The Geography of Job Tasks

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Abstract

Working in urban commuting zones (CZs) commands a large earnings premium, and this premium differs significantly by worker skill level. In this paper, we produce new descriptive evidence and introduce new measurement tools to understand the mechanisms behind the urban premium and why it differs by worker skill level. We use the near-universe of job vacancies and develop granular measures of job tasks—based on the natural language employers use, rather than survey-based categories—that allow for differences within occupations and across CZs. We find evidence for three mechanisms behind the earnings premium. First, jobs are more interactive and analytic in urban CZs, even within narrow occupation categories. Second, the computer software requirements of jobs are more intensive in urban CZs. Third, urban workers are more specialized, with less overlap in the sets of tasks performed, within occupations. Furthermore, these differences across CZs are more pronounced for college-educated workers than for non-college workers. We show that job tasks and technologies account for a substantial portion of the urban CZ premium—even within-occupations—and this relationship is stronger for white-collar occupations.

JEL Codes: J20, J24, R12, R23

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1 Introduction

Rural-urban 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 city size (Baum-Snow et al., 2018; Autor, 2019). Furthermore, cities foster distinct types of work (Duranton and Puga, 2005; Davis and Dingel, 2020). For example, managerial, financial, and computer occupations are overrepresented in large cities, while maintenance, production, and material moving occupations employ a relatively large share of workers in rural areas.

While economists have studied how jobs vary with city 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 the content of occupations varies 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 city size. 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 urban earnings premium: increased worker interactions and coordination, the adoption of new technologies, and increased worker specialization. To date, these channels have eluded direct measurement at the job-level. In addition, the data allow us to study the sources of the stark difference in urban premium between workers of different skill levels.

We leverage the rich job description text and tools from natural language processing to extract detailed information about job tasks and technologies. Our task and technology measures are not fixed at the occupation level, and allow for differences in task content within and across regions. As we show in this paper, work is different in cities, even within occupations, and this heterogeneity is important for understanding both the urban wage premium and the larger skill premium in urban areas.

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 in the job description, thus imposing fewer ex ante restrictions on the classification of tasks. 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. For example, relative to the bottom population decile, commuting zones in the top population deciles have 0.20 to 0.30 standard deviations higher intensity of non-routine analytic and interactive tasks. This gradient remains significant even after conditioning on narrowly defined occupation categories (six-digit SOC codes), and hence is not merely driven by the composition of occupations across markets. We further decompose interactive tasks into those that capture interactions outside the firm and those that capture interactions within the firm. We find that the market size gradient is positive for both external and internal interactive tasks, and that this relationship is more pronounced for jobs requiring a college degree.[1] Our analysis using the granular task measures echoes these findings at a much higher resolution. The verb-noun pairs with the steepest urban gradients demonstrate the importance of problem-solving ("managing projects," "developing strategies," "problem-solving skills") and communication and worker interactions ("written communication," "maintaining relationships") in cities.

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 high- and low-skilled jobs. Measuring technology requirements as the appearance of O*NET's Hot Technologies in the job descriptions, we find that technology requirements increase with market size. The mean number of technologies mentioned per job ad is 0.10 and it is approximately 2.5 times higher in the 7th through 10th deciles relative to the 1st. About 15 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. This provides suggestive evidence that technologies are a mechanism behind the flattened urban wage premium for non-college workers. Aligned with this interpretation, the technologies with the steepest gradient for

[1] We 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 rural and urban labor markets.

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., 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 the job's tasks 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 within industries. 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. We find that within-occupation heterogeneity in interactive tasks, technology usage, and specialization account for 20.0 percent (6.0 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 22.8 percent (9.3 log points out of a total of 40.8) when we subset to white-collar occupations.

One should be cautious in interpreting these wage regressions as capturing causal estimates; for example, workers who sort into interactive or technology-intensive jobs may differ in other ways, unobservable to us. However, we believe these estimates are informative. They show, first, that jobs differ between large and small labor markets in ways that are both economically meaningful and that have been previously unmeasured. Second, existing theories—rooted in specialization, technology adoption, and face-to-face interaction—provide parsimonious characterizations of job differences that correlate with urban premia and urban skill premia. And, third, even if workers are differentially sorting into larger cities on the basis of unobservable characteristics, the way in which they sort is driven by matching with employers and the particular job tasks and technologies they demand.

Our paper contributes to the literature that studies the geography of job tasks and tech-

[2]These results complement an expanding literature on the spatial distribution of technology adoption. Eckert et al. (2019) 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.

nologies (e.g., Frank et al., 2018) and to research on geographic inequality (Eckert et al., 2019; Giannone, 2019; Couture and Handbury, 2020). Relative to this literature we make two contributions. First, this is the first paper to use job postings data to study the spatial distribution of job tasks and technologies.[3] We show that within-occupation heterogeneity is substantial and is important for explaining city size wage premia. Second, 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 use this approach to better characterize the nature of work across space—showing, for example, that work in cities is much more interactive—and to directly measure the degree of worker specialization. Our measures reveal that both the task content and the technology requirements of occupations shift from rural to urban markets, which suggests there are limits to worker mobility, even within the same occupation.

While prior work has established that new patents and new occupational titles appear in cities (Carlino et al., 2007; Lin, 2011), we show, for the first time, that new technologies are adopted by workers more frequently in larger cities. Using previously unavailable measures of technology use at the job-level, we show that the adoption of new technologies in cities is far more intensive for workers with a college degree relative to those with a high school degree. We then provide suggestive evidence that differential technology adoption is a key source of the differential returns to work in cities faced by white- and blue-collar workers.

Recent work also explores interactions between workers as a source of agglomeration, both theoretically (Davis and Dingel, 2019) and empirically (Bacolod et al., 2009b; Michaels et al., 2018). Our contribution to this literature is to evaluate, using the finest level of detail available on the nature of work, the mechanisms underlying the urban productivity gains from increased interaction. We show not only that interactions increase in city size, but also that cities are a locus of interactions both within and across firm boundaries. Furthermore, these relationships with city size are larger for high-skilled work. These findings are new to the literature, and show that differences in interaction intensities help account for the differing returns to employment in large cities by skill group.

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). 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. This approach departs from the literature, which has

[3] Previous research exploits job vacancy postings across different labor markets, without seeking to explain rural-urban inequality (Hershbein and Kahn, 2018; Deming and Kahn, 2018; Hemelt et al., 2020).

taken an indirect approach to measuring specialization, by counting the number of distinct occupations. We show that worker specialization increases in cities and that this increased specialization accounts for a substantial portion of the urban premium.

The outline for the remainder of the paper is as follows. In Section 2, we introduce our dataset and explain why it is a valuable and reliable source of information on differences in work content across labor markets. We present our main empirical results in Section 3, then discuss how these results reshape our understanding of the sources of agglomeration and of urban wage premia in Section 4. Section 5 concludes.[4]

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. A virtue 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 that contains 7.2 million ads.[5]

In addition to the full text content of each ad, the data include information EMSI extracts, including 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 employment decile. We exclude ads with fewer than the 1st and more than the 95th percentile word count.[6] We

[4]In the appendices, we provide additional information to validate our dataset (Appendix A) and our methodology to extract tasks and technologies from our job ad text (Appendix B). We then provide sensitivity analysis to Section 3's results in Appendix C.

[5]EMSI is the preferred data source for our purposes because it contains the complete job description text, which is ideal for extracting job tasks and measuring specialization. By contrast, the version of Burning Glass to which we 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.

[6]Dropping extremely short ads removes those that are unlikely to have meaningful task information,

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. We apply a chain-weighted price deflator for personal consumption expenditures to wages before averaging at the four-digit SOC. We link job ads data to the ACS by four-digit SOC and CZ, and therefore all wage regressions with occupation fixed effects have them 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.[7]

In Appendix A.3, we assess the representativeness of the online ads data, comparing our data with the Job Openings and Labor Turnover Survey (JOLTS) dataset. We find broad concurrence in the vacancy shares across industries, suggesting that online vacancies measure a fairly representative cross-section of total vacancies. The representativeness of online job postings has also been evaluated in Hershbein and Kahn (2018).

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, routine manual—following the categorization of Spitz-Oener (2006). We also map words into O*NET work activities, in order to validate our job ads-based task measures and to study different types of interactive tasks. See Appendix A.4 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

while dropping exceedingly long ads helps reduce computation time.

[7]In 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. However, only a small and not necessarily representative sample of ads have a posted salary in EMSI data. While the Occupational Employment Statistics Survey 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.

per 1,000 ad words.[8] We standardize each task to have mean zero and standard deviation one across all ads.[9]

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 work activities that reflect the actions required by 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." One advantage of this approach is it avoids using a researcher-defined mapping of words to task categories and leverages the rich database of text using tools from natural language processing. An additional advantage of this approach is that it defines tasks at a highly granular level, allowing us to measure the degree of specialization of jobs that share the same occupational code.

We describe the verb-noun approach to task measurement in detail in Appendix B and briefly outline it here. There are two steps to this 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.[10] To ensure the verb-noun pairs that we extract are actually tasks and not firm or worker characteristics, we search across job ads for keywords—"duties," "summary," "description," and "tasks"—that indicate that the job description will follow. We use the remaining portion of text in these ads and extract each verb and the next noun in each sentence, ignoring other parts of speech that may appear in between. We define the set of job tasks as the 500 most common verb-noun pairs from this step. 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.

We choose 500 tasks to balance the advantage of comprehensively characterizing jobs'

[8]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.

[9]In 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.

[10]We stem verbs and nouns 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).

[11]We use the entire job ad text when vectorizing, rather than a subset of the text (such as the text following "duties," "summary," "description," or "tasks"). 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.

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.

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.2 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," "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 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 Validation of Data and Task Measures

We demonstrate in Appendix A.4 that information contained in the online ad text captures real information about the labor market. We compare the education requirements extracted from the job ads with the education of employed workers in the 2010-2017 ACS in the same occupation-market. We find that these two measures of education are highly correlated—a relationship that holds across large and small markets, within and across occupations.

We also validate the task measures extracted from the ads and compare these measures with O*NET. In Appendix A.4, we show that occupation-level measures of O*NET Work Activities, which 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

[12] In 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.

reflect occupation-level content that is similar to the occupation-level content of O*NET. In our analysis, we leverage the additional within-occupation variation in tasks. As an additional robustness check, in Appendix B.5, we show that our task measures, constructed using either of the two approaches, account for variation in average wages at the occupation level, above and beyond what is captured by occupation fixed effects. These task measures 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. In Section 3.1, we describe the types of tasks most prevalent in large markets. We then demonstrate that cities are a locus of technology adoption in Section 3.2 and worker specialization in Section 3.3. In Section 3.4, we assess the implications of these relationships for the urban wage premium and the increased skill premium in cities.

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 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:

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

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

Figure 1, panel I, plots the coefficients on market size decile, $\beta_n^{(k)}$. The primary takeaway is that non-routine interactive and non-routine analytic tasks are increasing in market size, while routine manual tasks are decreasing in market size. According to panel I, the 10th population decile has 0.20 s.d. greater intensity of non-routine interactive tasks and 0.30 s.d. greater intensity of non-routine analytic tasks, while having approximately 0.20 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 0.05 s.d.), and routine manual tasks are mentioned less frequently (by 0.08 s.d.), in the top population decile CZs relative to the 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.

To 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

$$t_{kq} - t_{k\tilde{q}} = \sum_{o \in \mathcal{O}} (t_{koq} - t_{ko\tilde{q}}) \bar{s}_{oq\tilde{q}} + \sum_{o \in \mathcal{O}} \bar{t}_{koq\tilde{q}} (s_{oq} - s_{o\tilde{q}}), \tag{2}$$

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 (2) 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 2 presents the results of this decomposition. For non-routine analytic tasks, 23 percent of the variation between 1st quartile and 4th quartile CZs is within occupation. For non-routine interactive tasks, the corresponding figure is 35 percent. This result implies that standard data sources fail to capture much of the variation in tasks between rural and urban markets.

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 for interactive skills. 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. We dispense with this hedonic imputation approach, since we are able to observe directly how the jobs themselves vary *across* labor markets *within* occupations. We show in Section 3.4 that these within-occupation differences have important implications for wage differentials.

An additional new finding of our paper is that the relation of task contents and city size depends on a worker's education level. Panels III through VI of Figure 1 present the analysis for interactive and analytic tasks separately by the education requirement of the job ad. We find that jobs requiring a college degree in urban areas are far more intensive in interactive and analytic tasks compared with those in rural areas, while this gradient is flat for jobs requiring only a high school diploma. Our results show that both within and between occupations, jobs in cities 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 15 percentage points more of jobs in each of the highest three deciles compared with the lowest decile. Jobs that are intensive in only analytic tasks but not interactive tasks make up only about 4 percentage points more of jobs in the highest three deciles. 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 cities.

Interactive Tasks Inside and Outside the Firm

Having demonstrated the importance of interactive tasks in urban 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.[13] 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 tasks increase with market size. Compared with ads in the bottom population decile, ads in the top population deciles mention internal interactive tasks (by 0.20 s.d.) and external interactive tasks (by 0.25 s.d.) more frequently. When we include six-digit SOC occupation fixed effects, the gradients are substantially smaller, though still economically and statistically significant.

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

[13] We define *external interactive tasks* as O*NET activities "Selling or Influencing Others" and "Communicating with Persons Outside Organization," and we define *internal interactive tasks* as O*NET work activities "Guiding, Directing, and Motivating Subordinates," "Developing and Building Teams," "Coaching and Developing Others," "Coordinating the Work and Activities of Others," and "Communicating with Supervisors, Peers, or Subordinates." We list the word mappings in Appendix A.4.

is the first exercise to separately and jointly measure the city 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 cities 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 urban labor markets, but with the proviso that the tacit knowledge flows shared within urban environments 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 3 presents the largest positive and largest negative estimates across all tasks.

Our results echo, at a much higher resolution, what we found in Figure 1. Placing little guidance on the categorization of tasks, and using the natural language of the job ad descriptions to measure tasks, this exercise reveals that non-routine and abstract tasks have the steepest positive gradient. Examples include "managing projects," "problem-solving skills," and "developing strategies." Communication and group interactions are important, too, as illustrated by the gradients of "written communication" and "maintaining relationships." The tasks with the steepest negative gradient reflect more routine activities and emphasize following directions, including "operate cash-register," "greeting customers," and "maintaining inventory."[14]

We next perform the decomposition of equation 2 on these granular task measures to understand how much of the variation in these tasks across markets occurs within occupations versus between occupations. Table 4 reports the results for the decomposition applied to the five most common tasks. We also calculate the decomposition shares for each of the granular tasks and report the average, shown in the rightmost two columns in the bottom panel of the table. The main takeaway is that a substantial amount of variation in tasks across geography occurs within occupations. For example, 16 percent of variation in "written communication" from the smallest quartile CZs to the largest quartile occurs within occupations. An even larger share—62 percent—of "provide customer-service" occurs within occupations. Taking the median across all granular tasks, we find that 70 percent of the variation from smallest to largest quartile CZs occurs within occupations.

3.2 Technology Requirements Across Space

We next systematically explore the prevalence of new technologies in cities and study how this relationship varies with the educational requirements of jobs. We consider two questions: Are technological requirements more important in urban areas? And how does the technology gradient differ for jobs requiring a college degree compared with the gradient for jobs requiring a high school diploma? To answer these questions, we leverage the job postings data, which allow us to observe individual technologies at the job-level and 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.[15] Figure 3 presents a job ad-level regression of the number of technologies that

[14] For robustness, in Table B.5 we reproduce this table with six-digit SOC fixed effects. We also reproduce the table using verbs only, rather than verb-noun pairs, to represent tasks. For this exercise, we adopt the list of verbs from Michaels et al. (2018) rather than use the job ad text to define the set of tasks; see Table B.6. Both robustness exercises reveal a similar pattern of increased interactiveness and teamwork in urban areas. An important advantage of our measurement approach relative to Michaels et al. (2018) is that we extract parts of speech from the text of job ads rather than the text of occupational descriptions in the Dictionary of Occupational Titles. Thus, our task measures capture within-occupation variation and are defined in the field, using text by firms seeking workers. An additional advantage, which we explore in Section 3.3, is that we can develop new measures of specialization using these granular task measures.

[15] We 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

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 shows that approximately 15 percent of the gradient remains after including six-digit SOC fixed effects. Once again, the gradient is stronger for jobs requiring a college degree.

The results in Figure 3 allow us to draw three main conclusions. First, technology intensity is a dimension along which work varies greatly across labor markets: A job in a labor market at the top population decile has 0.2 more mentions of technologies relative to a job in the lowest decile, which has a mean of 0.1 mentions per ad. Second, the gap in technology intensity between college and non-college work becomes larger with labor market size.[16] Finally, a substantial fraction of this correlation with market size—but crucially not all—is contained in differences in occupations.[17]

We next narrow our focus to study more granular measures of technology adoption. Our data allow us to study individual technologies and identify those with 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 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 5. The technologies with the steepest positive gradient with market size are Microsoft Excel, Python, JavaScript, Microsoft Project, and Linux. 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).[18]

firm's social media page. We describe our criteria for identifying false positives of social media technologies in Appendix B.3.

[16]In 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 cities relative to rural areas 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 main takeaways are unchanged.

[17]Applying the equation 2 decomposition to the number of technologies, we find that about 90 percent of the variation in technologies between 1st quartile CZs and 4th quartile CZs occurs between occupations and about 10 percent within occupations.

[18]Table 5 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

These results show that cities are 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. An important new finding, uncovered by these data, is that while new technologies are adopted more intensively by workers in cities, there is a large education gap in technology adoption between college and non-college workers, one that widens with city size.[19] This result provides evidence that new technologies are complementary with higher levels of education, and that this complementarity is stronger in cities.

The job ads data also allow us to measure the specific *types* of technologies that differ in cities. We find that both more established technologies, such as the Microsoft suite, and newer ones, such as Ajax and Git, are more prevalent in cities. Moreover, as noted above, the types of technologies used in college and non-college work differ.

3.3 Specialization in Tasks Across Space

Economists since Adam Smith have pointed to worker specialization as a key force behind urban productivity gains (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 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

college degree or above, only Apache Pig has a statistically significant negative gradient (-0.0134).

[19] Spitz-Oener (2008) and Atalay et al. (2018) provide evidence that new technologies tend to complement 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 city size. Our analysis of new technologies also contributes to this literature in that it covers the U.S. in the 21st century.

is one, and if they have no tasks in common, their similarity is zero.[20] We define the task dissimilarity between jobs j and j' as one minus their cosine similarity: $d_{jj'} = 1 - V_j \cdot V_{j'}$.[21]

We define specialization within a firm-market as the average task dissimilarity between job j and other jobs in the firm-market pair. For this analysis, we denote a firm f as a firm name × six-digit industry NAICS code.[22] Define $d_{jfm} = 1 - V_{jfm} \cdot \overline{V}_{(-j)fm}$, where $\overline{V}_{(-j)fm}$ is the vector of average task content in firm-market fm, averaged over all jobs in the firm-market excluding job j. If the term d_{jfm} is larger, job j has less overlap in task content with other jobs in the firm-market fm. At the firm level, the degree of specialization is $d_{fm} = \frac{1}{n_{fm}} \sum_{j \in fm} d_{jfm}$, where n_{fm} is the number of jobs 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.[23] The average number of job ads in a firm-market cell is 8.3.

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

$$d_{cm} = \alpha_0 + \sum_{n=2}^{10} D_{mn} \alpha_n + x'_{cm} \delta + \epsilon_{cm}, \tag{3}$$

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.[24]

[20]Our 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, 2019). The job ads data allow us to form within-firm and within-occupation measures of specialization; in addition, our use of natural language processing tools allows us to extract much higher dimensional task vectors to measure specialization.

[21]The cosine similarity treats differences along all task dimensions equally. For example, two distinct writing-related tasks contribute the same to our specialization measure as a writing task and a machine-operation task. While one could imagine relaxing this assumption, our measure has the virtue of being transparent and easy to interpret. Moreover, we find no ex ante reason why this would introduce a bias when we examine how this measure co-varies with city size and wages below.

[22]We 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.

[23]In constructing the firm-market sample, we drop ads that contain zero tasks—approximately 15 percent of ads—and ads that are singletons in the firm-market cell, another 4 percent. In constructing the occupation-market sample, the respective numbers are 17 percent and 0.11 percent.

[24]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.

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.[25]

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

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

$$d_{im} = \alpha_0 + \sum_{n=2}^{10} D_{mn}\alpha_n + x_{im}^{'}\delta + \epsilon_{im}. \tag{4}$$

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 4. 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

[25] Conceivably, the sampling of job postings may lead to measurement error in specialization measures, and this measurement error may differ for large and small markets, since small markets may have fewer job ads in an occupation-market or firm-market cell. We reproduce Figure 4 with an additional control for the number of ads in the cell in Appendix C.2. Reassuringly, the estimates of this exercise are virtually identical to those in Figure 4.

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.[26] As we show in the following section, all of these differences have implications for wages.

3.4 Tasks, Technologies, and Wages

In previous sections, we have documented that interactive tasks, technology usage, and worker specialization all increase with city size. In this section, we show that within-occupation differences in these three factors help account for the urban wage premium and the differential premium faced across occupations.

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

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

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:

$$log(wage)_{om} = \gamma_0 + \gamma_1 t_{om} + \gamma_2 tech_{om} + \gamma_3 d_{om} + \gamma_4 ba_{om} + \xi_o + \epsilon_{om}. \tag{5}$$

We include four-digit occupation fixed effects, ξ_o, in some specifications of equation (5) to highlight the role of tasks and technologies in accounting for within-occupation wage differences across markets. We include the O*NET-based interactive task intensity measure in equation (5), motivated by our finding in section 3.1 that interactive tasks have a strong gradient with market size and that the gradients differ across college and non-college jobs. In equation (5), t_{om} is the occupation-market sum of O*NET internal and external interactive tasks, normalized to have mean zero and standard deviation one across jobs. The parameter γ_1 reflects the relationship between interactive tasks and wages. Similarly, γ_2 is informative about the extent technological requirements account for occupational differences in wages

[26] In 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.

across markets. The coefficient γ_3 represents the relationship between specialization and wages.[27]

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 urban premium. In addition, they demonstrate the value of using job ad text to measure job characteristics beyond occupational categories.

Table 6 reports the results. Column 1 shows that a one-standard-deviation increase in interactive tasks is associated with an increase in wages by approximately 12.6 percent, while a 0.1 increase in the number of technologies increases wages by 3.7 percent. A one-standard-deviation increase in task dissimilarity is associated with an increase in wages by 3.1 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 (5) separately by occupational category. We classify workers into white-collar and blue-collar workers by two-digit SOC code, as described in the table note.[28] Within-occupation differences in interactive tasks plays an important role in accounting for the wage premium, particularly for white-collar occupations. Similarly, columns 4-7 show that white-collar workers have a large urban 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

[27] Our preferred specification of equation 5 excludes CZ fixed effects. In this section, we apply our regression estimates 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 city size that the productivity grains 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.

[28] We 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 for this analysis, since specialization measures are defined at the occupation-market level.

so for blue-collar occupations.

We use these coefficient estimates to gauge the importance of interactive tasks, technologies, and worker specialization in accounting for urban wage premia. 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 O*NET task measure is approximately 0.16 standard deviations higher in top decile CZs relative to the bottom decile CZ. Hence, column 2 of Table 6 indicates that interactive tasks account for 0.58 ($\approx 0.16 \cdot 0.036$) 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 6 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 0.79 ($\approx 0.03 \cdot 0.263$) log points, where the 0.03 comes from the estimate reported in Figure 3, panel II. Together, the three variables account for 20 percent ($\approx 6.0/30.1$) of the urban wage premium. Furthermore, using the coefficient estimates from column 4, the three measures account for 23.2 percent (9.3 log points) of the 40.8 log point urban wage premium in white-collar occupations.[29] In sum, our interactive tasks, technologies, and specialization measures account for a substantial portion of the urban wage premium as well as the steeper urban wage premium for highly skilled workers that exists within occupations.[30]

4 Interpretation of Our Results

Our main result is that jobs are fundamentally different in cities. 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

[29]We 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 0.05 mentions, the task dissimilarity gap is 1.06 standard deviations, and the wage gap is 40.8 log points. Using the estimates from Table 6, the three components account for $(0.21 \cdot 0.054 + 0.05 \cdot 0.329 + 1.06 \cdot 0.063)/0.408 \approx 23.2\%$ of the wage gap between bottom and top population decile CZs.

[30]If we perform the analogous calculation conditional on the worker having a BA or above and the corresponding conditional estimates from Table 6 (columns 3 and 5), we obtain that interactive tasks, technologies, and specialization measures account for 18.4 percent of the 24.4 log point conditional urban wage premium, and 19.5 percent of the 32.8 log point conditional urban wage premium for white-collar workers.

with a degree of granularity that was not previously possible. In this section, we discuss how our understanding of the sources of the urban premium is enriched by these new facts and our new approach to task measurement.

An ongoing debate in the labor literature is whether the urban premium is due largely to the sorting of workers (Card et al., 2021) or the advantages 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, lack information on the content of work activities (Card et al., 2021). Our paper adds to this debate: Jobs themselves differ, and the urban 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 cities—our paper provides evidence that this sorting is a response to demand.[31] One implication of this finding is that the migration of workers is likely limited by the differing work activities demanded across space, which suggests that workers may capture some of the benefits of place-based policies (Kline and Moretti, 2014).

In addition to informing the sources of the urban premium, our findings inform why workers of different skill levels have different urban premia. In the 1970s and 80s, workers with a college degree had a steep urban wage premium that was paralleled by those without a college degree; since the 2000s, the premium for non-college educated workers has flattened (Baum-Snow et al., 2018; Autor, 2019). There is limited evidence on the mechanisms behind the college-non-college gap in the urban premium, because existing data sources do not allow researchers to comprehensively measure the content of jobs separately by worker education level. Our results provide evidence 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 urban premium. While specialization, and its significance as a mechanism for urban productivity gains, is one of the oldest theoretical ideas in economics, direct measurement of specialization

[31] 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.

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 within a common methodology, and has applications beyond the urban premium.[32] 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 in urban and rural areas and capture heterogeneity within occupations. We also introduce an approach to define job tasks at a granular level, and we use it to 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 city 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.

[32]For example, Autor (2013) points to the usefulness of measuring job tasks directly for understanding the impact of automation and points out the limitations of occupational categories: "[O]ffice clerical workers and assembly line machine operators have much in common from the perspective of the task framework: both make extensive use of routine tasks that have high potential for automation. Similarly, both truck drivers and food service workers engage intensively in non-routine manual tasks requiring detailed visual recognition and flexible adaptation to a changing physical environment, tasks that have proven extremely challenging to automate. Unfortunately, these overlaps among occupations in 'task space' are in no way visible from standard occupational classification schemes that group occupations roughly according to the services that they provide (health services, production, analysis, etc.) rather than the tasks that they encompass."

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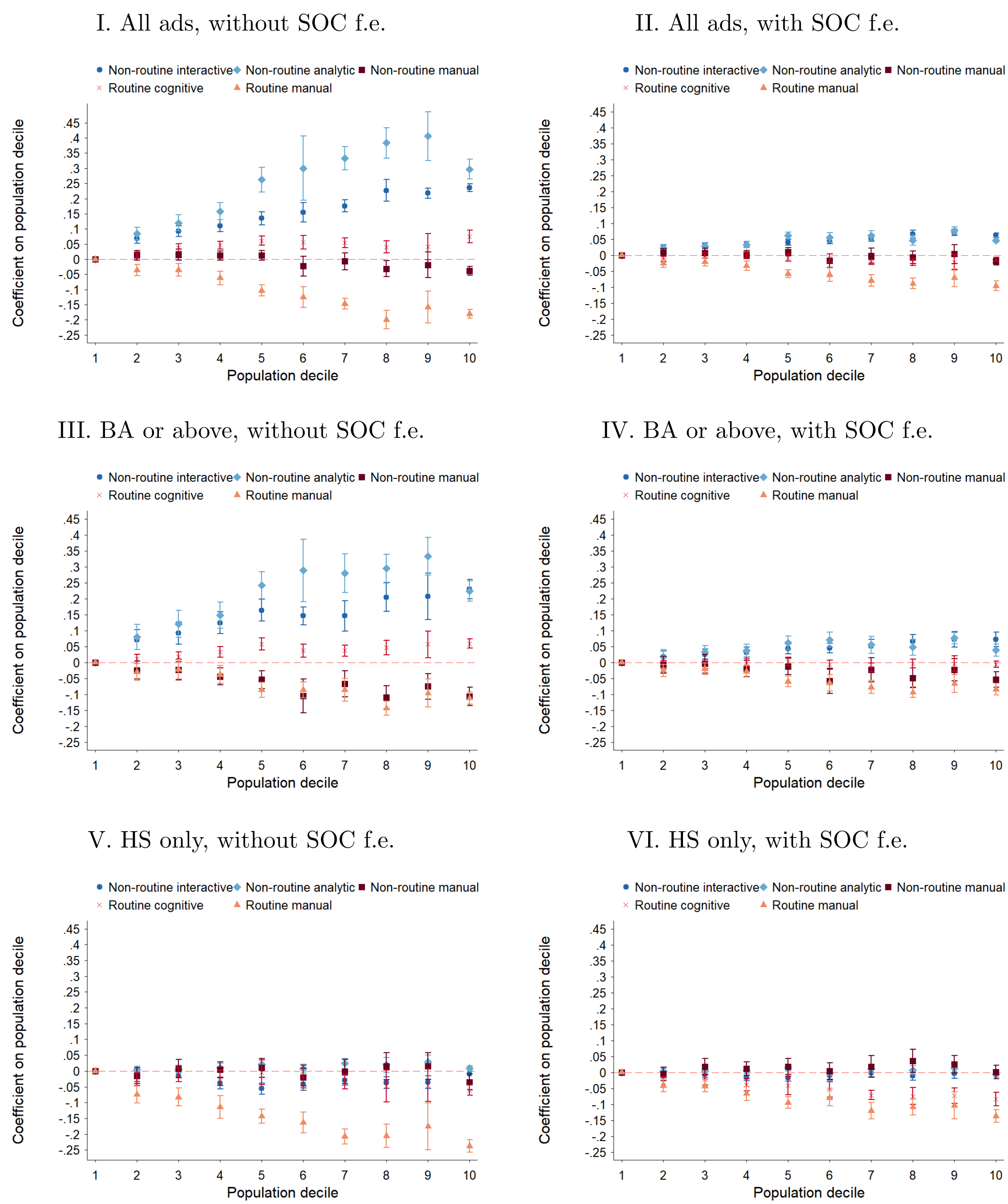
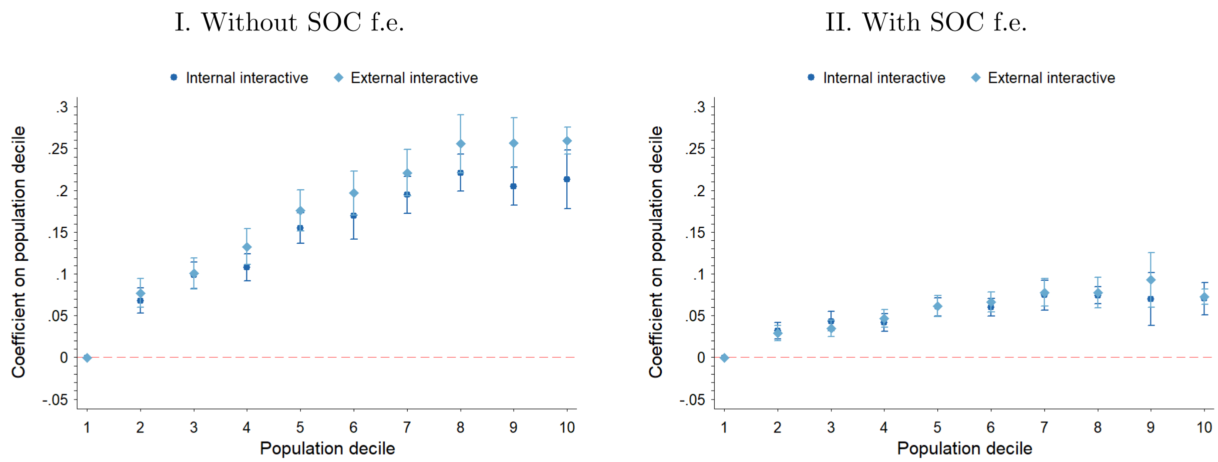
Figures and Tables

Figure 1: Tasks and Market Size



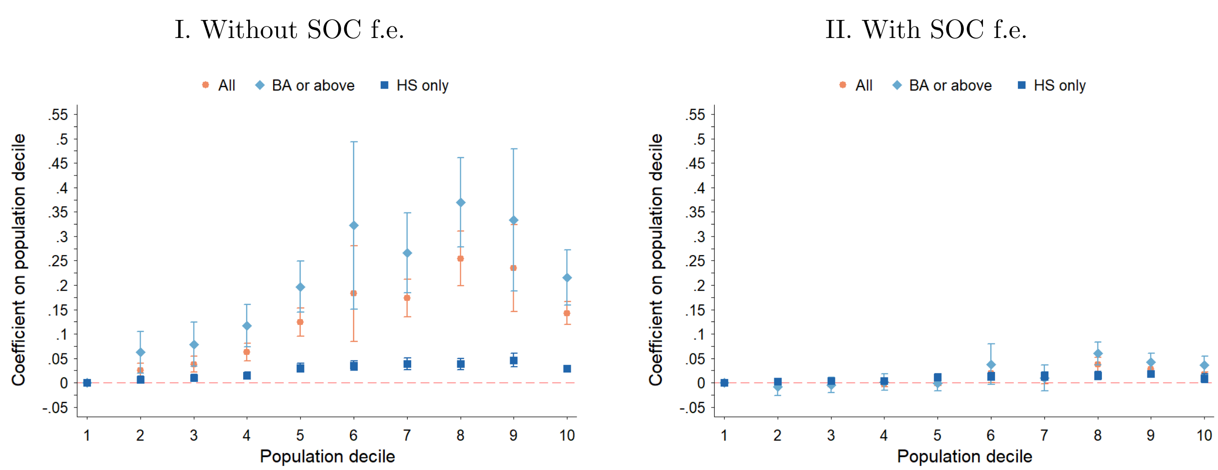
This figure presents estimates of equation (1), which depict the task gradient with market size. We control for log total ad words and, in the right panel, six-digit SOC fixed effects. The dependent variable is task intensity. Standard errors are clustered at the CZ level.

Figure 2: O*NET Interactive Tasks Gradient



This figure presents the estimates from a regression at the job vacancy level 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

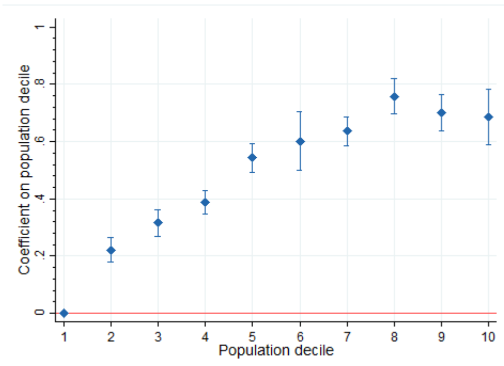


The dependent variable is the number of O*NET Hot Technologies mentioned in the ad, which is regressed on a vector of deciles for CZ. For reference, the 1st decile mean is 0.10 across all job ads, 0.26 for BA or above, and 0.08 for HS only. We control for log total ad words. Panel II includes six-digit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

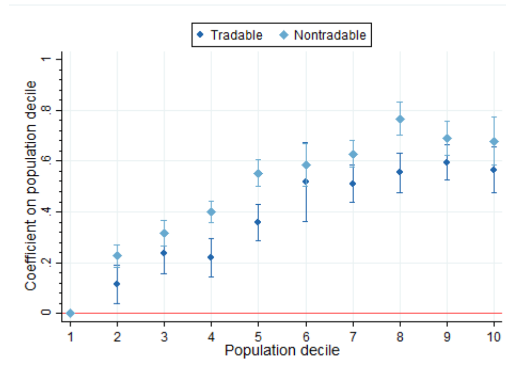
Figure 4: Specialization Gradient: Task Dissimilarity Within Firms and Occupations

A. Firms

I. All

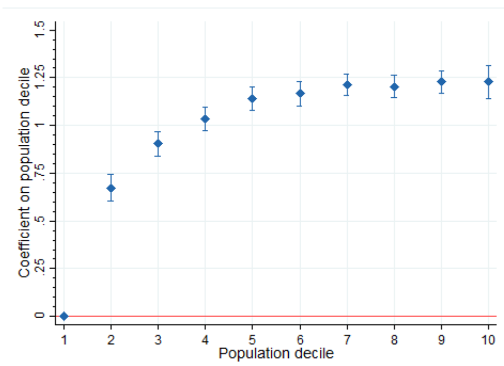


II. Tradable v. Nontradable

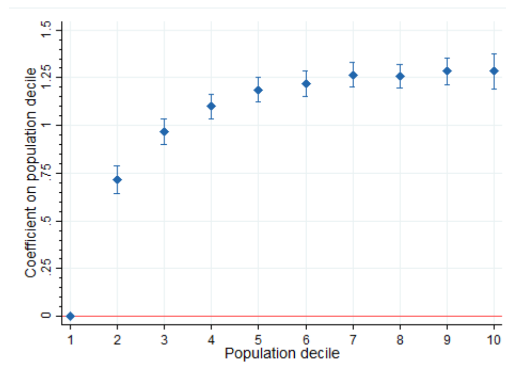


B. Occupations

III. Without SOC f.e.

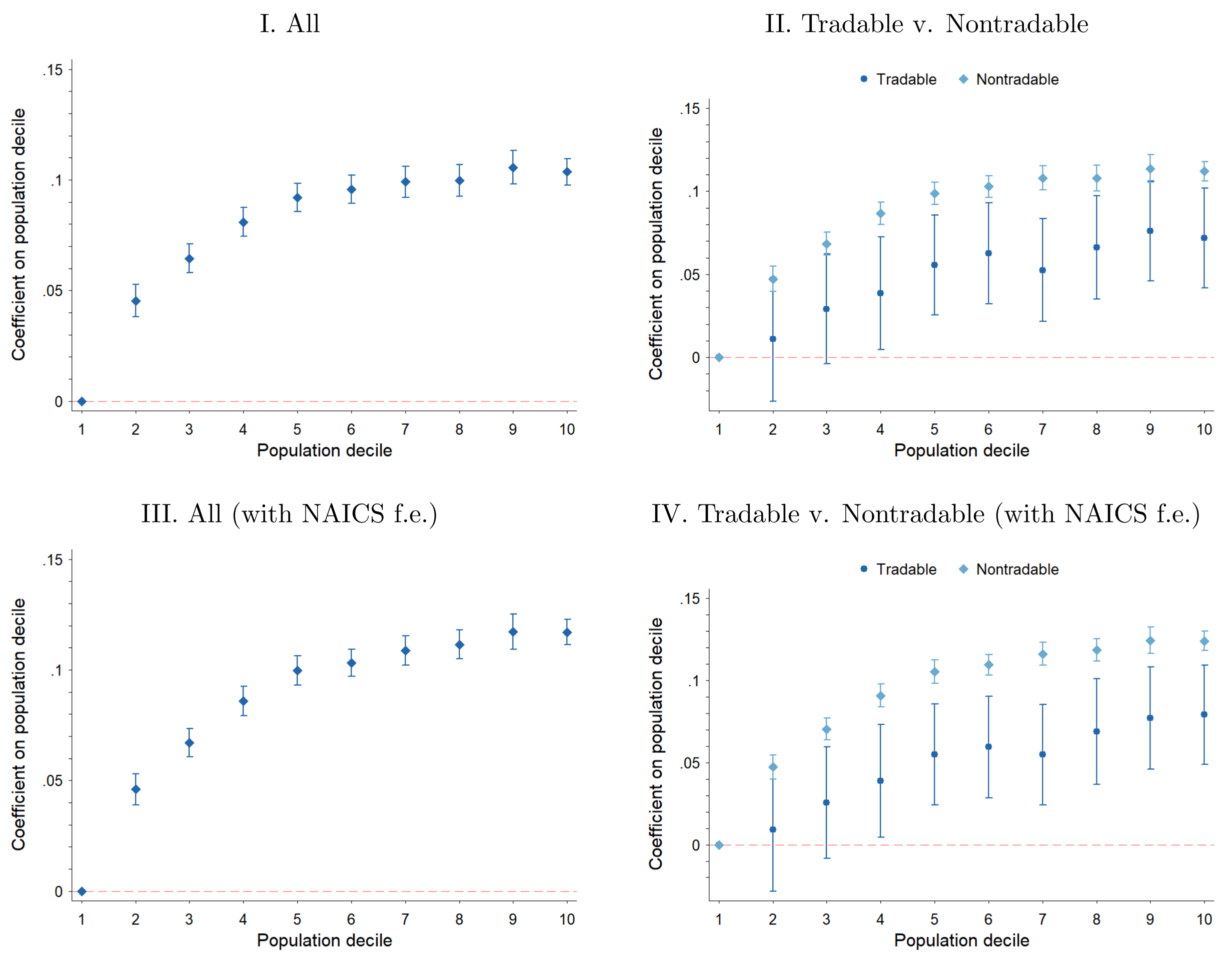


IV. With SOC f.e.



The figures above present estimates of equation (3) and study 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 CZ 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 CZ 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 figures above present estimates of equation (4) and study how task dissimilarity across firms in the same industry varies with market size. 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
Obs.		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).

Table 2: Task Decomposition Across Markets

	NR-Analytic		NR-Interactive		NR-Manual		R-Cognitive		R-Manual	
Q1	4.39		4.73		0.84		0.64		2.98	
Q2	4.76		5.18		0.77		0.67		2.86	
Q3	5.13		5.63		0.79		0.70		2.70	
Q4	7.07		6.41		0.78		0.77		2.31	
	Between and Within Occupational Decomposition									
	Between	Within	Between	Within	Between	Within	Between	Within	Between	Within
Q2-Q1	0.61	0.39	0.43	0.57	0.54	0.46	0.86	0.14	0.64	0.36
Q3-Q2	0.73	0.27	0.65	0.35	0.39	0.61	1.68	-0.68	0.40	0.60
Q4-Q3	0.81	0.19	0.78	0.22	-0.16	1.16	1.22	-0.22	0.57	0.43
Q4-Q1	0.77	0.23	0.65	0.35	0.50	0.50	1.06	-0.06	0.56	0.44

The top panel plots the average task content in each of four market size quartiles. Tasks are expressed as number of task-word mentions per 1,000 ad words. The bottom panel presents a decomposition of the within and between shares of the total difference between population quartiles.

Table 3: Tasks with the Steepest Gradient: Extracting Tasks Directly from Ads

Positive gradient		Negative gradient	
Task	$\hat{\beta}_{10}$	Task	$\hat{\beta}_{10}$
written communication	0.1596	maintain store	-0.1763
managing projects	0.1157	maximizes profitability	-0.1692
meet deadlines	0.1075	operating cash_register	-0.1653
providing support	0.0956	protect company	-0.1641
maintaining relationships	0.0943	make changes	-0.1431
written skills	0.0922	provide customer_service	-0.1394
problem_solving skills	0.0881	preventing trafficking	-0.1373
working relationships	0.0844	greeting customers	-0.1343
develop business	0.0833	skating carhop	-0.1334
developing strategies	0.0754	procedures cash	-0.1264
identify opportunities	0.0751	maintaining inventory	-0.1234
prioritize tasks	0.0739	assist store	-0.1221
develop relationship	0.0728	unloading trucks	-0.1191
make recommendations	0.0724	ensure employees	-0.1143
support business	0.0721	drive_in employees	-0.1104

We estimate equation (1) separately for each task, without any controls. 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.

Table 4: Granular Task Decomposition Across Markets

	Written Communication		Provide Customer-Service		Assisting Customers		Working Team		Ensure Compliance		All Tasks	
Q1	0.09		0.10		0.04		0.06		0.03			
Q2	0.09		0.10		0.04		0.06		0.03			
Q3	0.10		0.09		0.04		0.06		0.03			
Q4	0.14		0.06		0.03		0.08		0.04			
	Between and Within Occupational Decomposition											
	Between	Within	Between	Within	Between	Within	Between	Within	Between	Within	Between	Within
Q2-Q1	-2.28	3.28	-47.28	48.28	0.68	0.32	1.13	-0.13	0.48	0.52	0.24	0.76
Q3-Q2	1.14	-0.14	-0.31	1.31	3.39	-2.39	-1.76	2.76	0.63	0.37	0.31	0.69
Q4-Q3	0.78	0.22	0.61	0.39	0.76	0.24	0.89	0.11	0.53	0.47	0.71	0.29
Q4-Q1	0.84	0.16	0.38	0.62	0.69	0.31	1.27	-0.27	0.57	0.43	0.30	0.70

This table follows the construction of Table 2, except it presents the decomposition for each of the five most common verb-noun tasks. The rightmost decomposition 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 5: 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 6: Task Dissimilarity, Technologies, and Wages

	All			White-collar		Blue-collar	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Interactive tasks	0.126***	0.036***	0.022***	0.054***	0.028***	0.027***	0.024***
	(0.007)	(0.007)	(0.005)	(0.011)	(0.007)	(0.007)	(0.007)
Technology requirements	0.365***	0.263***	0.163***	0.329***	0.199***	-0.062**	-0.063***
	(0.012)	(0.037)	(0.023)	(0.041)	(0.026)	(0.025)	(0.024)
Task dissimilarity	0.031***	0.036***	0.029***	0.063***	0.048***	0.007**	0.006*
	(0.003)	(0.003)	(0.002)	(0.005)	(0.004)	(0.003)	(0.003)
BA or above			0.864***		0.931***		0.475***
			(0.070)		(0.077)		(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	0.247	0.810	0.840	0.768	0.820	0.568	0.581
Mean of dependent var.	10.769	10.769	10.769	10.968	10.968	10.561	10.561
Mean task dissimilarity	0.000	0.000	0.000	0.152	0.152	-0.178	-0.178
Mean technology requirements	0.224	0.224	0.224	0.299	0.299	0.105	0.105
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 codes 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%.

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 education 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.4, 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. In Appendix A.5, 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	506.8	42.2	16.9	54.9	Norfolk & Madison Counties, NE
2	575.0	67.3	72.9	304.7	Jackson & Hillsdale & Lenawee Counties, MI; Bloomington, IN
3	595.2	76.6	132.7	609.6	Wichita, KS
4	599.8	83.9	202.3	1,033.4	Tulsa, OK; Naples-Marco Island, FL
5	732.3	88.7	426.8	1,639.0	Nashville-Davidson-Murfreesboro, TN
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
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. This step drops another 503,051 ads. Finally, we drop ads that have no SOC code—another 102,154 ads. 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.[33] 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

[33]Figure A.1 presents a binscatter of an indicator for the job ad's being posted by a staffing firm, against the CZ population. The figure shows a slight positive gradient with market size.

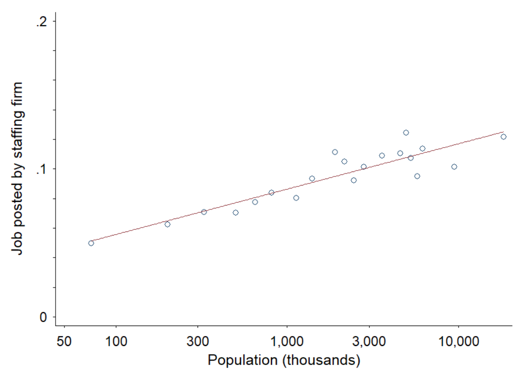
approximately 5.6 million ads for the sample used for the firm-level analysis.

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.

A.3 Representativeness of Online Vacancies

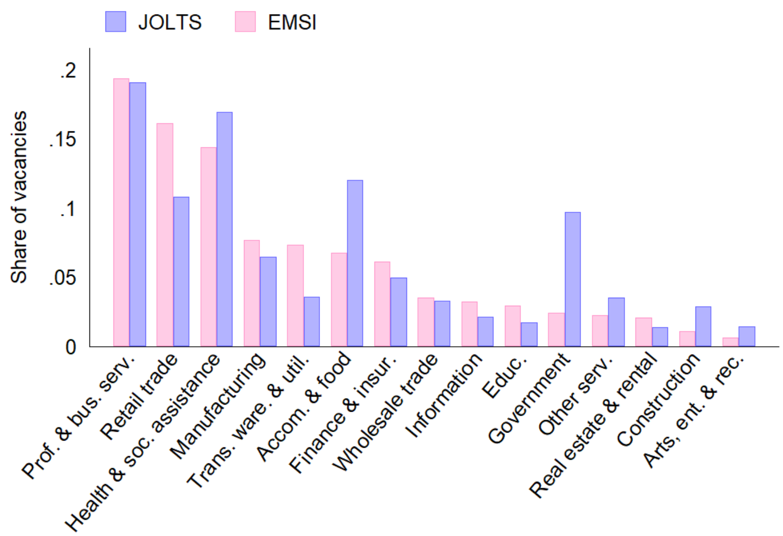
The standard resource for measuring job vacancies in the U.S. is the Job Openings and Labor Turnover Survey (JOLTS), conducted by the Bureau of Labor Statistics of the U.S. Department of Labor. The dataset consists of monthly job openings at the national level by major industry category.[34] JOLTS is based on a survey of a random subset of establishments covered by state or federal unemployment insurance laws.[35]

[34]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.

[35]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

Figure A.2 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.2: Distribution of EMSI Job Ads v. JOLTS



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

A.4 Education Requirements: Job Ads v. ACS Employment

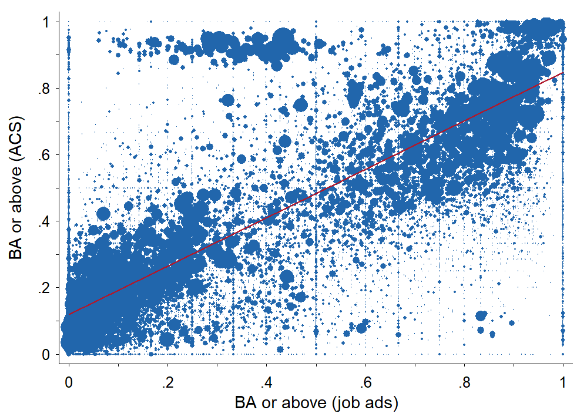
In this section, again with the aim of validating the EMSI dataset, we compare education levels across occupations and commuting zones. For each four-digit SOC $\times$ CZ, we compute the fraction of job ads requiring a BA degree or above (in ads mentioning an educational requirement) and the fraction of employed workers, measured in the ACS, with a BA degree or higher. Figure A.3 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

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.

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.4 plots the same regression by CZ population quartile, showing a strong correlation for both large and small labor markets.

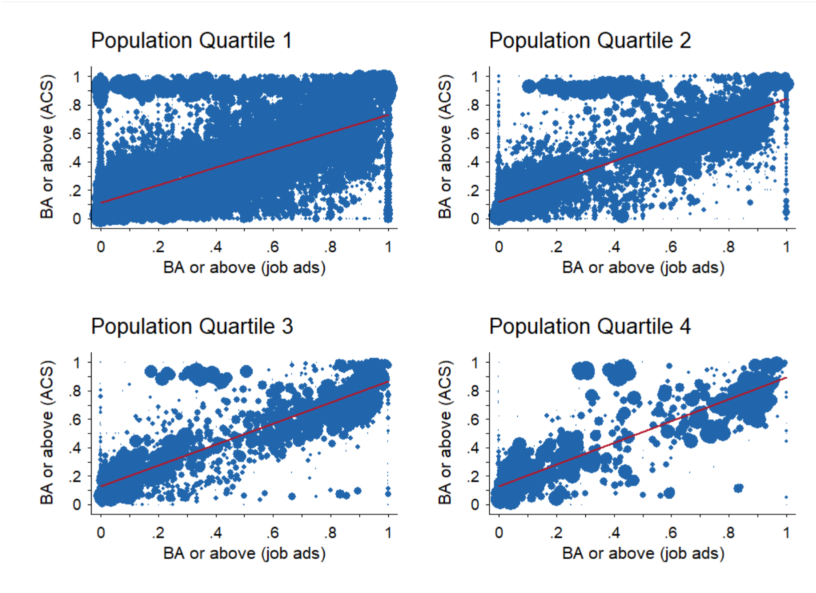
Using the same data, Figure A.5 depicts the gradient of educational requirements across CZ population deciles for the job vacancy data, and, next to it, the gradient of educational attainment of employed workers in the ACS. The gradient looks remarkably similar, both within and across occupations, suggesting again that the job vacancy data are picking up meaningful variation in the educational requirements of jobs across geography.

Figure A.3: Education Requirements in ACS v. Job Ads



Each dot in the figure above corresponds to a four-digit SOC $\times$ 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).

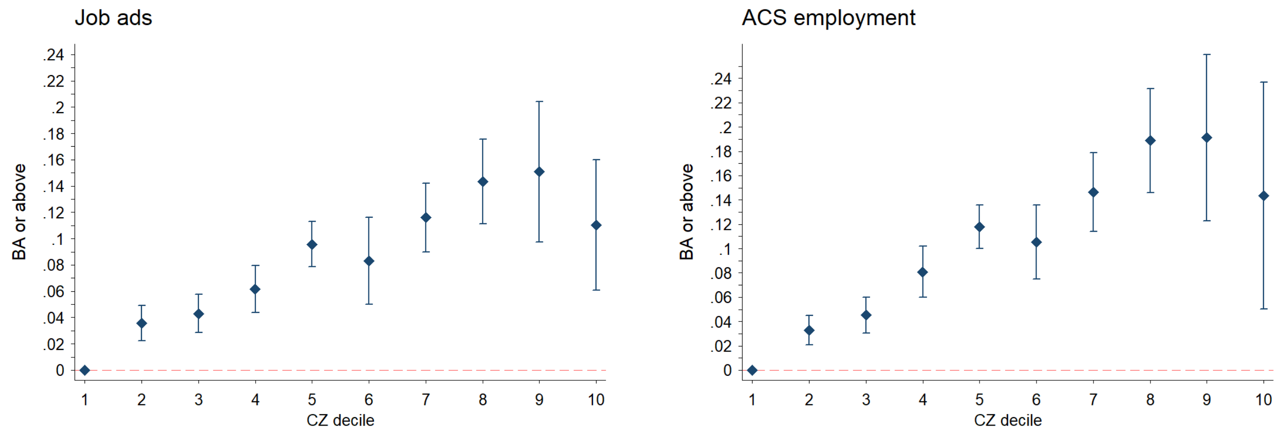
Figure A.4: Education Requirements in ACS v. Job Ads



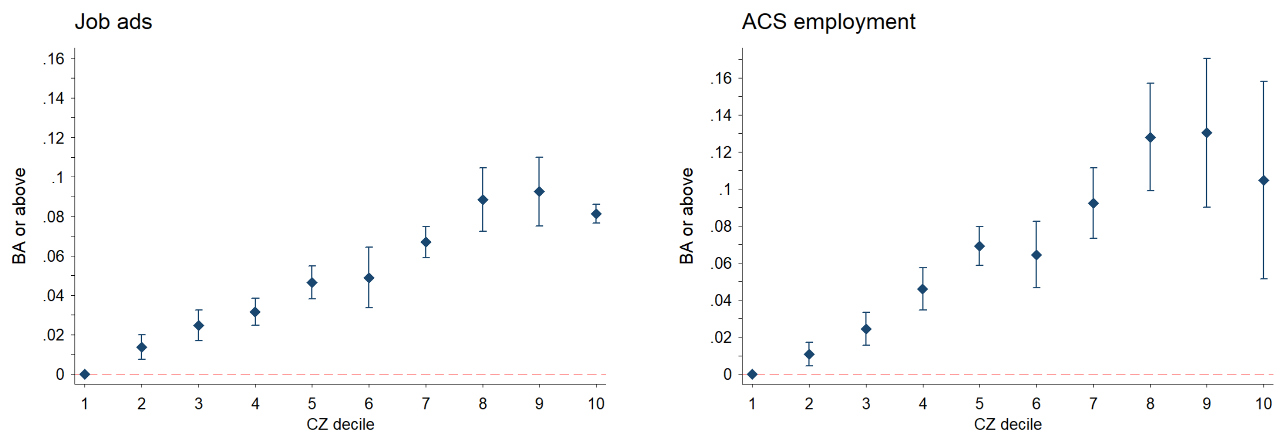
The figure above replicates Figure A.3 separately by CZ population quartile.

Figure A.5: Education Gradient with Market Size: ACS v. Job Ads

I. Without SOC f.e.



II. With SOC f.e.



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, in an occupation-market cell. 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. The bottom two panels reproduce the top two panels with four-digit fixed effects.

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.

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.[36] Note that this mapping is necessarily 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

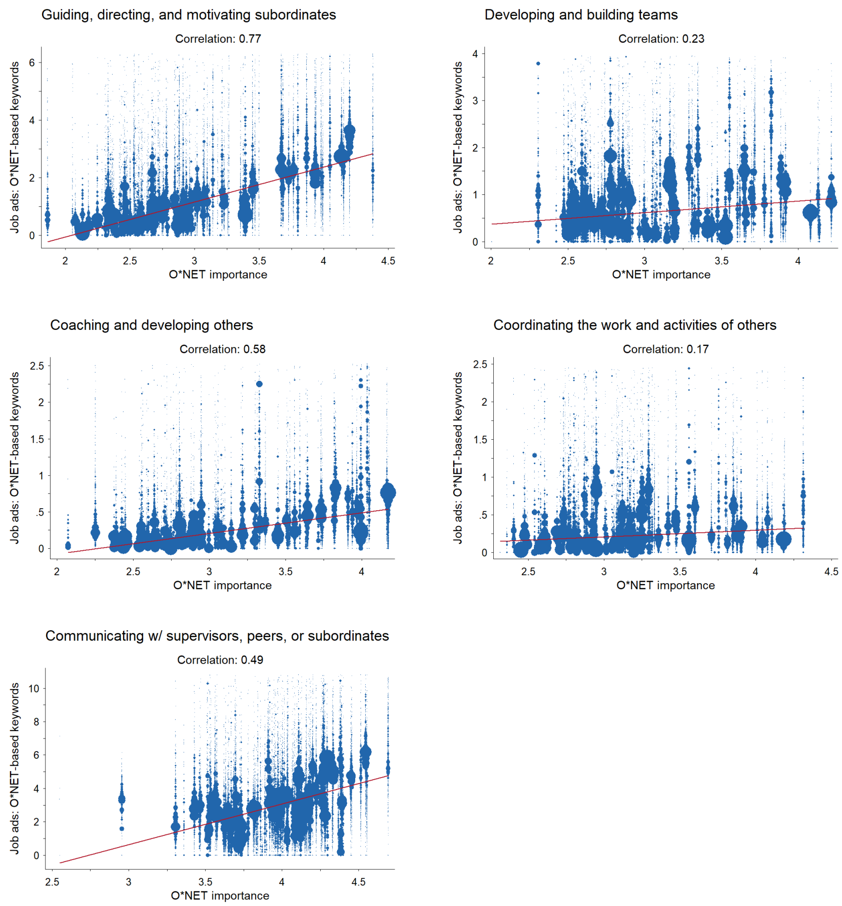
[36] We count instances of each word separately; for example, "public" and "relations" are searched for separately rather than as the bigram "public relations." We make one exception for "team build" because in our judgment "build" on its own is likely to return false positives. In Atalay et al. (2020)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

- *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

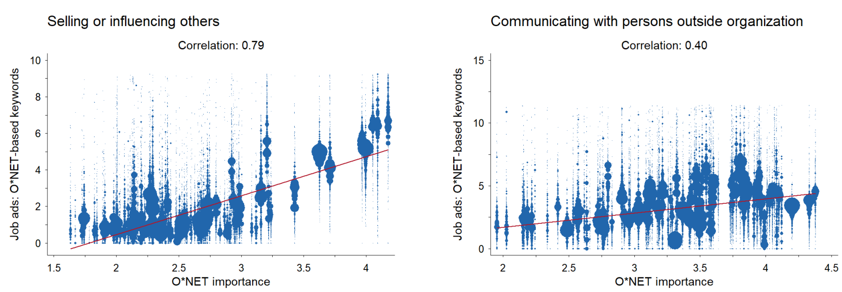
Figure A.6 demonstrates that our job ad-based task data have, for the most part, a high degree of correlation with O*NET tasks. We should not expect a perfect correlation, as O*NET itself has well-known limitations of small sample sizes, status quo bias, and subjective scales (Autor, 2013). But these correlations indicate that the job description text provides meaningful information about the task content of occupations.

Figure A.6: 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.)

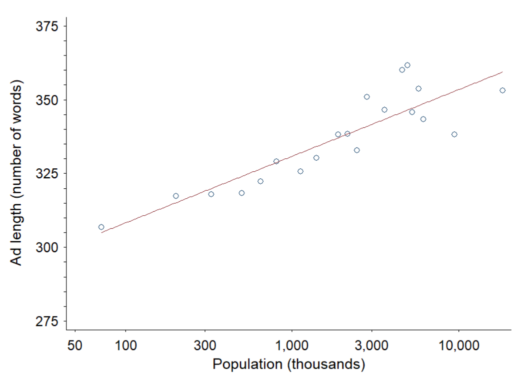
A.5 Job Ad Length and Description Keywords Across Space

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.7). 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, and normalize our granular task measures so that each task vector has unit length.

In Appendix B.1, we describe the approach to extracting job tasks from the text. The first step 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. Figure A.8 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.

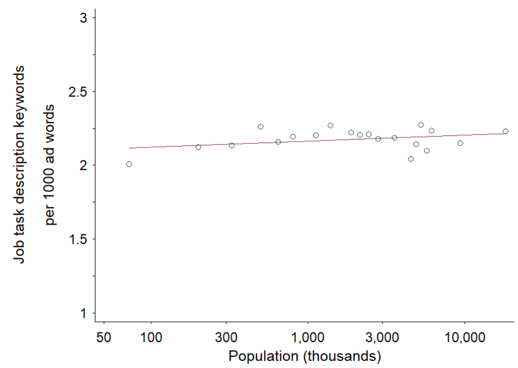
Lastly, we show that our novel task-extraction methodology—using job descriptions and parts of speech to let the text define the job tasks—passes a simple validation check. We calculate the cosine similarity between each job and the occupation-market average, and take the average. This exercise reveals 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.7: 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.8: 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," "tasks"—normalized per 1,000 ad words, against log CZ population.

B Task Extraction and Validation

This section outlines our approach to measuring job tasks. We first describe and illustrate the procedure for extracting job tasks from the text (Appendix B.1); present the most common tasks and technologies (Appendices B.2 and 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.5).

B.1 Extracting Job Tasks from the Raw Text

We first use the job ad text to generate a list of job tasks, which we call the *vocabulary of tasks*. Once we have the task vocabulary, we represent each job ad as a vector, of which each element corresponds to a distinct task.

We define a task as a verb-noun pair that occur within the same sentence. We use Python's NLTK library, which features a sentence tokenizer and parts of speech tagger. There are two main steps in extracting verb-noun pairs from the text:

1. We first isolate the section of the text that pertains to job tasks. The purpose of this step is to eliminate portions of the job ad that refer to worker skills or firm

characteristics. To do this we search for keywords in the text that suggest a list of tasks will follow. The keywords we use are "duties," "summary," "description," "tasks." We isolate the section of text that begins at one of these keywords and ends at the next period.[37]

2. Using the section of text extracted from step 1, we find all (verb stem, noun stem) pairs within the same sentence, and these make up our task vocabulary. Examples of pairs include "assist customers" and "provide advice." Since verbs and nouns are stemmed, "writing memo" and "writes memos" are recorded as the same task. This step works as follows: We extract each verb and the noun that appears next in the sentence. Hence, if the job ad says "writing lucid memos to prepare for depositions" or "writes legal memos for court hearings," these will both be recorded by our algorithm as "writes memos." If multiple verbs correspond to the same noun (for instance, "prepares and revises memos"), our algorithm extracts two distinct tasks: "prepares memos" and "revises memos."[38]

Once we have the vocabulary of tasks, according to steps 1 and 2 above, we vectorize all job ads according to the task vocabulary created in step 2. Hence, we are not limiting our analysis to ads with the keywords described in step 1. We represent each ad as a vector, in which each element of the vector corresponds to a particular task in the vocabulary and takes a value of one if the job ad has that particular task and zero otherwise.

[37] This 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 from rural to urban labor markets. Figure A.8 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.

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

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.

B.2 Task List

Below 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).

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

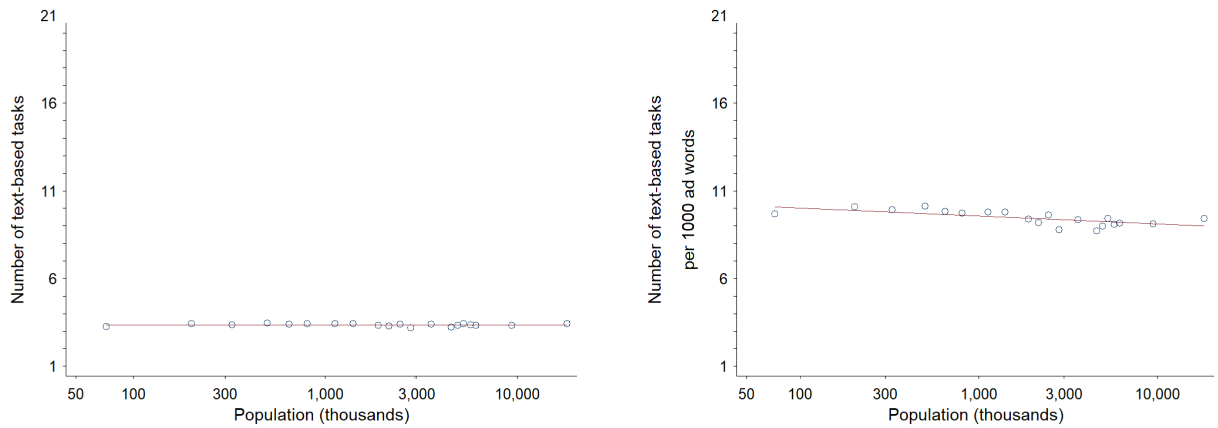
As described in the text, we exclude 101 tasks from the original list of 500 most common verb-noun pairs, using our judgment to select pairs that do not correspond to tasks. These excluded verb-noun pairs describe worker skills (e.g., "high school diploma," "ged years," "required bachelor"); firm attributes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

Table B.3: 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.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

Table B.5 replicates Table 3, except we include six-digit SOC fixed effects as controls. The sets of words with the steepest positive and negative gradients generally align with those in Table 3. Table B.6 reruns equation (1) and instead of using our task list extracted from the text itself, we use a predetermined list of verbs from Michaels et al. (2018). The takeaway is quite similar. Using only the 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: Extracting Tasks Directly from Ads (with SOC f.e.)

Positive gradient		Negative gradient	
Task	$\hat{\beta}_{10}$	Task	$\hat{\beta}_{10}$
achieving sales	0.0701	maximizes profitability	-0.1597
ensure safety	0.0686	protect company	-0.1501
written skills	0.0580	maintain store	-0.1339
stand walk	0.0573	operating cash_register	-0.1256
driving sales	0.0572	make changes	-0.1249
exceed sales	0.0556	greeting customers	-0.1094
providing environment	0.0523	procedures cash	-0.1080
providing coaching	0.0510	skating carhop	-0.1064
according company	0.0500	ensure employees	-0.1041
prioritize tasks	0.0500	unloading trucks	-0.1005
working relationships	0.0488	drive_in employees	-0.0981
handle tasks	0.0487	maintaining inventory	-0.0948
using eye	0.0461	assigned store	-0.0873
including nights	0.0449	working store	-0.0852
meet sales	0.0448	provide customer_service	-0.0848

The table above reproduces Table 3 with six-digit SOC f.e. as controls. All estimates are statistically significant at the 1 percent level.

Table B.6: Verbs with the Steepest Gradient

Positive gradient		Negative gradient	
Task	$\hat{\beta}_{10}$	Task	$\hat{\beta}_{10}$
design	0.0812	pay	-0.0625
project	0.0797	truck	-0.0623
experience	0.0660	store	-0.0559
research	0.0632	earn	-0.0513
develop	0.0616	clean	-0.0506
manage	0.0581	license	-0.0452
web	0.0560	fuel	-0.0448
finance	0.0499	get	-0.0421
analyze	0.0492	rotate	-0.0396
process	0.0483	authorize	-0.0392
create	0.0461	count	-0.0362
content	0.0437	trash	-0.0321
lead	0.0432	average	-0.0320
market	0.0431	retail	-0.0307
track	0.0426	sign	-0.0301

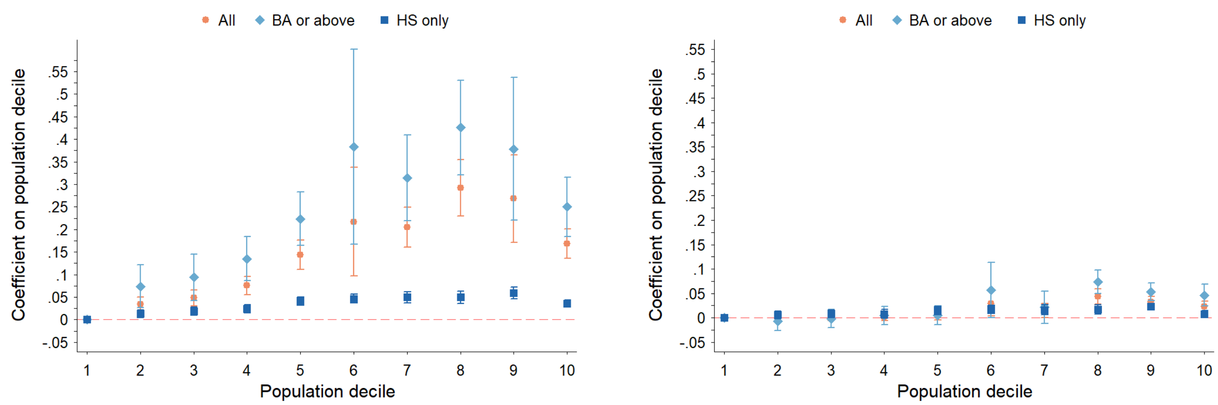
The table above reproduces Table 3, except it uses the list of verbs from Michaels et al. (2018) as tasks instead of the verb-noun pairs extracted from job descriptions. This exercise is conducted on a 1 percent sample of all job ads, rather than 5 percent, for computational speed, since the verb list 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)

I. Without SOC f.e. II. With SOC f.e.



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

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. We then 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.7 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. But the granular task measures account for an additional 1.9 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 college degree, non-routine analytic tasks have a stronger relationship with wages than for jobs requiring a high school diploma only.

Table B.8 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 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.7 and B.8 show that task variation across space accounts for variation in wages above and beyond occupation codes.

Table B.7: Wages and Tasks

	Baseline				HS only	BA or above
	(1)	(2)	(3)	(4)	(5)	(6)
Non-routine analytic	0.229***		0.050***	0.043***	0.020**	0.060***
	(0.013)		(0.010)	(0.012)	(0.008)	(0.016)
Non-routine interactive	0.085***		-0.003	-0.009	0.013	-0.005
	(0.012)		(0.006)	(0.006)	(0.010)	(0.009)
Routine cognitive	-0.008**		-0.021***	-0.003	-0.025***	-0.014
	(0.004)		(0.004)	(0.004)	(0.005)	(0.011)
Routine manual	0.059***		-0.018***	-0.009*	-0.020***	-0.056***
	(0.005)		(0.006)	(0.005)	(0.006)	(0.011)
Non-routine manual	0.040***		0.010*	0.001	0.005	-0.057***
	(0.008)		(0.005)	(0.005)	(0.005)	(0.013)
SOC f.e.	No	Yes	Yes	Yes	Yes	Yes
Text-based tasks	No	No	No	Yes	No	No
Number of observations	58,494	58,494	58,494	58,494	33,859	24,635
R^2	0.489	0.784	0.785	0.803	0.552	0.694
Adjusted R^2		0.784	0.785	0.802	0.551	0.693
Mean of dep. var.	10.65	10.65	10.65	10.65	10.44	10.94

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 cell. The only controls are education category dummies and four-digit SOC f.e., which are included in columns 2-5. Regressions are weighted by employment. Standard errors are clustered at the CZ level.

Table B.8: Wages and Task-Population Gradient

	HS only	BA or above
	(1)	(2)
Log pop.	0.043***	0.013***
× non-routine analytic	(0.006)	(0.004)
Log pop.	0.015**	0.029***
× non-routine interactive	(0.006)	(0.006)
Log pop.	0.002	0.009
× routine cognitive	(0.002)	(0.007)
Log pop.	-0.018***	-0.012***
× routine manual	(0.003)	(0.004)
Log pop.	0.002	-0.014
× non-routine manual	(0.003)	(0.009)
Log population	0.076***	0.081***
	(0.007)	(0.008)
SOC f.e.	Yes	Yes
Number of observations	33,859	24,635
R^2	0.594	0.766
Mean of dep. var.	10.44	10.94

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 3.1 and 3.2

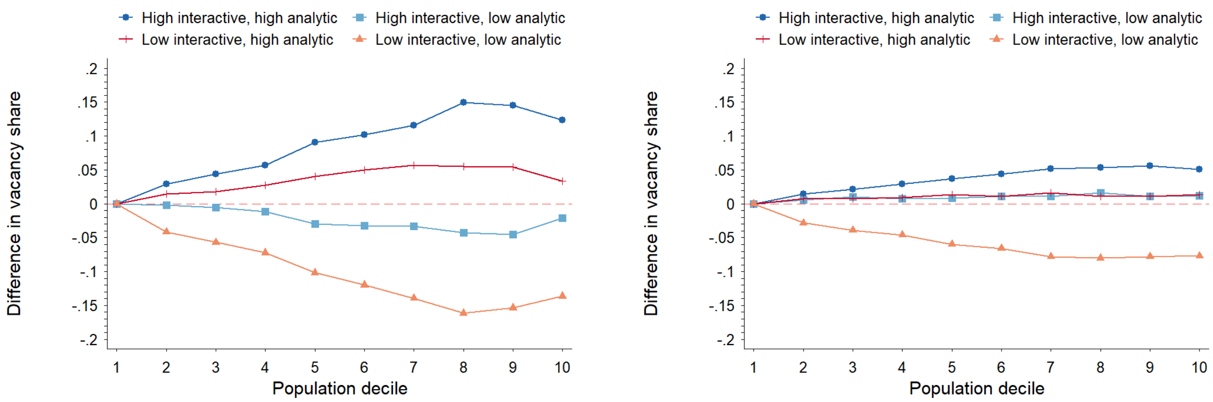
In this appendix, we present additional figures on the relationships among job tasks and population.

Figure C.1 considers whether there is evidence for jobs being jointly intensive in interactive and analytic tasks in large markets, as Deming (2017) finds them to be increasingly important over time. 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 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 15 percentage points more of jobs in each of the highest three deciles compared with the lowest decile. Jobs that are intensive in only analytic tasks but not interactive tasks make up only about 4 percentage points more of jobs in the highest three deciles, 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.

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 occupation fixed effects, the difference between these gradients is minor.

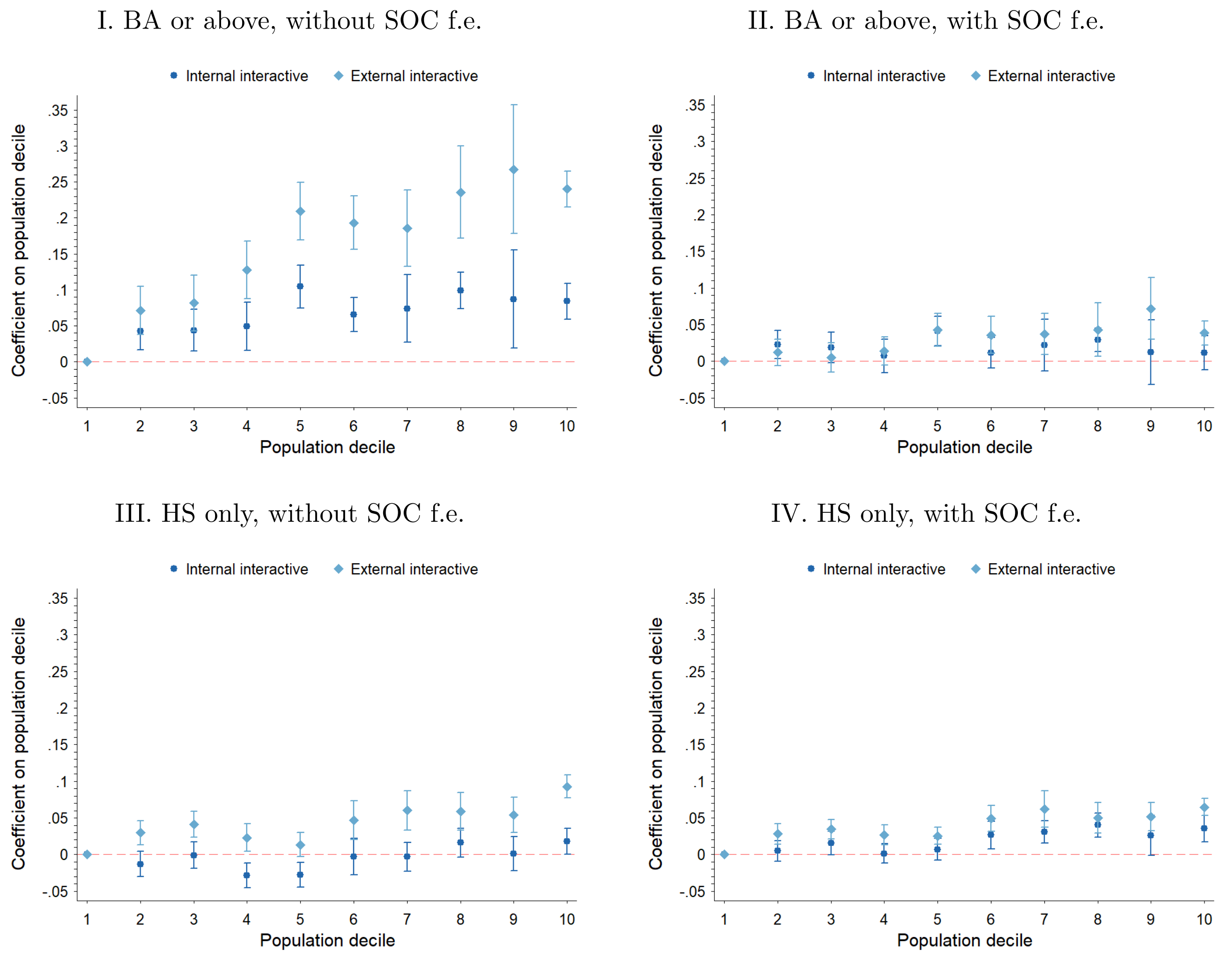
In Figure C.3, we explore whether the key tasks and technologies gradients of Figures 1 and 3 might be sensitive to the time period studied. Specifically, a potential concern is that a rapidly changing labor market in cities relative to rural areas might generate changing gradients over time. To explore 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 time periods.

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, and hence the right panel reflects within-occupation changes in task content across space.

Figure C.2: O*NET Interactive Tasks Gradient

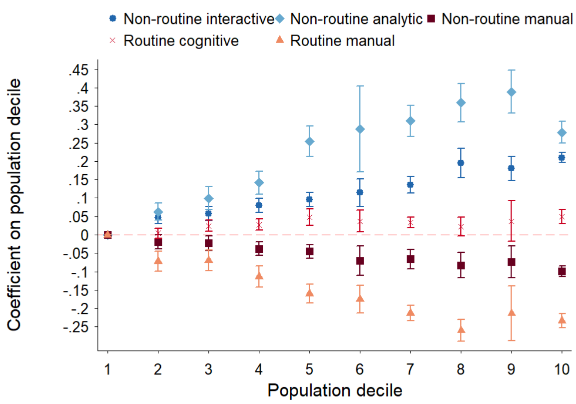


This figure reproduces Figure 2 separately by the educational requirement of the job. Panels I and II restrict the sample to ads requiring a BA or above, while panels III and IV restrict the sample to ads requiring high school only.

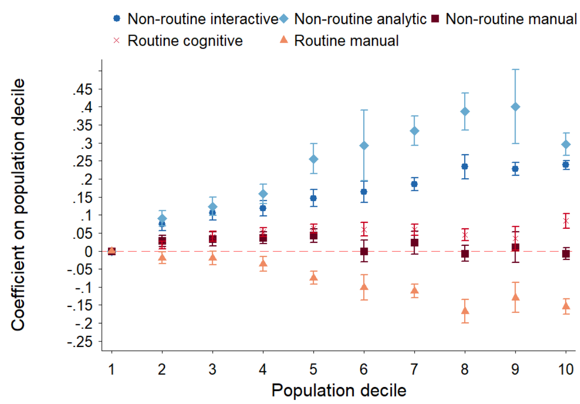
Figure C.3: Tasks and Technologies Gradient by Sample Period

A. Tasks

I. 2012-2014

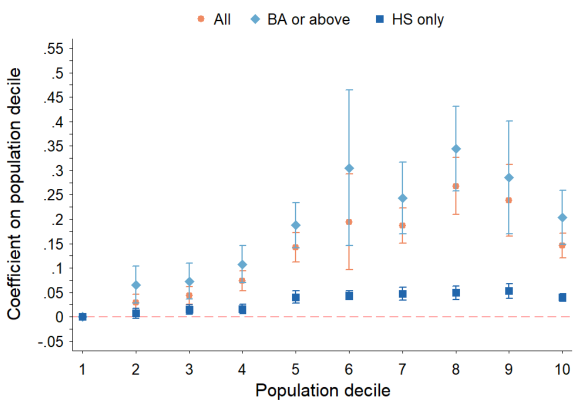


II. 2015-2017

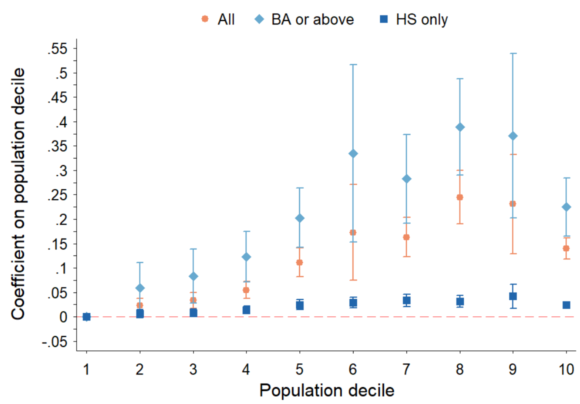


B. Technologies

III. 2012-2014



IV. 2015-2017



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

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

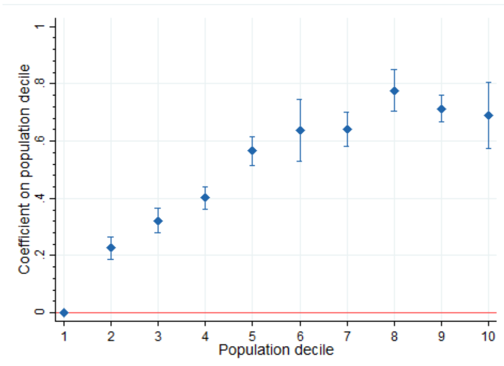
Our measurement approach requires setting a threshold for the number of tasks (verb-noun pairs) we use to study specialization. In the paper, we use a task list of 500 verb-noun pairs, which we winnow to 399 by excluding those that, according to our judgment, do not reflect job tasks.

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.4 shows that the results are not sensitive to increasing the number of tasks to 2,000. Figure C.5 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.5 shows that the results are not sensitive to reducing the number of tasks to 300.

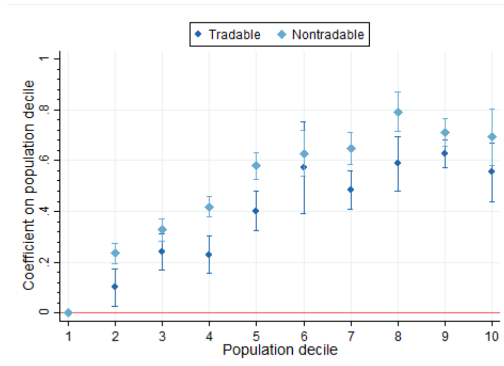
Figure C.4: Specialization Gradient: Task Dissimilarity Within Firms and Occupations (with 2,000 Tasks)

A. Firms

I. All

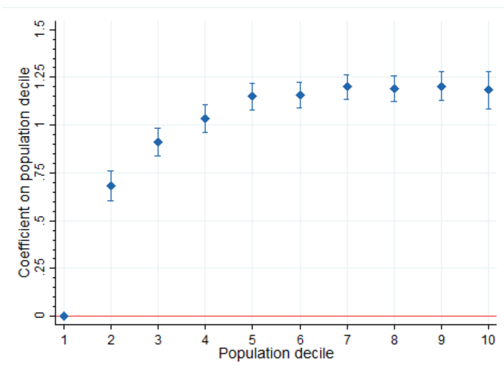


II. Tradable v. Nontradable

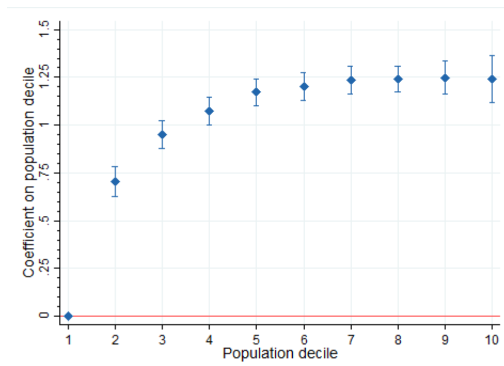


B. Occupations

III. Without SOC f.e.

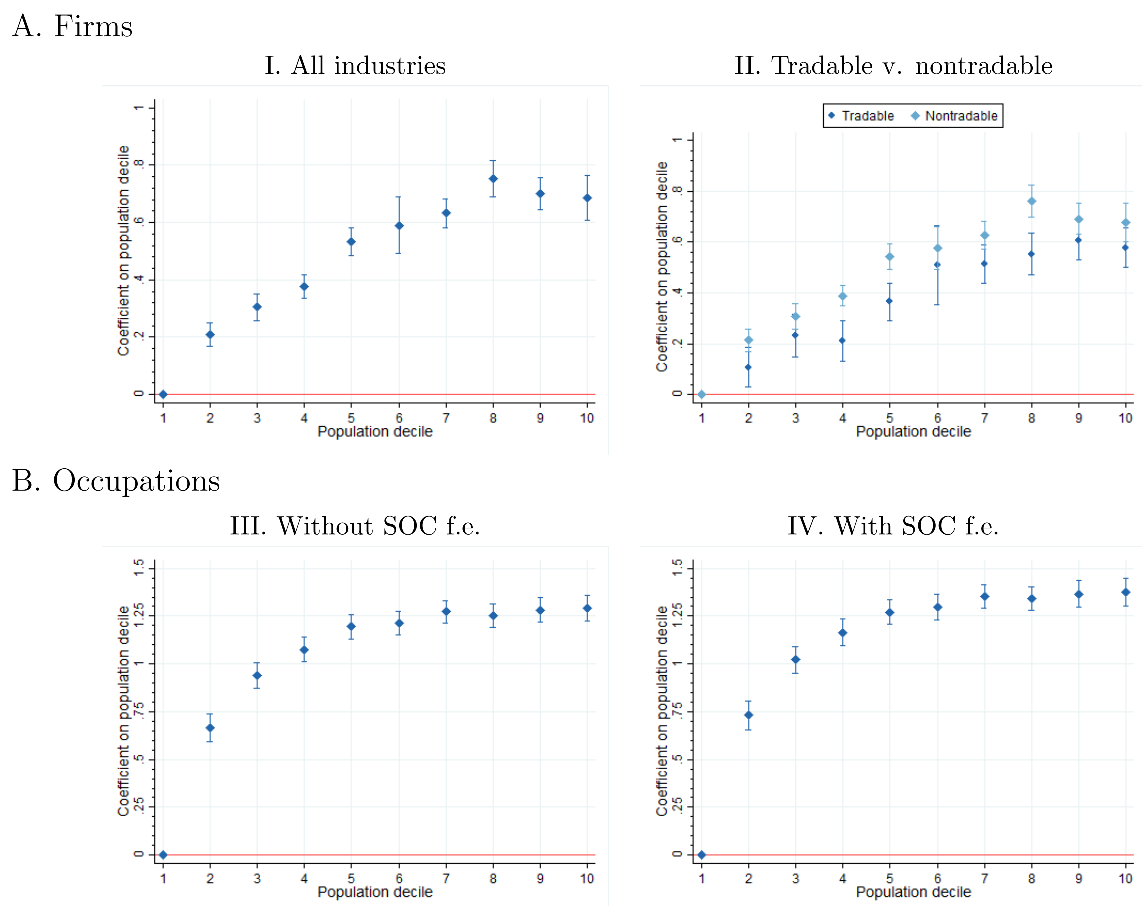


IV. With SOC f.e.



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 CZ decile mean for the top left panel is -0.51, and for the top right panel is -0.54 for the nontradable sample and -0.06 for the tradable sample. The 1st CZ decile mean for the bottom two panels is -1.00.

Figure C.5: Specialization Gradient: Task Dissimilarity Within Firms and Occupations (300 Tasks)

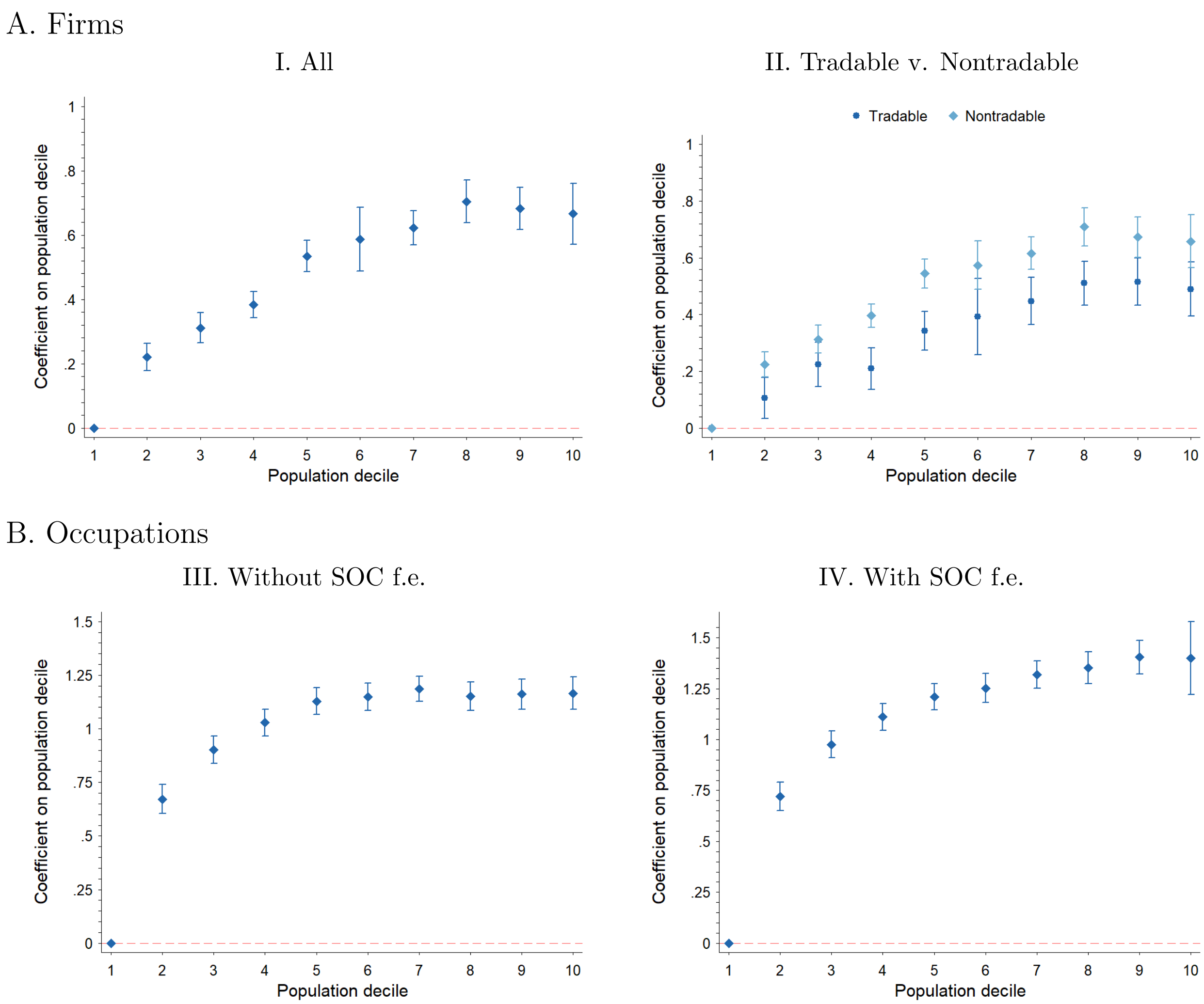


This figure reproduces Figure 4 using a task list of 300 verb-noun pairs. For reference, the 1st CZ decile mean for the top left panel is -0.51, and for the top right panel is -0.53 for the nontradable sample and -0.06 for the tradable sample. The 1st CZ decile mean for the bottom two panels is -1.06.

Measurement Error and Robustness to Controls

We consider the possibility that the sampling of job postings may create measurement error in specialization measures, and that this measurement error may differ by large v. small markets, since small markets may have fewer job ads in an occupation-market or firm-market cell. 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.6 below, are virtually identical to Figure 4.

Figure C.6: Specialization Gradient: Task Dissimilarity Within Firms and Occupations



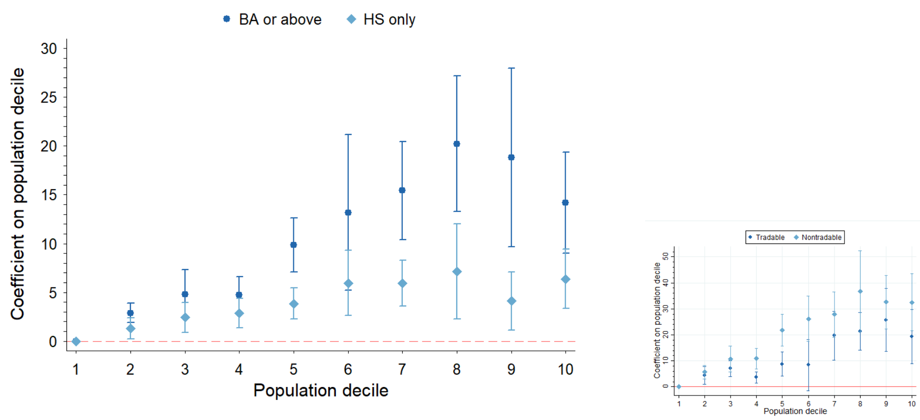
The figures above reproduce Figure 4 with an additional control for the number of ads in the cell.

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.7, using our job vacancy data to count distinct job titles within a firm name × six-digit industry NAICS × 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.7: Specialization Gradient: Number of Job Titles

I. BA or above v. HS only II. Tradable v. Nontradable



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 robust and clustered at the CZ level. The figure plots the coefficients on the CZ size deciles. For reference, in the left panel, the 1st decile CZ mean for BA or above is 2.58 and for HS only is 3.11. In the right panel, the 1st decile CZ mean for tradable is 9.96 and for nontradable is 10.68.

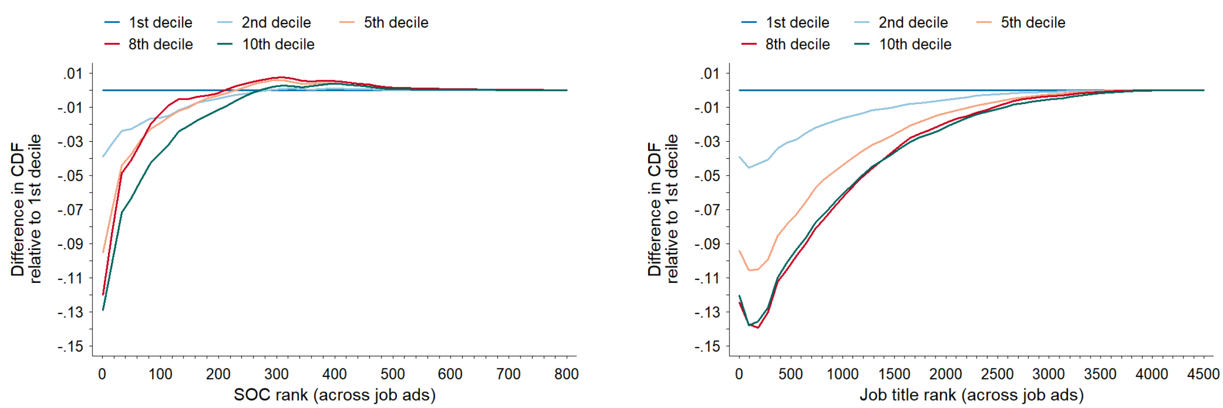
The Distribution of Common and Rare Occupations

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 decile CZ. The left panel of Figure C.8 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 11-13 percentage points lower share of these occupations compared with the 1st CZ 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 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 Current Population Survey (CPS), and hence represents an additional virtue 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.8: 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 order of their shares of all job ads in the sample, from highest to lowest. 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

Table C.1 reproduces Table 6, the main wage regression table, 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 6. Note that the number of observations is slightly higher compared to Table 6. Since longer task vectors are more likely to have a non-zero element, 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.2 reproduces Table 6 with task dissimilarity measures in the occupation-CZ based on 300 tasks, a lower resolution, and shows very similar results.

Table C.3 reproduces Table 6 with CZ fixed effects. The goal is to understand whether specialization and technologies have an effect on wages after controlling for city size and other unobserved features of the labor market. Table C.3 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 city 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. The technologies coefficient is also diminished once we control for CZ f.e., which is consistent with market size enhancing the relationship between technologies and productivity.

Table C.1: Task Dissimilarity, Technologies, and Wages (with 2,000 Tasks)

	All			White-collar		Blue-collar	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Interactive tasks	0.120***	0.037***	0.023***	0.053***	0.028***	0.028***	0.025***
	(0.007)	(0.007)	(0.005)	(0.010)	(0.007)	(0.007)	(0.006)
Technology requirements	0.355***	0.261***	0.162***	0.325***	0.197***	-0.058**	-0.059**
	(0.012)	(0.036)	(0.023)	(0.041)	(0.026)	(0.024)	(0.024)
Task dissimilarity	0.052***	0.036***	0.028***	0.067***	0.049***	0.005*	0.004
	(0.003)	(0.003)	(0.002)	(0.006)	(0.004)	(0.003)	(0.003)
BA or above			0.860***		0.923***		0.478***
			(0.070)		(0.077)		(0.059)
SOC f.e.	No	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	45,602	45,602	45,602	24,681	24,681	11,476	11,476
R^2	0.252	0.810	0.839	0.769	0.819	0.567	0.580
Mean of dependent var.	10.768	10.768	10.768	10.968	10.968	10.561	10.561
Mean task dissimilarity	0.000	0.000	0.000	0.178	0.178	-0.232	-0.232
Mean technology requirements	0.224	0.224	0.224	0.298	0.298	0.105	0.105
Mean interactive tasks	0.000	0.000	0.000	0.434	0.434	-0.912	-0.912
Mean BA or above	0.363	0.363	0.363	0.518	0.518	0.076	0.076

This table reproduces Table 6, 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.2: Task Dissimilarity, Technologies, and Wages (with 300 Tasks)

	All			White-collar		Blue-collar	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Interactive tasks	0.126***	0.037***	0.023***	0.055***	0.029***	0.027***	0.024***
	(0.007)	(0.007)	(0.005)	(0.011)	(0.007)	(0.007)	(0.007)
Technology requirements	0.364***	0.265***	0.165***	0.330***	0.199***	-0.062**	-0.063**
	(0.012)	(0.037)	(0.023)	(0.041)	(0.026)	(0.025)	(0.024)
Task dissimilarity	0.040***	0.037***	0.029***	0.063***	0.048***	0.006	0.005
	(0.004)	(0.004)	(0.003)	(0.005)	(0.004)	(0.003)	(0.003)
BA or above			0.862***		0.931***		0.475***
			(0.069)		(0.077)		(0.059)
SOC f.e.	No	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	44,393	44,393	44,393	24,281	24,281	11,100	11,100
R^2	0.249	0.811	0.841	0.769	0.820	0.569	0.582
Mean of dependent var.	10.769	10.769	10.769	10.968	10.968	10.562	10.562
Mean task dissimilarity	0.000	0.000	0.000	0.142	0.142	-0.213	-0.213
Mean technology requirements	0.224	0.224	0.224	0.299	0.299	0.105	0.105
Mean interactive tasks	0.000	0.000	0.000	0.434	0.434	-0.919	-0.919
Mean BA or above	0.363	0.363	0.363	0.517	0.517	0.076	0.076

This table reproduces Table 6, except the task dissimilarity measures in the occupation-CZ are constructed based on extracting 300 tasks.

Table C.3: Task Dissimilarity, Technologies, and Wages: Adding CZ Fixed Effects

	All			White-collar		Blue-collar	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Interactive tasks	0.124***	0.006*	0.004	0.002	-0.000	0.004	0.004
	(0.007)	(0.004)	(0.004)	(0.006)	(0.006)	(0.006)	(0.006)
Technology requirements	0.326***	0.116***	0.085***	0.100***	0.076***	-0.061***	-0.063***
	(0.010)	(0.018)	(0.014)	(0.016)	(0.014)	(0.020)	(0.020)
Task dissimilarity	0.006**	-0.002	0.001	0.002	0.006***	-0.001	0.000
	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)
BA or above			0.510***		0.482***		0.312***
			(0.026)		(0.024)		(0.040)
SOC f.e.	No	Yes	Yes	Yes	Yes	Yes	Yes
CZ f.e.	Yes	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	0.314	0.871	0.879	0.871	0.881	0.696	0.700
Mean of dependent var.	10.769	10.769	10.769	10.968	10.968	10.561	10.561
Mean task dissimilarity	0.000	0.000	0.000	0.152	0.152	-0.178	-0.178
Mean technology requirements	0.224	0.224	0.224	0.299	0.299	0.105	0.105
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

This table reproduces Table 6 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 1.2 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[39] and external-to-the-firm interactive tasks.[40] As in Section 3.1,

[39] 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."

[40] 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," "Communication Skills," "Digital Marketing," "Market Planning," "Marketing," "Marketing Communica-

we compute the number of task mentions per 1000 ad words. Second, as in Section 3.2, for each ad we compute whether the ad mentions individual O*NET Hot Technologies. So that we can compute specialization, as in Section 3.3, 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 3.3, 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.9 replicates Figure 2. As in Section 3.1, external tasks increase in city size, both within and between six-digit SOC occupations. However, potentially due to the smaller sample size, the relationship between city size and internal tasks is no longer statistically significant.

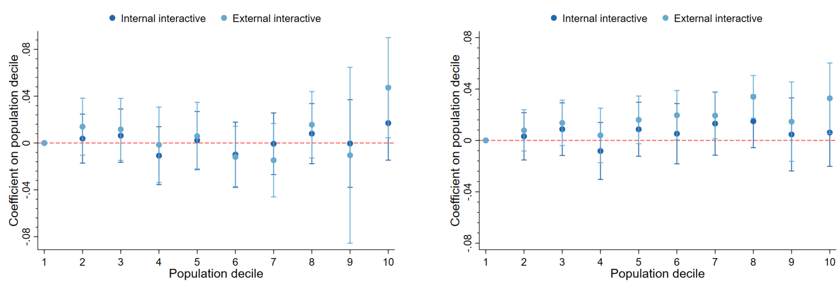
Second, we reproduce Figure 4. As in Figure 4, Figure C.10 indicates that within-occupation and within-firm specialization is greater in more populous commuting zones, with a steeper gradient for firms in nontradable industries than for firms in tradable industries (panel II).

Finally, we reproduce Table 6. As in Table 6, Table C.4 indicates that wages are higher in markets with greater specialization, with greater technology usage, with greater interactive task intensity, and with a greater share of workers with a college degree. Furthermore, also as in Table 6, the relationships between wages and within-occupation × market specialization, technology intensity, and interactive task intensity are each stronger in white-collar than in blue-collar occupations.

tions," "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.9: O*NET Interactive Tasks Gradient

I. Without SOC f.e. | II. With SOC f.e.

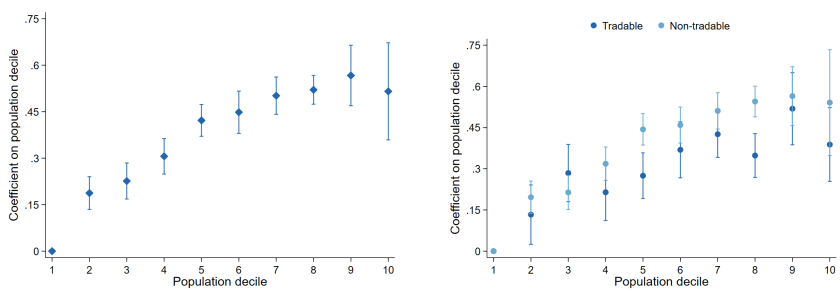


See the caption for Figure 2. In contrast, our task measures here come from our analysis using Burning Glass data.

Figure C.10: Specialization Gradient: Task Dissimilarity Within Firms and Occupations

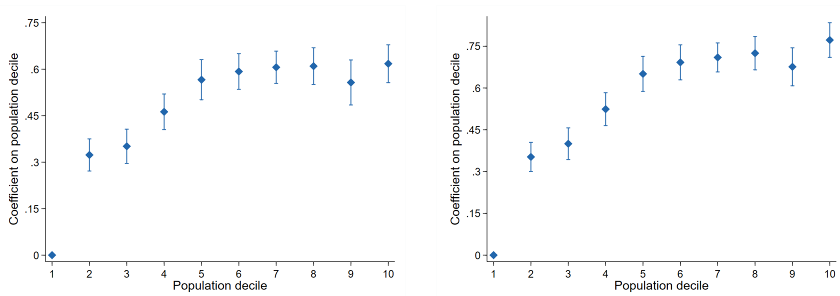
A. Firms

I. All | II. Tradable v. 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 our analysis using Burning Glass data.

Table C.4: Task Dissimilarity, Technologies, and Wages

	All			White collar		Blue collar	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Task dissimilarity	0.069***	0.022***	0.017***	0.053***	0.044***	0.010***	0.010***
	(0.005)	(0.003)	(0.002)	(0.011)	(0.008)	(0.003)	(0.003)
Technology requirements	0.285***	0.174***	0.114***	0.224***	0.142***	0.010	0.004
	(0.007)	(0.021)	(0.014)	(0.038)	(0.016)	(0.015)	(0.015)
Interactive Tasks	0.060***	0.007*	0.004	0.010**	0.005	0.001	0.001
	(0.006)	(0.004)	(0.004)	(0.003)	(0.004)	(0.006)	(0.005)
Education			0.518***		0.647***		0.087*
			(0.076)		(0.135)		(0.040)
SOC f.e.	No	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	32,623	32,623	32,623	20,194	20,194	7,099	7,099
R^2	0.200	0.823	0.833	0.774	0.795	0.577	0.578
Mean of dependent var.	10.783	10.783	10.783	10.971	10.971	10.567	10.567
Mean task dissimilarity	-0.000	-0.000	-0.000	0.078	0.078	-0.083	-0.083
Mean technology requirements	0.573	0.573	0.573	0.771	0.771	0.244	0.244
Mean interactive tasks	0.000	0.000	0.000	0.309	0.309	-0.691	-0.691
Mean BA or above	0.384	0.384	0.384	0.553	0.553	0.069	0.069

See the caption for Table 6. In contrast, the task dissimilarity and technology measures here come from our analysis using Burning Glass data.