewer than the 1st and more than the 95th percentile word count.⁵ We make a few additional minor restrictions, which are detailed in Appendix [A.2](#), and which leave us with a sample of 6.3 million ads for the occupational analysis and 5.6 million ads for the firm-level analysis.

For the several exercises that require wages at the occupation level and for the construction of employment weights, we use the 2010-2017 American Community Survey (ACS) ([Ruggles et al., 2020](#)), and restrict the sample to full-time, full-year workers, defined as working at least 40 weeks in the past year and 35 or more hours per week. Our measure of wages is total annual pre-tax wage and salary income (“wages” throughout the paper), which we adjust by CPI-U to constant 2012 dollars before averaging to the four-digit SOC-by-CZ cell. We link job ads data to the ACS by four-digit SOC and CZ, and therefore when wage regressions include occupation fixed effects, these are defined at the four-digit level. We use four-digit SOCs for this analysis because of the larger available sample sizes in the ACS SOC×CZ cells.⁶ In a robustness analysis, we use Burning Glass data, which contains wages extracted from job ads (see Appendix [C.5](#)).

2.1 Measuring Tasks: Extraction and Classification

We extract job tasks from the job descriptions using two approaches. Our first approach follows our earlier work ([Atalay et al., 2018, 2020](#)) and maps keywords in the job descriptions to task categories. We map words into five task categories—non-routine interactive, non-routine analytic, non-routine manual, routine cognitive, and routine manual—following the categorization of [Spitz-Oener \(2006\)](#). We also map words into O*NET work activities, to validate our text-based task measures and to study different types of interactive tasks. See

⁵Dropping extremely short ads removes those that are unlikely to have meaningful task information, while dropping exceedingly long ads helps reduce computation time.

⁶In principle, we could measure wages at a finer level of detail, using either wages from the individual job ads or from 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.

Appendix A.5 for more details on the word mappings. For job ad j and task category k , our measure of task intensity is the number of distinct task-specific word mentions per 1,000 ad words.⁷ We standardize each task to have mean zero and standard deviation one across all ads.⁸

Our second approach is new to this paper and uses verb-noun pairs in the job descriptions to define the set of job tasks. The motivation behind this approach is that job tasks are the activities required of workers in the position. By pairing verbs with nouns we more narrowly define the action and are able 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 is less reliant on researcher discretion, permits task measurement at a granular level, and thus allows us to measure specialization among jobs within the same occupation, industry, or firm.

There are two steps to the task extraction process: first, to define the set of tasks, and second, to vectorize ads according to the set of tasks defined in the first step. To proceed with the first step, we define a task as a (verb stem, noun stem) pair that occurs within the same sentence.

To ensure the verb-noun pairs that we extract are actually tasks and not firm or worker characteristics, we first isolate the section of the text that pertains to job tasks. We search for keywords in the text that suggest a list of tasks will follow. The keywords we use are “duties,” “summary,” “description,” and “tasks.” We isolate the section of text that begins at one of these keywords through the end of the ad.⁹ Then, using Python’s NLTK library, which features a sentence tokenizer and parts-of-speech tagger, we extract each verb and the next noun in each sentence, ignoring other parts of speech that may appear in between. Hence, whether the job ad says “perform commercial, residential, and industrial electrical maintenance,” as it does in the sample ad of Table B.1, or simply “perform maintenance,” our algorithm will record “perform maintenance” as the task. If multiple verbs correspond to the same noun (for instance, “serve and assist customers”), our algorithm extracts two

⁷We 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.

⁸In Atalay et al. (2020), we show robustness to the choice of word mappings—e.g., by including and excluding synonyms of words in the mapping to tasks—and to alternative task units.

⁹This step significantly improves the precision of the task extraction. Note that not all ads will have these keywords, and hence an important check is whether the presence of these words varies systematically with CZ size. Figure A.11 investigates this relationship and finds little evidence for a systematic pattern. In step 2, when we vectorize all job ads based on the task vocabulary created in this step, we do not restrict the data to jobs that include these keywords. Also, in step 2, we perform the vectorization on all ad text, not just the portion of text that follows a keyword.

distinct tasks: “serve customers” and “assist customers.”¹⁰ 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 choose 500 tasks to balance the advantage of comprehensively characterizing jobs’ tasks against the costs of computational time. We reproduce the key results using the 2,000 most common tasks (a higher resolution) and using the 300 most common tasks (a lower resolution) in Appendices C.1 and C.3 and obtain nearly identical results. We also show that when we use a natural language processing approach to aggregate granular tasks that are similar in meaning (e.g., “identifies problems” and “resolve issue”) we get nearly identical results (see Appendix C.2).

In the second step, we search through the full text of each ad for the appearance of each of these 500 verb-noun pairs and vectorize each job ad.¹¹ Verb-noun pairs that appear multiple times in an ad are counted only once, and hence each element of the vector is a zero or one. Table B.1 provides two example job ads with their full text, along with the verb-noun pairs extracted by the algorithm.

In our main analysis with 500 tasks, we exclude 101 verb-noun pairs that in our judgment do not correspond to job tasks, such as “send resume” and “is position,” and hence the number of tasks used in the analysis is 399. Appendix B.1 lists these 399 verb-noun pairs and the 101 excluded pairs.¹²

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.” While the task extraction process is not perfect, a key strength of our approach is that it allows the text used by employers, describing the jobs they intend to fill, to define the set of tasks.

To illustrate the value of natural language processing for extracting job tasks, Table 1 lists the most common tasks for each of four occupations: Electricians, Supervisors of Retail Sales, Registered Nurses, and Lawyers. The tasks are broadly aligned with our prior intuition for what workers in these different occupations do. For instance, Electricians need to “use

¹⁰We 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”).

¹¹We use the entire job ad text when vectorizing, rather than a subset of the text. The reason is that not all ads have a section of text with keywords that indicate job tasks will follow. As a result, there is a tradeoff between being able to vectorize all ads and reducing bias from potentially counting instances of verb-nouns that do not refer to job tasks.

¹²In our robustness exercises with 2,000 tasks, we do not exclude any verb-noun pairs. Hence, our main analysis is not sensitive to the exclusion of selected verb-noun pairs.

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.

2.2 Job Ads: Coverage, Representativeness, and Selection

Before using the content of online job ads to study the labor market, we must evaluate the coverage of job ads across space and whether online job ads are a reasonable representation of overall vacancies. In Appendices A.3 and A.4, we consider the coverage and representativeness of the online job ad data. We first document that our 5 percent sample of ads span four-digit SOC by CZ cells representing 98.3 percent of ACS employment. We then evaluate the representativeness of our data, comparing it to the Job Openings and Labor Turnover Survey (JOLTS) dataset. Consistent with a similar check in [Hershbein and Kahn \(2018\)](#), we find broad concurrence in the industry composition between the EMSI data and JOLTS. Finally, in Appendix A.4, we use the Current Population Survey (CPS) Computer and Internet Use Supplement to measure the propensity of workers to find employment through on-line job ads (as opposed to through other channels). The importance of online job ads is invariant to CZ size in the aggregate, within occupations, and separately for workers with and without a college degree.

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

O*NET is one of the most widely-used data sources for measuring job tasks, and it 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](#)). Despite its popularity and usefulness, O*NET faces a limitation of being based on surveys with small sample sizes—approximately 39 respondents per occupation and item ([Handel, 2016](#))—and offering measures at the occupation-level only.

Since O*NET is the benchmark, we first examine how well job ads can approximate an O*NET-based analysis of tasks and market size. Note that job ads represent vacancies—a flow—whereas O*NET is a survey of employed workers—a stock. Therefore, we consider the extent to which vacancies capture information about employed workers. We construct O*NET measures of job tasks following the selection of survey items and categorization of [Acemoglu and Autor \(2011\)](#), and construct occupation-level tasks using job ads following

the [Spitz-Oener \(2006\)](#) categorization described above. We then study the task gradient with market size using the two distinct occupation-level task measures (O*NET v. job ads), where the variation in tasks across markets is due solely to variation in employment shares. We demonstrate in [Appendix A.5](#) that the task gradients are strikingly similar across data sources.

Second, we extract occupation-level tasks from the text of job ads to mimic O*NET work activities. For this exercise, we rely on words from O*NET task descriptions and construct tasks in the job ads data based on these words. We show in [Appendix A.5](#) that the occupation-level measures of O*NET work activities that we construct from the text of online ads are highly correlated with those occupations’ measures in the O*NET database. Thus, the tasks extracted from the job ads reflect occupation-level content that is similar to the occupation-level content of O*NET. Of course, job ad data have additional within-occupation variation in tasks that we are shutting down for these two validation exercises; in our main analysis, we leverage the additional within-occupation variation in tasks.¹³

Finally, to demonstrate the value of the within-occupation variation in tasks, we show 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. These results are presented in [Appendix B.6](#). The job ads data therefore capture occupational characteristics beyond what is available in O*NET, and these characteristics are reflected in market wages.

3 The Geography of Tasks and Technologies

This section presents the main analysis of the geography of job tasks, technology requirements, and worker specialization.

3.1 Job Tasks Across Space

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

¹³One survey that contains within-occupation variation in task measures—though with much smaller sample sizes and less granular geographic and task measurement—is the Princeton Data Improvement Initiative (PDII). In [Appendix A.5](#), we study the within-occupation correlation of tasks measured in the PDII and tasks measured in job vacancies and find broad alignment between the two.

approximately the same number of employed workers. We estimate:

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

where D_{jn} are indicators for market size decile n , with the 1st decile serving as the reference group, and x_j represents a control for ad length and, in some specifications, six-digit SOC fixed effects. The coefficients of interest, $\beta_n^{(k)}$, capture the task intensities relative to the 1st decile market size.¹⁴ Standard errors are clustered at the commuting zone level.

Figure 1, panel I, plots the coefficients on market size decile, $\beta_n^{(k)}$, based on estimates of equation (1). The primary takeaway is that non-routine interactive and non-routine analytic tasks are increasing in market size, while routine manual tasks are decreasing in market size. According to panel I, jobs in population decile 10 have 0.24 s.d. greater intensity of non-routine interactive tasks and 0.30 s.d. greater intensity of non-routine analytic tasks, while having approximately 0.18 s.d. lower intensity of routine manual tasks. Panel II includes six-digit SOC fixed effects, and shows that the gradients diminish. This weaker gradient is unsurprising and indeed reassuring, since occupational categories are designed to group jobs by their work activities. Nevertheless, even within occupations, non-routine interactive and analytic tasks are mentioned more frequently (by 0.06 s.d. and 0.05 s.d., respectively), and routine manual tasks are mentioned less frequently (by 0.10 s.d.), in the top population decile CZs relative to the bottom decile. Hence, while much of the variation in job tasks across geography is captured by the composition of occupations, a strong gradient remains even within occupations, which is missed in standard data sources such as O*NET. Taking the ratio of the point estimate for decile 10 in Panel II relative to the estimate for decile 10 in Panel I, about 16 percent of the gradient remains with six-digit SOC fixed effects for non-routine analytic tasks and 27 percent of the gradient remains for non-routine interactive tasks. For routine manual tasks, about 53 percent of the gradient remains.¹⁵

Our findings deepen our knowledge of how work differs across labor markets of different sizes, going beyond standard educational and occupational classifications. Bacolod et al. (2009a) document that the urban wage premium is partly a premium on cognitive and interactive skills and also that, in contrast, there is no urban premium on physical skills. In related work, Bacolod et al. (2009b) document that agglomeration increases the demand

¹⁴Section 3.4 presents the elasticities of tasks—as well as technologies and worker specialization—with respect to a continuous measure of log population, following a two-step procedure (Combes and Gobillon, 2015).

¹⁵In Appendix C.1, we perform a decomposition to further evaluate how much of the variation in tasks across geography is due to within- versus between-occupation variation in task content.

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. An advantage of our approach is that we are able to directly observe how jobs themselves vary across labor markets within occupations. This fine level of detail allows us to show that the extent to which occupations themselves vary across CZs accounts for a sizable share of these premia. We also show in Section 3.3 that workers and firms specialize more in larger markets in the space of tasks. Lastly, in Section 3.5 we show that these within-occupation differences have important implications for wage differentials.

We additionally explore whether the relationship between task contents and CZ size depends on a worker’s education level. Panels III through VI of Figure 1 present this analysis. 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 skills 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 12.3 percentage points more of jobs in the highest decile compared with the lowest decile. Jobs that are intensive in only analytic tasks but not interactive tasks make up only about 3.4 percentage points more of jobs in the highest decile. These qualitative findings also 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 study the nature of interactive tasks and specifically assess the importance of interactions *inside* the firm relative to interactions *outside* the firm.

We use task measures that map to O*NET task categories that separately measure external and internal interactive tasks.¹⁶ We regress each task-intensity measure on commuting zone size deciles, with controls for ad length and, where indicated, six-digit SOC fixed effects. Figure 2 plots the coefficients on market size decile, with the 1st decile as the reference decile. This figure shows that both external-to-the-firm and internal-to-the-firm interactive

¹⁶We define *external interactive tasks* as O*NET activities “Selling or Influencing Others” and “Communicating with Persons Outside Organization,” and we define *internal interactive tasks* as O*NET work activities “Guiding, Directing, and Motivating Subordinates,” “Developing and Building Teams,” “Coaching and Developing Others,” “Coordinating the Work and Activities of Others,” and “Communicating with Supervisors, Peers, or Subordinates.” We list the word mappings in Appendix A.5.

tasks increase with market size. Compared with ads in the bottom population decile, ads in the top population decile mention internal interactive tasks (by 0.21 s.d.) and external interactive tasks (by 0.26 s.d.) more frequently. When we include six-digit SOC fixed effects, the gradients are 0.07 for both—about 30 percent as large.

Our results indicate that both types of interactive tasks—those related to interactions within and across firm boundaries—increase with market size. As far as we are aware, this is the first exercise to separately and jointly measure the CZ size gradient of external and internal interactions. Moreover, exploiting the richness of our data, in Figure C.2, we show that both of these gradients are largely driven by occupations requiring a college degree.

These results are important since they 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, beginning with Marshall (1890), and more recently including Arzaghi and Henderson (2008) and Davis and Henderson (2008), argues that communication across firms—either among firms within the same industry or between customers and suppliers—is a key source behind agglomeration of economic activity. More broadly, we add to the evidence discussed in Davis and Dingel (2019) about cities as loci of interaction, showing that both internal and external interactions matter, and that skilled workers are key to these information flows. Underpinning all this work is the idea that large markets reduce the cost of face-to-face meetings, facilitating tacit knowledge flows among 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 capture the relative difference in task k intensity between 10th decile market size and 1st decile market size. The coefficients are normalized by dividing by the standard deviation of the task and then sorted by magnitude. Table 2 presents the largest positive and largest negative estimates across all tasks, both with and without SOC f.e.

Our results echo, at a much higher resolution, what we found in Figure 1. Placing little guidance on the categorization of tasks, and using the natural language of the job ad descrip-

tions to measure tasks, this exercise reveals that non-routine and abstract tasks have the steepest positive gradient. Examples include “managing projects,” “problem-solving skills,” and “developing strategies.” Communication and group interactions are important, too, as illustrated by the gradients of “written communication” and “maintaining relationships.” The tasks with the steepest negative gradient reflect more routine activities and emphasize following directions, including “operate cash-register,” “greeting customers,” and “maintaining inventory.” Table 2 also shows the steepest positive and negative gradients with six-digit SOC fixed effects and the patterns are similar. The correlation of task rankings with and without SOC f.e. is 0.67.¹⁷

3.2 Technology Requirements Across Space

We next systematically explore the importance of new technologies in large CZs and study how this relationship varies with the educational requirements of jobs. Our analysis is motivated by prior work that finds cities are at the forefront of innovation (Carlino et al., 2007; Lin, 2011). We leverage the rich text data available in job postings, which allow us to observe individual technologies at the job-level and allow us to study precisely how technological adoption differs for college and non-college 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.¹⁸ 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. Panel I is without any occupation controls, and panel II includes six-digit SOC fixed effects. Panel I shows an increase in technological requirements with labor market size. Note that the technology gradient appears only for jobs requiring a college degree. Panel II includes six-digit SOC fixed effects. Once again, the gradient is stronger for jobs requiring a college degree.

The results in Figure 3 provide three main conclusions. First, technology intensity is a

¹⁷For 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 using verbs only, rather than verb-noun pairs, to represent tasks using the list of verbs from Michaels et al. (2018); see Table B.7. Both robustness exercises reveal a similar pattern of increased interactiveness and teamwork in large CZs.

¹⁸We list the technologies in Appendix B.3; the list is also available on the O*NET website: https://www.onetonline.org/search/hot_tech/. We accessed the data August 27, 2019 and note that 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. Appendix B.5 reproduces the main analysis including R and C and shows that the results are unchanged. We also flag and exclude false positives of social media technologies (Facebook, YouTube, and LinkedIn) in our main analysis, since these technologies are likely to be mentioned in the context of encouraging the job applicant to visit the firm’s social media page. We describe our criteria for identifying false positives of social media technologies in Appendix B.3.

dimension along which work varies greatly across labor markets: A job in population decile 10 has 0.14 more mentions of technologies relative to a job in the lowest decile, which has a mean of 0.10 mentions per ad. Second, the gap in technology intensity between college and non-college work becomes larger with labor market size.¹⁹ 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 11 percent as large in Panel I as in Panel II, implying that 11 percent of the CZ size premium reflects within-occupation differences.

We next narrow our focus to study more granular measures of technology adoption, examining which technologies have the steepest positive gradient with respect to labor market size. We estimate equation (1), replacing the dependent variable with $tech_{jn}^{(\ell)}$, an indicator for job ad j being located in market size decile n requiring technology ℓ . We run this regression for each of the 180 technologies, and sort by $\beta_{10}^{(\ell)}$, after normalizing the estimates by dividing by the standard deviation of $tech_{jn}^{(\ell)}$. The results are presented in Table 3. The technologies with the steepest positive gradient with market size are Microsoft Excel, Python, JavaScript, Microsoft Project, and Linux. Furthermore, both more established technologies, such as the Microsoft suite, and newer ones, such as Ajax and Git, are more prevalent in larger CZs. Separating the analysis by education, 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).²⁰

These results show that large CZs are also at the forefront of new technology adoption. Our results complement the findings in the literature that new patents and new occupational titles appear with greater frequency in cities (Carlino et al., 2007; Lin, 2011). Unlike prior work, our granular data allow us to observe technology use at the job-level, technology-by-technology. Importantly, while new technologies are adopted more intensively by workers in large CZs, we find a large education gap in technology adoption between college and non-college workers, one that widens with CZ size.²¹ Hence, new technologies are complementary

¹⁹In Appendix C.1, we explore whether the gradients for tasks and technologies might be sensitive to the time period studied. Specifically, a potential concern is that a rapidly changing labor market in large v. small CZs might generate changing gradients over time. We divide the sample period into two approximately equal periods, 2012-2014 and 2015-2017, and re-estimate panel I for each time period. The broad descriptive patterns are similar across time periods.

²⁰Table 3 omits technologies with the steepest negative gradient because the estimates are small in magnitude and only two are statistically significant at the 5 percent level. First, pooling all ads, the coefficient estimate for Swift is -0.0593 and is significantly different from 0. It is likely that for many job ads, “swift” is simply an adverb and not a reference to a technological requirement. For jobs requiring a high school diploma, no technologies have a negative gradient that are statistically significant. For jobs requiring a college degree or above, only Apache Pig has a statistically significant negative gradient (-0.0134).

²¹Spitz-Oener (2008) and Atalay et al. (2018) provide evidence that new technologies tend to complement

with higher levels of education, and this complementarity is stronger in large CZs.

3.3 Specialization in Tasks Across Space

Since Adam Smith, economists have pointed to worker specialization as a key force behind the productivity gains in large markets (Young, 1928; Stigler, 1951; Becker and Murphy, 1992). Smith noted that larger markets allow workers to specialize in narrower sets of activities and, as a result, become more productive. But specialization in tasks has eluded direct measurement.

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.

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

The inner product between two task vectors is their cosine similarity, which takes a value between zero and one. Intuitively, if two jobs have perfect overlap in tasks, their similarity is one, and if they have no tasks in common, their similarity is zero.²² We define the task dissimilarity between job ads j and j' as one minus their cosine similarity: $d_{jj'} = 1 - V_j \cdot V_{j'}$.

We define specialization within a firm-market as the average task dissimilarity between job ad j and other ads in the firm-market pair. For this analysis, we denote a firm f as a firm name $\times$ six-digit industry NAICS code.²³ Define $d_{jfm} = 1 - V_{jfm} \cdot \bar{V}_{(-j)fm}$, where $\bar{V}_{(-j)fm}$ is the vector of average 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

analytic tasks. To the extent that analytic tasks are more intensive for college workers (compared to non-college workers) we uncover here that these complementarities are stronger with CZ size. Our analysis of new technologies also contributes to this literature in that it covers the U.S. in the 21st century.

²²Our specialization measure is related to work that computes occupational distances using the Dictionary of Occupational Titles or O*NET to study earnings losses from unemployment (Poletaev and Robinson, 2008; Macaluso, 2022). The job ads data allow us to form within-firm and within-occupation measures of specialization using much higher dimensional task vectors.

²³We group by both firm name and industry because the same firm name may, in certain cases, correspond to two separate firms in two different industries. Since these cases are rare, our results are essentially unchanged when grouping by firm name only.

is $d_{fm} = \frac{1}{n_{fm}} \sum_{j \in fm} d_{jfm}$, where n_{fm} is the number of job ads in the firm-market. We emphasize that we cannot construct dissimilarity for all workers in the firm-market but only for vacancies, which capture newly formed jobs.²⁴

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. In our analysis we explore dissimilarity along these two dimensions. We estimate the following regression:

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

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.²⁵

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

We perform several checks on the measurement of worker specialization and reexamine the gradient. First, we note that some tasks are intuitively similar, such as “provide feedback” and “provide recommendations.” We check the sensitivity to aggregating tasks with similar meaning, using a modeling approach from natural language processing to aggregate tasks (see Appendix C.2), and show the results are nearly identical. Within the same appendix, we apply three exercises to investigate whether the sampling of job postings may lead to measurement error in specialization measures, since small markets may have fewer job ads in an occupation-market or firm-market cell.²⁶

²⁴In constructing the firm-market sample, we drop ads that contain zero tasks—approximately 15 percent of ads—and ads that are singletons in the firm-market cell, another 4 percent. In constructing the occupation-market sample, the respective numbers are 17 percent and 0.11 percent. The average number of job ads in a firm-market cell is 8.3, and the median is 5.

²⁵In our analysis of specialization within occupations, we use four-digit (rather than six-digit) SOC codes as our unit of analysis, to have more job ads in cells with which to calculate task dissimilarity.

²⁶First, we confirm that the patterns in Figure 4 are robust to controlling for the number of ads in the cell (Figure C.11). Second, we reproduce Figure 4, panel A, for firm-markets with above the median number of postings and for those with below the median number of postings (Figure C.12). The results for the two groups look quite similar. Third, we do a placebo-type analysis of national chains and show that these chains

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 $d_{im} = \frac{1}{n_{im}} \sum_{f,m} d_{fim}$; 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:

$$d_{im} = \alpha_0 + \sum_{n=2}^{10} D_{mn} \alpha_n + x'_{im} \delta + \epsilon_{im}. \quad (3)$$

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 of equation (3). The main takeaway is that firms are located further apart in task space in larger markets, especially so for firms in nontradable industries.

All of these results together reveal that, as market size grows, there is an increase in both within- and between-firm specialization in tasks. Our approach to measuring specialization has several advantages. It is comprehensive, in that it characterizes the universe of job postings, while simultaneously providing fine measures of specialization. Thus, we go beyond case studies that have provided detailed analyses of specific occupations, such as doctors (Baumgardner, 1988) and lawyers (Garicano and Hubbard, 2009). We also complement the literature that measures specialization as occupational diversity (Bacolod et al., 2009b; Duranton and Jayet, 2011; Tian, 2019) in that we construct specialization measures based directly on job tasks and are thus able to speak about specialization in tasks themselves.²⁷

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

²⁷In Appendix C.2., we reproduce the findings of this literature. We document that occupations that are rare as a share of the entire U.S. labor market make up a greater share of larger markets relative to smaller markets, replicating Duranton and Jayet’s (2011) analysis of French labor markets. We also reproduce the finding of Tian (2019) in the U.S. context, showing that, conditional on the number of ads posted by the firm, there are more distinct job titles per firm in larger markets.

As we show in Section 3.5, all of these differences have implications for wages.

3.4 Elasticities with Respect to Log Population

Our main figures present the intensity of tasks, technologies, and the degree of specialization with market size deciles. Researchers may be interested in a single number that summarizes the elasticity of each of these outcomes with respect to log population. In this section, we adopt a second, complementary, empirical approach to 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. We report the slope estimate in the second step along with the standard error (in parentheses) in Table 4. Most elasticities diminish with the inclusion of occupation fixed effects, but important differences remain: about 29 percent of the elasticity for non-routine interactive tasks remains with SOC fixed effects, and about 15 percent of the elasticity for non-routine analytic tasks remains. The elasticity for occupation-market specialization does not diminish with SOC fixed effects.

3.5 Tasks, Technologies, and Wages

In previous sections, we have documented that interactive tasks, technology usage, and worker specialization all increase with CZ size.²⁸ In this section, we demonstrate that earnings are positively associated with these three factors, and, as a result, help explain differences in earnings observed between large and small CZs.

We compute the mean task dissimilarity within each occupation-CZ pair,

$$d_{om} = \frac{1}{n_{om}} \sum_{j \in om} (1 - V_{jom} \cdot \bar{V}_{(-j)om}),$$

the mean number of technological requirements at the occupation-CZ, $tech_{om}$, and, using our ACS sample, the fraction of employed workers in the occupation-CZ with a BA or above, ba_{om} .

We run the following regression:

²⁸We 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.

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

We include four-digit occupation fixed effects, ξ_o , in some specifications of equation (4) to highlight the role of tasks and technologies in accounting for within-occupation wage differences across markets. In equation (4), t_{om} is the occupation-market sum of internal and external interactive tasks, normalized to have mean zero and standard deviation one across jobs.²⁹

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. Nevertheless, it is valuable to assess whether within-occupation differences in tasks and technologies account for variation in wages across geography, beyond what is captured by differences in worker skills or occupation categories, and γ_1 , γ_2 , and γ_3 are key parameters for doing so. 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 large CZ premium. In addition, they demonstrate the value of using job ad text to measure job characteristics beyond occupational categories.

Table 5 reports the results. Column 1 shows that a one-standard-deviation increase in interactive tasks is associated with an increase in wages by approximately 12.3 percent, while a 0.1 increase in the number of technology mentions increases wages by 3.9 percent. A one-standard-deviation increase in task dissimilarity is associated with an increase in wages by 3.3 percent. Adding SOC fixed effects in column 2 weakens the coefficients on interactive tasks and technologies, but these estimates remain economically and statistically significant. Column 3, which controls for education, shows that measures of interactive tasks, technologies, and specialization account for variation in wages above occupational categories and worker education. This result emphasizes the importance of measurement within occupational categories for understanding wage inequality across geography.

Columns 4-7 re-estimate equation (4) separately by occupational category. We classify workers into white-collar and blue-collar workers by two-digit SOC, as described in the table note.³⁰ Within-occupation differences in interactive tasks plays an important role in ac-

²⁹Our preferred specification of equation (4) 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. Furthermore, Smith’s theory of specialization predicts that it is through market size that the productivity gains of specialization are realized. Nevertheless, Appendix C.3 presents the results with CZ fixed effects, showing that, consistent with this theory, 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.

³⁰We analyze white- and blue-collar occupations to study two occupation groups that have, respectively, higher-educated and lower-educated workers. We require subgroups at the occupation level (and not ac-

counting for the wage premium, particularly for white-collar occupations. Similarly, columns 4-7 show that white-collar workers have a within-occupation premium for technological requirements, while blue-collar workers do not. Lastly, note that within occupation-CZ task dissimilarity is associated with a wage premium for white-collar occupations, but much less so for blue-collar occupations.³¹

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 10th population decile have wages that are 30.1 log points higher than those in the bottom decile. The intensity of the interactive task measure, aggregating internal and external interactions, is approximately 0.16 standard deviations higher in top decile CZs relative to bottom decile CZs. Hence, column 2 of Table 5 indicates that interactive tasks account for 0.54 ($\approx 0.16 \cdot 0.034$) log points of the within-occupation difference in wages for workers living in top and bottom population deciles. As panel IV of Figure 4 indicates, specialization in top decile CZs is 1.28 standard deviations greater than in bottom decile CZs. Thus, column 2 of Table 5 reveals that our specialization measure accounts for 4.6 ($\approx 1.28 \cdot 0.036$) log points of the difference in wages for workers living in top and bottom population deciles. The technology measures account for an additional 1.02 ($\approx 0.03 \cdot 0.340$) log points, where the 0.03 comes from the estimate reported in Figure 3, panel II. Together, the three variables account for 21 percent ($\approx 6.2/30.1$) of the CZ size-wage premium. Furthermore, using the coefficient estimates from column 4, the three measures account for 22.8 percent (9.3 log points) of the 40.8 log point CZ size-wage premium in white-collar occupations.³² In sum, our interactive tasks, technologies, 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.³³

cording to education) for this analysis, since specialization measures are defined at the occupation-market level.

³¹These regressions rely on wage data from the ACS. Wages are available in a subsample of job ads in the Burning Glass data. We discuss the selection of job ads with posted wages in Appendix C.5. We reproduce Table 5 using wage data from Burning Glass in Appendix Table C.12 and find estimates that are surprisingly similar in magnitude, despite potential selection concerns.

³²We make this calculation as follows: Between top and bottom population deciles, the white-collar interactive task gap is 0.21 standard deviations, the technology gap is 0.04 mentions, the task dissimilarity gap is 1.06 standard deviations, and the wage gap is 40.8 log points. Using the estimates from Table 5, the three components account for $(0.21 \cdot 0.054 + 0.04 \cdot 0.367 + 1.06 \cdot 0.063)/0.408 \approx 22.8\%$ of the wage gap between bottom and top population decile CZs.

³³If we perform the analogous calculation conditional on the worker having a BA or above and the corresponding conditional estimates from Table 5 (columns 3 and 5), we obtain that interactive tasks, technologies, and specialization measures account for 18.7 percent of the 24.4 log point conditional CZ size-wage premium, and 19.3 percent of the 32.8 log point conditional CZ size-wage premium for white-collar workers.

4 Interpretation of Our Results

Our main result is that jobs are fundamentally different in large CZs. They involve more human-to-human interaction, greater use of information and communication technologies, and increased worker specialization. Moreover, the differences in work practices that we document are more pronounced for higher-educated workers, and their association with wages are larger for higher-skilled, white-collar occupations. Our data allow us to document these findings with a degree of granularity that was not previously possible. In this section, we discuss how our understanding of the sources of the CZ size-wage premium is enriched by these new facts and our new approach to task measurement.

An ongoing debate in the labor literature is whether the market size premium is due largely to the sorting of workers (Card et al., 2021) or the productivity benefits of workers' locations (De la Roca and Puga, 2017), with significant implications for the effectiveness of place-based v. worker-based policies (Kline and Moretti, 2014). A key limitation of existing research is that even the best administrative datasets in the U.S., such as the Longitudinal Employer-Household Dynamics program used in Card et al. (2021), lack information on the content of work activities. Our paper adds to this debate: Jobs themselves differ, and the CZ size-wage premium is not just a reflection of worker unobservables. To the extent that the selection of workers is important—e.g., workers with communication skills or greater facility with new technologies may sort into large CZs—our paper provides evidence that this sorting is a response to demand.³⁴ One implication of this finding is that the migration of workers is likely limited by the differing work activities demanded across space.

In addition to informing the sources of the CZ size-wage premium, our findings inform why workers of different skill levels have different CZ size premia. There is limited evidence on the mechanisms behind the college-non-college gap in the CZ size premium, because existing data sources do not allow researchers to comprehensively measure the content of jobs separately by worker education level. We document that the college-non-college gap is due in part to differences in interactive tasks, the use of new technologies, and worker specialization. We show that while college workers have a positive gradient for interactive tasks and the adoption of new technologies, these gradients are flat for non-college workers. In addition, our wage regressions show that these three mechanisms are far more important for white-collar occupations than for blue-collar occupations.

Lastly, our results provide the most direct empirical evidence to date that the degree of worker specialization increases with market size and is an important component of the CZ

³⁴While 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.

size-wage premium. While specialization, and its significance as a mechanism for productivity gains, is one of the oldest theoretical ideas in economics, direct measurement of specialization has been elusive due to the limitations of existing data sources. The state-of-the-art method is to count the number of distinct, or rare, occupations in a market without directly utilizing information on the sets of tasks that workers perform (Duranton and Jayet, 2011; Tian, 2019). Hence, prior research does not capture the relationship within or between occupations, which may have more or less overlap in tasks. In addition, our approach allows us to measure within- and between-firm specialization using a common methodology, and has applications beyond the CZ size premium. Our empirical evidence shows that both coordination within firms and worker specialization rise together with market size, lending empirical support to the theoretical insight of Becker and Murphy (1992).

5 Conclusion

By applying tools from natural language processing to rich textual data from online job ads, we examine in detail the differential task and technology content of jobs between large and small commuting zones. We also introduce an approach to define job tasks at a granular level. With our granular task measures, we characterize the relation between market size and specialization—a key driver of productivity that has eluded direct measurement. We have shown that the task content of occupations is critical to understand why average wages and the skill premium rise with CZ size. We believe, moreover, that the 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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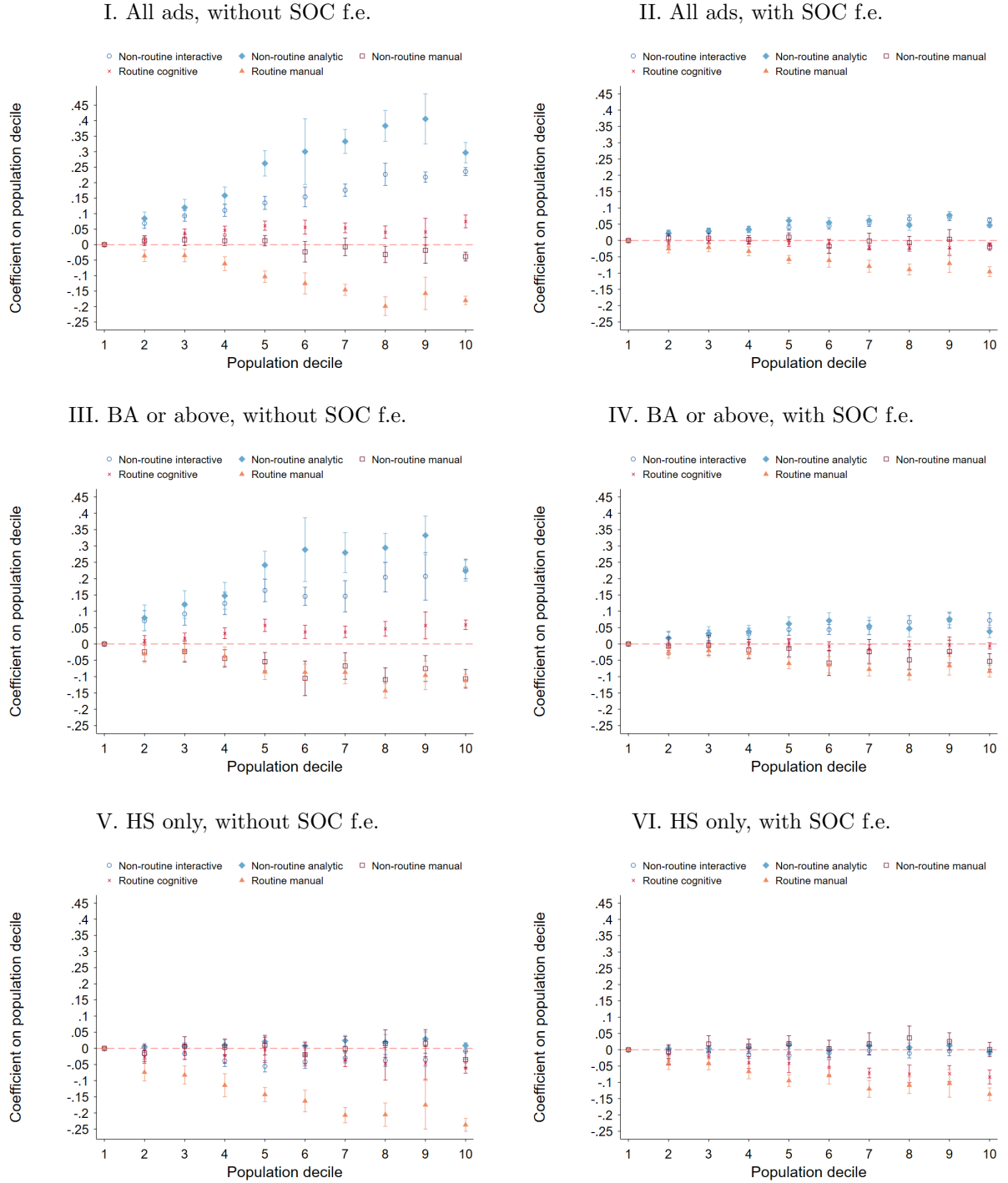
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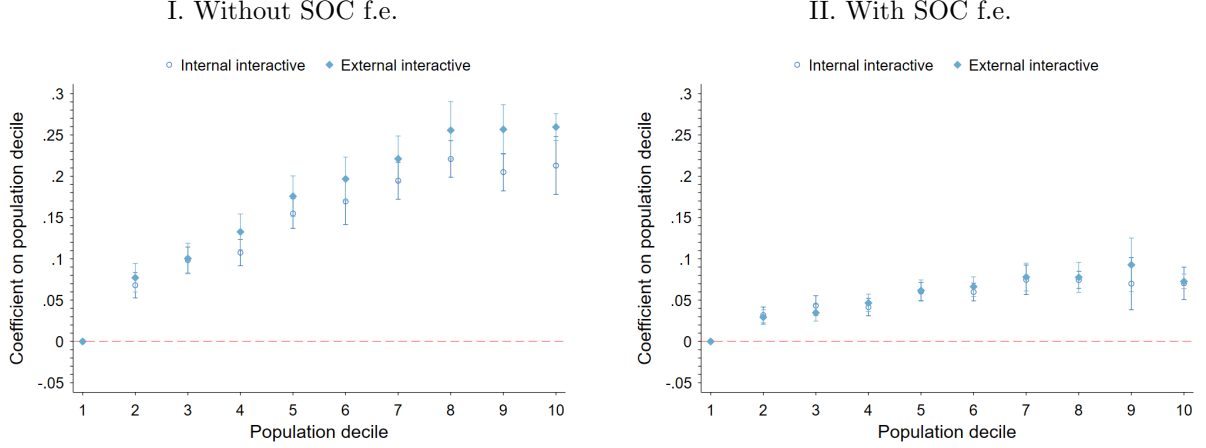
Figures and Tables

Figure 1: Tasks and Market Size



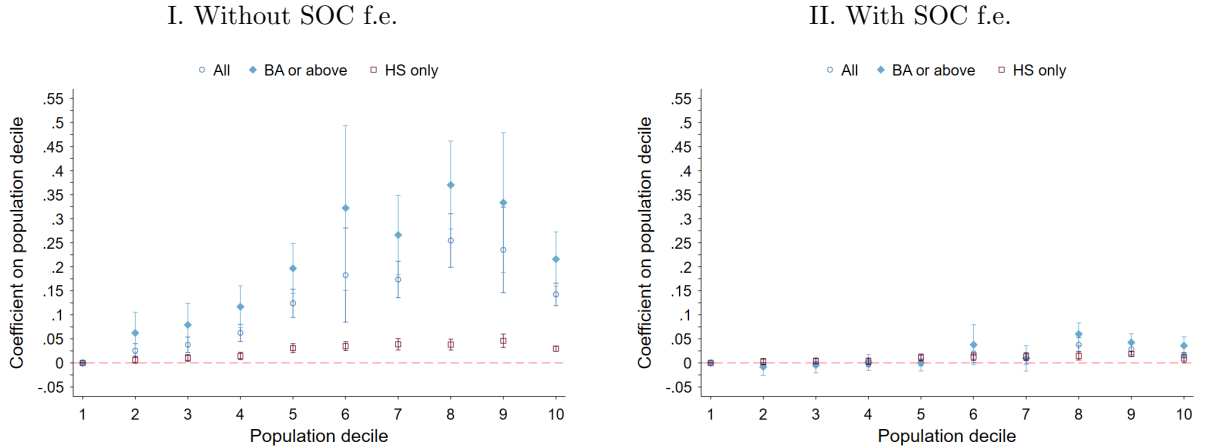
This figure presents estimates of equation (1). We control for log total ad words and, in the right panels, six-digit SOC fixed effects. The dependent variable is task intensity. Standard errors are clustered at the CZ level.

Figure 2: O*NET Interactive Tasks Gradient



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

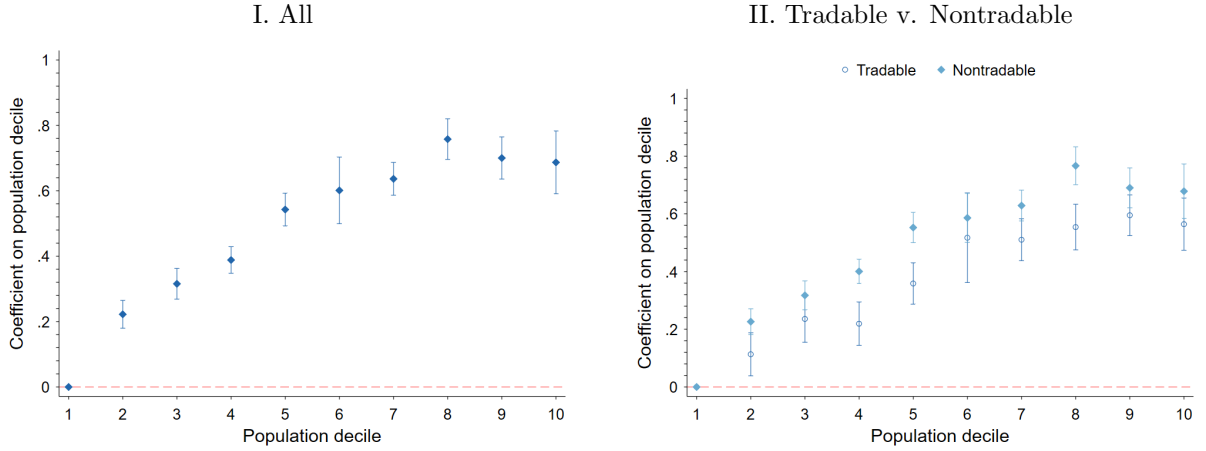
Figure 3: The Technology Gradient



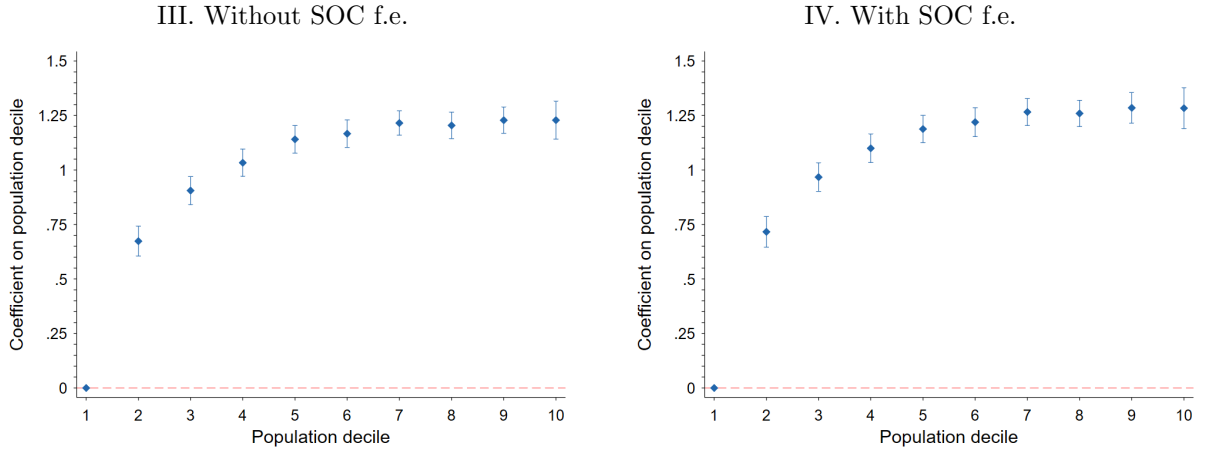
The dependent variable is the number of O*NET Hot Technologies mentioned in the ad, which is regressed on a vector of deciles for CZ size. For reference, the 1st population decile mean is 0.10 across all job ads, 0.26 for BA or above, and 0.08 for HS only. We control for log total ad words. Panel II includes six-digit SOC fixed effects. Standard errors are clustered at the CZ level.

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

A. Firms

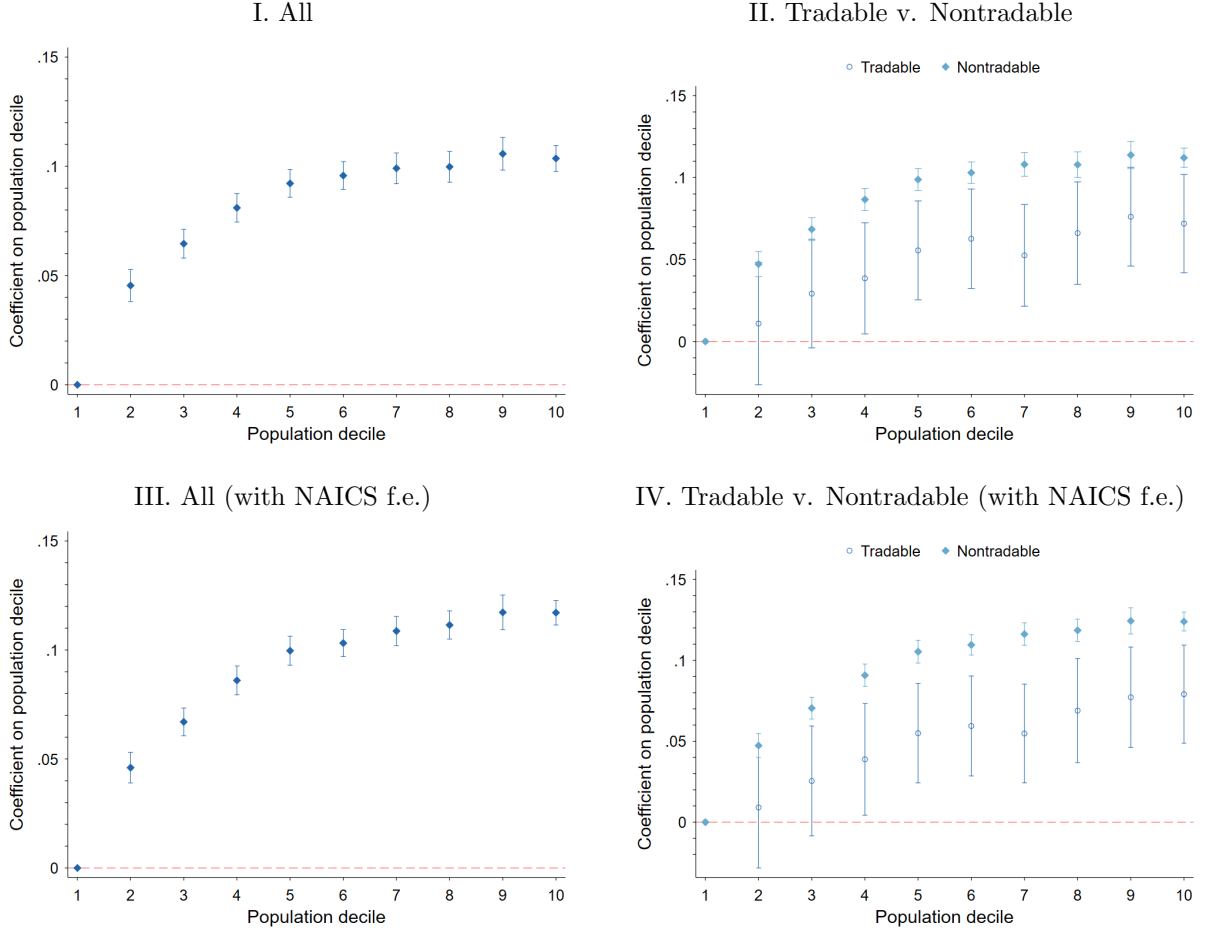


B. Occupations



The figure presents estimates of equation (2) and studies how task dissimilarity within the firm (panel A) and within the occupation (panel B) vary with market size. Panel A uses the firm-market sample, and the dependent variable is the mean task dissimilarity in the firm-market, while panel B uses the occupation-market sample, and the dependent variable is mean task dissimilarity in the occupation-market. We control for log total ad words, which is averaged to the cell level. Firm-market regressions are weighted by number of ads in the cell; occupation-market regressions are weighted by ACS employment in the cell. Standard errors are clustered at the CZ level. For reference, the 1st population decile mean for the top left panel is -0.51, and for the top right panel is -0.54 for the nontradable sample and -0.03 for the tradable sample. The 1st population decile mean for the bottom two panels is -1.92. We define tradable by two-digit NAICS code: agriculture, forestry, fishing and hunting (11), mining, quarrying, and oil and gas extraction (21), and manufacturing (31-33).

Figure 5: Specialization Gradient: Task Dissimilarity Across Firms



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

Table 1: Most Common Tasks for Selected Occupations

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

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

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

Positive Gradient				Negative gradient			
No SOC f.e.		SOC f.e.		No SOC f.e.		SOC f.e.	
Task	$\hat{\beta}_{10}$	Task	$\hat{\beta}_{10}$	Task	$\hat{\beta}_{10}$	Task	$\hat{\beta}_{10}$
written communication	0.1596	achieving sales	0.0701	maintain store	-0.1763	maximizes profitability	-0.1597
managing projects	0.1157	ensure safety	0.0686	maximizes profitability	-0.1692	protect company	-0.1501
meet deadlines	0.1075	written skills	0.0580	operating cash_register	-0.1653	maintain store	-0.1339
providing support	0.0956	stand walk	0.0573	protect company	-0.1641	operating cash_register	-0.1256
maintaining relationships	0.0943	driving sales	0.0572	make changes	-0.1431	make changes	-0.1249
written skills	0.0922	exceed sales	0.0556	provide customer_service	-0.1394	greeting customers	-0.1094
problem_solving skills	0.0881	providing environment	0.0523	preventing trafficking	-0.1373	procedures cash	-0.1080
working relationships	0.0844	providing coaching	0.0510	greeting customers	-0.1343	skating carhop	-0.1064
develop business	0.0833	according company	0.0500	skating carhop	-0.1334	ensure employees	-0.1041
developing strategies	0.0754	prioritize tasks	0.0500	procedures cash	-0.1264	unloading trucks	-0.1005
identify opportunities	0.0751	working relationships	0.0488	maintaining inventory	-0.1234	drive_in employees	-0.0981
prioritize tasks	0.0739	handle tasks	0.0487	assist store	-0.1221	maintaining inventory	-0.0948
develop relationship	0.0728	using eye	0.0461	unloading trucks	-0.1191	assigned store	-0.0873
make recommendations	0.0724	including nights	0.0449	ensure employees	-0.1143	working store	-0.0852
support business	0.0721	meet sales	0.0448	drive_in employees	-0.1104	provide customer_service	-0.0848

We estimate equation (1) separately for each task, without any controls, and again with six-digit SOC f.e. We normalize the estimates by dividing by the standard deviation of the task. The table above presents the tasks with the steepest positive and negative gradients with respect to market size, as captured by $\hat{\beta}_{10}$, which reflects the difference between 10th and 1st decile market size. All coefficients are statistically significant at the 1 percent level. The correlation between the task rankings, with and without SOC f.e. is 0.67.

Table 3: Technologies with the Steepest Gradient

All		College		High School	
Technology	$\hat{\beta}_{10}$	Technology	$\hat{\beta}_{10}$	Technology	$\hat{\beta}_{10}$
Microsoft Excel	0.1131	Geographic Information System (GIS)	0.1036	Microsoft Excel	0.0721
Python	0.0843	Python	0.0980	Microsoft Outlook	0.0527
JavaScript	0.0837	Microsoft Excel	0.0889	Microsoft Word	0.0453
Microsoft Project	0.0789	JavaScript	0.0844	Microsoft Office	0.0412
Linux	0.0785	SAS	0.0710	React	0.0277
Microsoft Word	0.0751	Linux	0.0708	Microsoft Access	0.0250
Microsoft Office	0.0720	Microsoft Project	0.0706	Microsoft Powerpoint	0.0239
SAP	0.0686	Microsoft Access	0.0650	Tax Software	0.0224
Microsoft Access	0.0685	Git	0.0644	Objective C	0.0216
Microsoft Powerpoint	0.0680	Microsoft Powerpoint	0.0597	YouTube	0.0214
Microsoft Outlook	0.0630	MySQL	0.0591	Facebook	0.0210
MySQL	0.0595	Tax Software	0.0553	Swift	0.0186
Unix	0.0589	Microsoft Office	0.0550	Python	0.0179
SAS	0.0584	Unix	0.0549	Epic Systems	0.0170
Geographic Information System (GIS)	0.0579	C++	0.0546	Ajax	0.0170

We estimate equation (1) where the dependent variable is a specific technology requirement, excluding controls. We estimate this regression separately for each O*NET technology. All coefficients are normalized by dividing by the standard deviation of the technology. We report the technologies with the steepest positive gradient with respect to market size, $\hat{\beta}_{10}$, which reflects the 10th decile technology intensity relative to the 1st decile. All estimates are statistically significant at the 5 percent level, with the following exceptions in the High School column: React ($p = 0.48$) and Ajax ($p = 0.09$).

Table 4: Coefficients with Respect to Log Population

	All		BA or above		HS only	
	No SOC f.e.	SOC f.e.	No SOC f.e.	SOC f.e.	No SOC f.e.	SOC f.e.
Non-routine analytic	0.086 (0.003)	0.013 (0.001)	0.069 (0.003)	0.012 (0.002)	0.004 (0.001)	0.001 (0.001)
Non-routine interactive	0.051 (0.001)	0.015 (0.001)	0.048 (0.002)	0.017 (0.001)	-0.004 (0.001)	-0.000 (0.001)
Non-routine manual	-0.010 (0.001)	-0.003 (0.001)	-0.024 (0.002)	-0.011 (0.002)	-0.001 (0.002)	0.005 (0.002)
Routine cognitive	0.012 (0.001)	-0.004 (0.001)	0.013 (0.001)	-0.001 (0.001)	-0.011 (0.002)	-0.017 (0.001)
Routine manual	-0.044 (0.002)	-0.021 (0.001)	-0.030 (0.002)	-0.022 (0.001)	-0.047 (0.002)	-0.027 (0.001)
O*NET Internal Interactive	0.048 (0.001)	0.015 (0.001)	0.020 (0.002)	0.003 (0.002)	0.006 (0.001)	0.009 (0.001)
O*NET External Interactive	0.059 (0.001)	0.019 (0.001)	0.059 (0.002)	0.014 (0.002)	0.015 (0.001)	0.012 (0.001)
Technologies	0.053 (0.002)	0.008 (0.001)	0.076 (0.004)	0.013 (0.001)	0.010 (0.001)	0.004 (0.000)
Specialization (SOC-CZ)	0.236 (0.006)	0.245 (0.007)				
	Non-Tradable	Tradable				
Specialization (Firm-CZ)	0.174 (0.004)	0.164 (0.007)				

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

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

	All			White-collar		Blue-collar	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Interactive tasks	0.123*** (0.007)	0.034*** (0.007)	0.021*** (0.005)	0.053*** (0.011)	0.028*** (0.007)	0.027*** (0.007)	0.024*** (0.006)
Technology requirements	0.385*** (0.013)	0.340*** (0.042)	0.212*** (0.026)	0.367*** (0.047)	0.214*** (0.029)	0.001 (0.029)	-0.004 (0.028)
Task dissimilarity	0.033*** (0.003)	0.036*** (0.003)	0.029*** (0.002)	0.062*** (0.006)	0.047*** (0.004)	0.007** (0.003)	0.006* (0.003)
BA or above			0.859*** (0.069)		0.933*** (0.077)		0.474*** (0.059)
SOC f.e.	No	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	44,956	44,956	44,956	24,370	24,370	11,247	11,247
R^2	0.240	0.811	0.840	0.768	0.819	0.568	0.580
Mean of dependent var.	10.784	10.784	10.784	10.983	10.983	10.576	10.576
Mean task dissimilarity	0.000	0.000	0.000	0.152	0.152	-0.178	-0.178
Mean technology requirements	0.157	0.157	0.157	0.223	0.223	0.043	0.043
Mean interactive tasks	0.000	0.000	0.000	0.435	0.435	-0.915	-0.915
Mean BA or above	0.363	0.363	0.363	0.517	0.517	0.076	0.076

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