Estimating Labor Market Power*

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Abstract

Job differentiation gives employers market power, allowing them to pay workers less than their marginal productivity. We estimate a differentiated jobs model using application data from Careerbuilder.com. We find direct evidence of substantial job differentiation. Without the use of instruments for wages, job applications appear very inelastic with respect to wages. Plausible instruments produce elastic firm level application supply curves. Under some assumptions, the implied market level labor supply elasticity is 0.5, while the firm level labor elasticity is 4.8. This suggests that workers may produce 21% more than their wage level, consistent with significant monopsony power.

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1 Introduction

There is a growing literature on monopsony or oligopsony power in US labor markets (Manning, 2021). As recognized by Robinson (1933), job differentiation is one possible source of imperfect competition in the labor market. When jobs are differentiated, workers cannot costlessly substitute between jobs: even if a job pays more than another job, it is likely to be different in ways that are relevant to the worker's well-being, e.g. the alternative job may be further from the worker's home (Marinescu and Rathelot, 2018). Such job differentiation can allow firms to pay workers less than their marginal revenue product. Card et al. (2018) point out that a simple "product differentiation" model of jobs can reconcile many interesting facts about labor markets. In their conclusion, they suggest that labor economics should perhaps move in the direction of Industrial Organization (IO), studying supply and demand in specific labor markets, with an emphasis on differentiated jobs.

In this paper, we take one step in the empirical implementation of that suggestion, leveraging rich data on worker and job characteristics. We adopt a firmly IO-style approach to the question, which will bring some advantages but also leave open questions for further research. Specifically, we model job application choice, at the worker level, using a classic parametric discrete-choice framework.

We use a large online job posting and applications dataset from CareerBuilder.com. Azar, Marinescu and Steinbaum (2022) employ this data source to document labor market concentration and the association between concentration and wages, and Marinescu and Rathelot (2018) use the data to estimate workers' preference for nearby jobs and the degree of geographic mismatch. We use the data to estimate a nested logit model of unemployed workers' demand for differentiated jobs. As in IO models following on Berry (1994), each choice (here, a job) has both observed and unobserved characteristics. Jobs are observably differentiated in terms of location (ZIP code), occupation and the wage being offered. Importantly, workers' ZIP code is also known, which allows us to estimate the role of distance in workers' preferences.

Our data has a panel structure of jobs within (labor) markets, with heterogeneous decision-makers (workers) who choose among these jobs. As suggested by the nonparametric identification argument of Berry and Haile (2022), this data structure allows us to exploit within-market (cross-worker) variation as well as between-market variation in the wages and characteristics of job vacancies. Berry and Haile

(2022) advance a "fixed-effects" style panel-data argument that inspires our approach to identification and estimation. Our approach then allows us to exploit several sources of data variation as we explore the sources of job differentiation. We show how different data sources and assumptions can sequentially combine to uncover the nature of the job differentiation. In each step of our sequential approach, additional assumptions generate additional insights about job differentiation. In particular, our estimation follows a two-step strategy that is broadly suggested by the identification arguments in Berry and Haile (2022). In a third step, we make additional assumptions to convert job application elasticities into labor supply elasticities, and to derive the wage markdown.

In our first step, we use our applicant/worker data with a nested logit approach to examine the degree of job differentiation and its sources. In this step, we estimate a job-specific utility that accounts for all job-specific variables (including the posted wage). The first step results allow us to explore the role of geography and occupation in differentiated jobs, without using any of our later assumptions.

The nested logit model has two "levels". In the bottom level multinomial logit, a worker chooses which job to apply to within a given labor market (a 6-digit SOC occupation by commuting zone) and week; this is a conditional application probability, and thus is only estimated for workers who apply in the market-week. We then focus on workers who applied in the focal labor market in at least one week. In the top level logit each worker chooses whether to apply to this focal labor market in the given week. The worker's decision depends on the expected value of applying to that market, which we obtain from the bottom level logit.

In the bottom level multinomial logit, we estimate job fixed effects, which are closely related to the number of applications that each job receives. Importantly, these job fixed effects also take into account variation in the *competition* with other jobs across weeks. So, for example, if a job gets many applications in a given week, it could mean that the job is great, or it could mean that there are few other desirable jobs in that week. Thus, job fixed effects are identified off of differences in the number of applications across jobs as well as variation in choice sets across weeks. An additional source of variation that is useful for the identification of substitution patterns across jobs is the geographic distance between a worker and a job. The distance of the worker from job B is naturally excluded from the worker's preference for job A.

In the top level logit, with market and week fixed effects, we explain each worker's choice of whether to apply to a given market as a function of the expected utility (inclusive value) of doing so, as calculated using the bottom level logit results. This relies on two sources of variation. First, there is market-week variation in the value of applying to a market (classic panel identification for the market level panel). Second, there is variation in job valuation across workers in the same market due to distance, which leads to variation in the inclusive value *within* markets and across weeks: that is, workers who happen to be closer to the available jobs in a given market-week have a higher inclusive value for applying within the market. In the top level logit, the coefficient on the inclusive value (the nesting parameter) measures the impact of a higher inclusive value on the probability of applying in that market-week. While the bottom level logit takes into account within-market competition between jobs, this top level logit also takes into account competition across markets and the relative attractiveness of jobs in a market-week.

Because of the nature of the nested logit, sources of identification in the bottom and top level logit are combined to yield the final job utilities. These job utilities can be seen as adjusted job application numbers, taking into account the competition of other jobs both within market (from the bottom level logit) and across markets (from the top level logit). The number of applications by itself— which one can use in a descriptive approach as in Marinescu and Wolthoff (2016) —is not a sufficient statistic for the utility of a job: the number of applications reflects the utility of this job *relative* to other jobs it competes with.

The results from our nested logit model imply a substantial degree of job differentiation. We find a nesting parameter well below one, which implies that there is a correlation between the unobserved utilities of jobs within a market (defined as an SOC-6 occupation by commuting zone). This means that within-market jobs compete more tightly with each other than with jobs in different markets. Using a decomposition of variance, we find that two thirds of the variance in the total utility of a job is explained by worker-job match specific utility, with only a third explained by factors common across all workers, such as the wage. We do observe one dimension of the match-specific utility: geographic distance. We find that 18% of the variance in the total utility of a job is explained by the geographic distance (ZIP code to ZIP code) between the job and the job seeker. Overall, we find that jobs are meaningfully differentiated both within and across markets, with both occupation and geographic distance playing important roles.

In a second step, we use the results from our nested logit approach to understand the impact of the wage on the average value of a job to workers. We regress our estimated job utilities (or values) on wages and job/firm characteristics, yielding wage coefficients that are necessary for the calculation of wage elasticities. Note that some non-wage job characteristics will be observed to us, but many will not. These unobserved (to us) job characteristics could, for example, involve employment benefits and/or the employment-related reputation of the firm. The presence of unobserved job characteristics creates a classic endogeneity problem, similar to the endogeneity of price in the estimation of differentiated product models of supply and demand. We find that when the endogeneity problem is ignored, simple OLS estimates can produce downward sloping labor supply curves. This is likely due to a negative correlation between wages and unobserved application-relevant characteristics.

This endogeneity problem can be addressed via instrumental variables that shift firm level wages but not worker preferences. Our preferred instruments take advantage of the fact that wages are often set, in part, at the firm level (Chen, 2021; Hazell, Patterson and Sarsons, 2021). We construct instruments from competitive conditions faced by the firm in the *other* markets where it posts job vacancies. Specifically, our preferred instrument is the predicted wage in the other markets the firm is also posting in (excluding the same occupation and the same commuting zone).

These two steps produce a set of job application elasticities that account for wage endogeneity as well as heterogeneous worker taste for differentiated jobs. We derive application elasticities at the firm level, vacancy level and market level. Our use of application data has the advantage of directly measuring a labor supply side response. However, the wage elasticity of applications is not a labor supply elasticity.

In a third step, we draw on a set of results from the literature: under some strong but somewhat plausible assumptions, these results allow us to translate our vacancy demand result into firm and market level labor supply wage elasticities. Unlike some other work, we do not attempt to estimate the labor demand side of the model. Instead, we illustratively use a very simple posted wage model to translate our estimated firm level application elasticities into wage markdowns, $(\text{MRP}_L - w)/w$, where MRP_L is the marginal revenue product of labor and w is the wage. We find that the average markdown is about 21%, implying that workers are about 21% more productive than their wages. As an illustration of the policy-relevance of this degree of market power, we can use the *market level* labor supply elasticity to determine if a labor market is a valid antitrust market using a critical elasticity test (Harris and Simons, 1991). We find that market level elasticities are low enough to typically make an SOC-6 occupation by commuting zone a plausible definition of the labor market.

Broadly, our contribution is to dig into the mechanisms behind monopsony power (see reviews by Manning (2021); Sokolova and Sorensen (2021)) by using an industrial organization model based on job differentiation, with detailed microdata from the most common occupations in the US. This approach adds to three other strands in the monopsony literature: general equilibrium (GE) macroeconomic models of oligopsonistic markets (Berger, Herkenhoff and Mongey, 2022), bargaining models of imperfect competition (Jarosch, Nimczik and Sorkin, 2019), and approaches based at least partly on assumptions about the production function (Yeh, Macaluso and Hershbein, 2022; Lamadon, Mogstad and Setzler, 2022). Our paper is most closely related to two other papers adopting an IO approach. A working paper by Kroft et al. (2022) looks at one industry, construction, and considers a monopsonisitically competitive model of the market for construction workers. Another working paper by Roussille and Scuderi (2022) takes an approach that is perhaps the closest to ours. They use data on full-time, high-wage engineering jobs with a discrete choice model to calculate a wage markdown. Their data from Hired.com has a number of institutional features that they exploit to obtain relatively rich estimates of both labor supply and demand without requiring an instrument.

Our data and estimation strategy make three contributions to the literature. First, we identify job differentiation using explicit choice sets for workers: that is, unlike most of the literature, we know which jobs workers are considering, and not just the jobs workers ended up taking. Among monopsony papers cited in the above paragraph, only Roussille and Scuderi (2022) have explicit data on job options. Second, we can directly identify job differentiation using our nested logit, and we identify the role of geographic distance. Our findings on geographic distance add to the literature on the role of geographic distance in explaining job applications patterns (Marinescu and Rathelot, 2018; Le Barbanchon, Rathelot and Roulet, 2021). Third, our instrumental variable approach allows us to estimate job application elasticities at the firm level *and* at the market level, with the market level elasticity being especially relevant for antitrust policy. The generality of our instrumental variable strategy allows us to estimate elasticities for a broad range of occupations, industries and locations, in contrast with Kroft et al. (2022) and Roussille and Scuderi (2022), who focus on more specific markets.

The rest of the paper proceeds as follows. In section 2, we discuss the data and the estimation methods. In section 3, we present the empirical results, focusing on job differentiation and the wage elasticity of job applications. In section 4, we show how our wage elasticity of job applications can be used to calculate the wage markdown, and we discuss the implications for antitrust policy. Finally, section 5 concludes.

2 Data and estimation

2.1 Data

Our data includes information on unemployed job seekers, job vacancies and job seekers' applications to these vacancies on the online job board CareerBuilder.com, the largest US employment website[1]. This data set covers job search activity between April and June 2012 on CareerBuilder.com. We drop job seekers who do not live in the US, who live in Alaska or Puerto Rico, and job seekers whose location is unknown. This same data was used by Marinescu and Rathelot (2018), who show that it is broadly representative of vacancies and unemployed job seekers in the US.

In order to be able to reliably estimate the value of each vacancy to job applicants, we restrict the sample to job vacancies with at least five applications. We define a labor market as an occupation at the 6-digit standard occupational class (SOC) level (for example, "Registered Nurses") and a commuting zone. We then merge our application data with the data used in Azar, Marinescu and Steinbaum (2022), in order to obtain the names of the companies posting the jobs, which will be critical for our calculation of *firm*-level elasticities and to our instrument for the wage. As a result of the merge, the data is restricted to the SOCs used in Azar, Marinescu and Steinbaum (2022) (Table 1), which are the most common ones for job vacancies. The data contains the zip code location of job seekers and job vacancies, which allows us to calculate the geographic distance between the job seeker and the vacancy. We drop from the sample markets that did not have at least two vacancies every week during the second quarter of 2012, or for which there was no week with two vacancies in different zipcodes (otherwise, we cannot identify the distance coefficient for that market). We end up with 822 commuting zone-occupation pairs.

We present summary statistics in Table 2. For each market in our sample between April and June 2012, there are on average 50 jobs, and 732 users collectively sending 1957 applications On average, a job seeker sends 7 applications and a job receives 39 applications.

The dataset contains information on posted wages for 41.8% of job vacancies (Table 2). When a range

[1] Monster.com is the other leading job board and is comparable in size. Which of CareerBuilder or Monster is larger depends on the exact size metric used.

Table 1. List of occupations: 6-digit SOC occupations present in our sample

SOC code	Occupation description
11-3011	Administrative services managers
13-2011	Accountants and Auditors
13-2051	Financial Analysts
13-2052	Personal financial advisers
13-2053	Insurance Underwriters
13-2061	Financial Examiners
15-1041	Computer support specialists
17-2111	Health and Safety Engineers, Except Mining Safety Engineers and Inspectors
17-2112	Industrial engineers
29-1111	Registered nurses
41-4011	Sales representatives, wholesale & manufacturing, technical & scientific products
41-9041	Telemarketers
43-3031	Bookkeeping, accounting, and auditing clerks
43-4051	Customer service representatives
43-6011	Executive secretaries and administrative assistants
43-6012	Legal Secretaries
43-6013	Medical secretaries
43-6014	Secretaries and Administrative Assistants, Except Legal, Medical, and Executive
47-1011	First-Line Supervisors of Construction Trades and Extraction Workers
49-3041	Farm equipment mechanics
49-3042	Mobile Heavy Equipment Mechanics, Except Engines
49-3043	Rail Car Repairers
51-1011	First-line supervisors/managers of production and operating workers
53-3031	Driver/sales workers
53-3032	Truck drivers, heavy and tractor-trailer
53-3033	Light Truck or Delivery Services Drivers

is provided, we take the middle of the range,[2] as in Marinescu and Wolthoff (2016); the average wage is \$36k annually. For the nested logit model, we use job vacancies both with and without wages.

Table 2. Summary statistics

	Count	Mean	Sd	Min	25%	50%	75%	Max
Jobs Data								
Jobs Per Market	822	49.80	68.14	2	14	26	54	576
Jobs Per Market-Week	10272	14.15	20.08	1	4	7	15	246
Duration of Job Listing	40932	6.03	1.58	1	5	7	7	7
Applications Data								
Users Per Market	8822	731.75	986.80	10	177	375.5	818	8229
Apps Per Market	822	1956.91	4084.01	12	267	626.5	1643	43168
Apps Per Job	40932	39.30	68.84	5	8	16	39	1359
Apps Per User	241563	6.66	13.91	1	1	3	7	1060
Apps Per User-Week	512962	3.14	5.12	1	1	2	3	392
Wage Regression Data								
Log Wage	16769	10.40	0.48	6.215	10.086	10.309	10.714	13.218
Wage	16769	36921.57	20585.02	500	24000	30000	45000	550000
High Minus Low Wage	16769	10463.24	15551.21	0	2000	5000	10000	380000
Percent Jobs Posted Wage	40100	0.42	0.49	0	0	0	1	1
Duration	40100	27.74	6.23	1	30	30	31	69

2.2 Econometric model: basic assumptions

We define a labor market as a commuting zone and occupation (SOC-6). Markets are indexed by m. We observe a labor market over several weeks t. Market m has N_m active users over our sample period. An active user in market m is defined as anyone who has ever applied in a market in any of the 13 weeks of our data. On any given week t, there is a set $\mathcal{J}_{mt}$ of active vacancies in market m. In any given week t, a worker decides to apply or not apply to market m. Choosing not to apply gives workers the value of the outside option ($j = 0$), i.e. either applying to another SOC-6 by CZ market or not applying at all. Conditional on applying to market m, the worker chooses which vacancy to apply to.[3]

The utility of individual i from applying to job vacancy $j \in J_{mt}$ in week t is:

$$u_{ijmt} = \delta_j + \gamma z_{ijm} + \nu_{imt}(\lambda_m) + \lambda_m \epsilon_{ijmt}, \tag{1}$$

[2]The average length of the provided range is \$10,000, including the cases where an exact amount is specified so that the range is zero

[3]The majority of workers (68.4%) only apply to one job in a given market and week. For workers who apply to multiple vacancies in a market and week, we treat each application as a separate decision.

where z_{ijm} is the log of the distance between the user and job vacancy j. All of the within-market jobs are in the same nested logit group. The only other choice in the model is to apply out of market: this is the outside option. We denote the nest with the within-market jobs as $g = 1$, and the outside option as $g = 0$.

The utility of applying outside of the market shifts over time (to roughly capture changes in outside of market job availability) and is modeled as

$$u_{iomt} = \bar{\bar{\delta}}_t - \theta \tilde{z}_{im} + \epsilon_{i0mt}. \tag{2}$$

The dummy variable $\tilde{z}_{im}$ equals one if the active job applicant lives inside of the market m commuting zone. This shifter does not vary across jobs within a market, and we except that it will decrease the utility of outside-market jobs.

In equations (1)-(2), the random utility shocks are $\nu_{imt}(\lambda_m)$ and ϵ_{ijmt}. We assume that these random utility shocks have the appropriate distributions to generate the classic nested logit functional form, as in Cardell (1997). The term ϵ_{ijmt} is a random "match value" for the match between worker i and a particular job j. The parameter λ_m is a market-specific nesting parameter, and $\nu_{imt}(\lambda_m)$ is a "nested logit" random taste that is present in the utilities for within-market job vacancies and differentiates the job vacancies in the market from the outside option.

Finally, the critical term δ_j is McFadden's "alternative-specific constant" (or "mean utility") which captures the average level of utility of a job vacancy for different workers and across periods. It is defined as:

$$\delta_j = \beta x_j - \alpha \log w_j + \xi_j, \tag{3}$$

where w_j is the wage posted by the job vacancy. The observed characteristics of the job, x_j, include log employment of the firm posting the vacancy, squared log employment, and market fixed effects. In some specifications, we also include job title fixed effects, because they are a very strong predictor of posted wages (Marinescu and Wolthoff, 2016). Following Berry (1994), we allow for an unobserved component of the mean utility of a job, ξ_j. This captures unobserved job attributes that are not present in the data. These could include better or worse working conditions or benefits. The unobservable may also include the perceived stringency of (unobserved to us) job qualifications. In the context of job applications, a job that is too hard to get is job that is not desirable to apply for. While there is evidence that workers indeed avoid jobs they are not qualified for (Marinescu and Wolthoff, 2016), there is no evidence that they avoid jobs with many applicants (Gee, 2018). To the extent that job seekers do not seek to avoid jobs with many applicants, they do not need to consider other job seekers' strategies when applying to a job, but can instead focus on the attributes of the job. It is natural to assume that the unobservable job attributes are correlated with the wage. For example, a firm offering good benefits and stable employment may offer lower wages, whereas jobs with stringent qualifications may have high wages.

The bottom level of the nested logit requires us to estimate many job fixed effects. To reduce computational burden, we estimate the lower level logit parameters, including the effect of distance on job desirability, from a purely within-market logit analysis of workers' choices. Specifically, we estimate our nested logit model sequentially in two steps (see Train, 2009), with a bottom level within-market choice and top level choice of whether to apply in the market. This allows us to recover many job-specific effects. The two-step process mimics part of our informal identification argument and allows us to impose additional assumptions only as they are needed.

We now explain the specific procedure used to estimate the bottom and top levels of the nested logit. We will then discuss the estimation of the impact of wages on job utility, which is a separate regression.

2.3 Bottom level logit: choosing between jobs within a market

The "bottom level" probability that user i applies to job j conditional to applying to a job in market m in week t is

$$s_{ijmt|g=1} = \frac{\exp\left[(\delta_j + \gamma z_{ijm})/\lambda_m\right]}{\sum_{k\in\mathcal{J}_{mt}} \exp\left[(\delta_k + \gamma z_{ikm})/\lambda_m\right]}. \tag{4}$$

The data structure for this bottom level conditional logit model is as follows. First, as a reminder, only job seekers who applied at least once (in any week) in the market are retained. Then, for each application a job seeker actually sent, we construct the set of possible choices as the jobs available that week in that market.

Note that the bottom level logit probabilities in (4) stay constant if each δ_j is increased or decreased by the same amount. To deal with this, in each market define one job $j = r(m)$ as a "reference job". In the bottom level analysis, the desirability of each job in the market will be measured relative to this reference job. Specifically, subtracting $\delta_{r(m)}/\lambda_m$ from each of the job-fixed effects δ_j/λ_m in (4), the expression

$$s_{ijmt|g=1} = \frac{\exp\left[((\delta_j - \delta_{r(m)}) + \gamma z_{ijm})/\lambda_m\right]}{\sum_{k \in \mathcal{J}_{mt}} \exp\left[((\delta_k - \delta_{r(m)}) + \gamma z_{ikm})/\lambda_m\right]}. \tag{5}$$

produces the exact same within-market choice probabilities as the original expression (4). Note, however, that the level of $\delta_{r(m)}/\lambda_m$ does matter for the top-level probability of making a within-market application. We return to this below.

At the bottom level, a key question is whether we need different reference jobs in each week. If we use a single reference job in each market, can we identify $(\delta_k - \delta_{r(m)})/\lambda_m$ for jobs appearing in all weeks of the data, even if the reference job $r(m)$ and job k are not active in the same week? In Appendix B, we discuss the proof that the answer is "yes" as long as, in every week, some job persists from week t to $t+1$. We call this the "persistent job assumption." The "job that persists" can be different for each pair of adjacent weeks in the data.

For each market, we estimate the bottom level multinomial logit with choice probabilities given by (4) via Maximum Likelihood using the asclogit command in Stata. This produces estimates of the relative job "fixed effects", $(\delta_k - \delta_{r(m)})/\lambda_m$, for each job j that appears in that market in some week, as well as the market level coefficient on z_{ijm}, γ/λ_m.

Our bottom level estimates of the relative job fixed effects are closely related to the number of applications that jobs receive on average across weeks after conditioning on distance z_{ijm}. Recall that a job typically appears in the dataset in multiple weeks: a median job lasts 6 weeks, as seen in Table 2. Conceptually, our bottom level estimates take into account the fact that a job gets more applications when competing against less attractive jobs, and fewer applications when competing against more attractive jobs. Econometrically, this across-week variation aids identification of job fixed effects δ_j/λ_m, as the same job is compared to different alternatives in different weeks. This across-week variation also further aids estimation by creating additional choice opportunities (effectively increasing sample size relative to the number of parameters).

The coefficient on distance γ/λ_m is identified off of variation in distance to jobs across workers: the distance of the worker from job B is naturally excluded from the worker's preference for job A. This kind of exclusion restriction is also helpful in the identification of discrete choice preferences (Lewbel (2014) and Berry and Haile (2022)).

Given the bottom level results, we obtain the predicted probability of choosing each vacancy conditional on applying to a job in the market, $s_{ijmt|g}$, which we will later use for elasticity calculations.

While the bottom level logit only takes into account competition among jobs *within* market m, the λ_m parameter takes into account competition *across* markets. λ_m will be estimated from the top level of the nested logit, which we describe in the next subsection. This will then allow us to identify δ_j, γ and θ.

2.4 Top level logit: choosing whether to apply to a market

The probability of applying within market in a given week depends on the nested logit "inclusive value" (Train, 2009). This is the expected value, across the distribution of random utility shocks, of choosing the best job in the market conditional on the job fixed effects and the location of applicant. Up to a constant, the inclusive value of a within-market application is

$$I_{imt} = \log \sum_{k \in J_{mt}} \exp\left[(\delta_k + \gamma z_{ikm})/\lambda_m\right]. \tag{6}$$

We need to account for the fact that we recover only relative job fixed effects in the bottom level logit. Rewriting the inclusive value,

$$\begin{aligned} I_{imt} &= \log \sum_{k \in J_{mt}} \exp\left[(\delta_k - \delta_{r(m)} + \delta_{r(m)} + \gamma z_{ikm})/\lambda_m\right] \\ &= \log \sum_{k \in J_{mt}} \exp\left[\delta_{r(m)}/\lambda_m\right] \exp\left[(\delta_k - \delta_{r(m)} + \delta_{r(m)} + \gamma z_{ikm})/\lambda_m\right] \\ &= \delta_{r(m)}/\lambda_m + \log \sum_{k \in J_{mt}} \exp\left[(\delta_k - \delta_{r(m)} + \delta_{r(m)} + \gamma z_{ikm})/\lambda_m\right] \\ &\equiv \delta_{r(m)}/\lambda + \bar{I}_{imt}(z_{im}) \end{aligned} \tag{7}$$

The last equality defines $\bar{I}_{imt}(z_{im})$ as the component of the inclusive value that we can obtain from the bottom level logit results.

The top level probability of applying within market in week t is then a simple binary logit with

$$\bar{s}_{imt} = \frac{e^{\lambda_m I_{imt}}}{e^{\bar{\delta}_t - \theta \bar{z}_{imt}} + e^{\lambda_m I_{imt}}}. \tag{8}$$

Note that λ_m appears as a coefficient on the within-market inclusive value and that the denominator of the expression accounts for the value of the outside market option. Using (7), we can rewrite (8) as a binary logit probability of the form:

$$\bar{s}_{imt} = \frac{e^{\delta_{r(m)} - \bar{\delta}_t + \theta \tilde{z}_{imt} + \lambda_m \bar{I}_{imt}}}{1 + e^{\delta_{r(m)} - \bar{\delta}_t + \theta \tilde{z}_{imt} + \lambda_m \bar{I}_{imt}}}. \tag{9}$$

This is the probability of a within-market application that we use to estimate the top level.

We estimate this equation pooling observations from all markets; an observation is a market-week by job seeker[4]. The job seeker may have applied either to a vacancy in the market, or to the outside option. The estimation includes market effects, whose coefficients are $\delta_{r(m)}$. Thus, the top level estimation recovers the job fixed effect for the reference job in each market. We also include week fixed effects, whose coefficients are $-\delta_t$. The coefficient θ is recovered from variation in job-seeker location (in or out of the commuting zone.)

The coefficient on the bottom level component of the inclusive value is the nesting parameter λ_m. (In our baseline model we hold λ_m fixed across markets). We then recover δ_j for the non-reference jobs from our bottom level estimates of $(\delta_j - \delta_{r(m)})/\lambda_m$ together with our top level estimates of λ_m and $\delta_{r(m)}$. We also recover the predicted top level probability from the function $\bar{s}_{imt}$ evaluated with the estimated coefficients using the individual data.

Our estimation relies on two sources of variation. First, there is market-week variation in the value of applying to a market (classic panel identification for the market level panel). Second, there is variation in job valuation across workers in the same market due to distance, which leads to variation in the inclusive value *within* markets and across weeks: that is, workers who happen to be closer to the available jobs in a given market-week have a higher inclusive value for applying within the market. In the top level logit, the coefficient on the inclusive value (the nesting parameter) measures the impact of a higher inclusive value on the probability of applying in that market-week. While the bottom level logit takes into account within-market competition between jobs, this top level logit also takes into account competition across markets and the relative attractiveness of jobs in a market-week.

The overall probability that user i applies to job j in market m in week t is the probability that they

[4] If the job seeker applies to more than one job in a given week and a given market, there is a second observation for the job seeker in that week for that market.

apply to market m (equation 9) *times* the probability that they apply to a particular job j in that market conditional on applying in that market (equation 4),

$$s_{ijmt} = s_{ijmt|g=1}\bar{s}_{imt}.$$

The expected share of applications to job vacancy j in market m in week t is simply the average of the probabilities across job seekers:

$$s_{jmt} = \frac{1}{N_m}\sum_{i=1}^{N_m} s_{ijmt}. \tag{10}$$

Similarly, the expected share of applications to market m in week t is the average of the probabilities of applying inside the market across job seekers:

$$s_{gmt} = \frac{1}{N_m}\sum_{i=1}^{N_m} s_{igmt}. \tag{11}$$

2.5 The impact of the wage on the utility of a job

As in Berry (1994), we then run a regression of the estimated job values δ_j on the log wage and the number of employees of the firm and the square of the number of employees of the firm (equation 3). We do this using either OLS or, because wages are likely correlated with the unobserved job quality ξ_j, via the use of instrumental variables for the wage. We control for job title fixed effects in some regressions.

As explained in Berry and Haile (2021), an advantage of our worker-level application data is that we only need instruments for wages and not any additional instruments for the endogenous market shares that would appear in a market level analysis (Berry and Haile, 2014).

2.6 Wage and nesting parameters flexibility

We estimate three versions of the model, with different levels of flexibility for the wage and nesting parameters. In the first version, we treat both the wage coefficient α and the nesting parameter λ as constant across markets. We call this version "homogenous", as coefficients are assumed to be the same across markets. In a second version of the model, we allow for the α and λ parameters to be different for low-skill and high-skill occupations, and for rural and urban commuting zones. We call this version of the model "heterogenous". To classify occupations into low or high skill, we use wages from the Bureau of Labor Statistcs Occupational Employment Statistics (OES). In particular, we classify an occupation into the "low-skill" group if the mean hourly wage in 2012 for its 3-digit SOC code (minor group) in the OES is below the median across the applications in our sample (18.16 in 2012 dollars), and into the "high-skill" group if it is above the median. We classify a commuting zone as "rural" if its population density is below the median across the applications in our sample (520 people per square mile[5]), and "urban" if its population density is above the median. We call this version, with heterogeneity across two wage categories by two population density categories, the "heterogeneous" version of the model.

Our third version allows for the α and λ parameters to vary freely across 6-digit SOC occupations, as well as continuously with population density (using a quadratic in population density). We call this the "detailed" version of the model, noting that there is not enough power to reliably estimate parameters for all markets. We will therefore only report results for this version as part of our additional results section.

In all three versions, for the top level logit we include the following controls: a dummy for whether the applicant is in the same commuting zone as the job vacancy, market (CZ×SOC) fixed effects, and year-week fixed effects.

For the wage equation that relates the job fixed effects to job characteristics (including the wage), we include market (CZ×SOC) fixed effects, firm size measured as the log number of employees, and firm size squared. In some specifications, we also include job title fixed effects.

2.6.1 Instruments for the wage

Since the wage is endogenous, likely correlated with unobserved job characteristics, we need to instrument for it in the equation for job quality (eq. 3), where an observation is a job vacancy. We consider three broad strategies to construct instruments for the wage. One is to use variation in the choice set of job seekers, the so-called "BLP" instruments, as in Berry, Levinsohn and Pakes (1995), Nevo (2000) and Berry and Haile (2014). Another set of instruments is based on the idea that multi-location firms may try to limit within-firm cross-location variation in wages. Reasons for this could have to do with fairness norms or with the ease of setting wage policy at the firm level. For all sets of instruments, we have to consider whether they are likely to be correlated with unobserved (to us) job characteristics.

[5] A density of at least 1,000 people per square mile is one of the criteria for an urbanized area as defined by Census: https://www2.census.gov/geo/pdfs/reference/GARM/Ch12GARM.pdf

To construct instruments that measure the variation in possible choice sets across markets, we look at the characteristics of other job vacancies in the market, such as the number of vacancies, and the size of the other firms that post in the market. If the model is correct, these are excluded because they do not enter the formula for the utility of user i for job j (see Berry and Haile, 2014). One potential problem with our implementation of these instruments in the present context is that wages might be set at the level of the firm (across markets) and not respond much to local market conditions and particularly not to short term changes in these conditions. This would lead the instruments to poorly predict wages (lack relevance).

We consider two variants of instruments based on the job characteristics: first a simple version instrumenting only with the number of vacancies in the market, and then a version instrumenting with the number of vacancies in the market, the sum across other vacancies of log employment of the posting firm, and the sum across other vacancies of the square of log employment of the posting firm.[6] In the latter case, since we have more than one instrument, we estimate the equation using 2-step GMM.

One alternative set of instruments is a variant of the "Hausman instruments" often used in the industrial organization literature (Hausman, Leonard and Zona, 1994). For example, the price of Cheerios in Atlanta in a given week would be instrumented by the average price of Cheerios in that week across all US cities except Atlanta. The Hausman idea of instruments based on prices in other markets relies on costs being correlated across locations, but demand shocks that are not correlated across locations. In the context of wages, the similar condition for the estimation of labor supply is that firms' within-market wage decisions reflect a common (across markets) firm level marginal productivity (labor demand), but not common shocks to unobserved job characteristics.

Alternatively, if firms set wages with some effort to reduce cross-location wage inequality, variation in competitive labor market conditions across the markets where a firm operates can lead to correlated wages, within-firm across markets. This will lead to other market wages that predict own-market wages but are naturally excluded from own-market labor supply decisions. DellaVigna and Gentzkow (2019) discuss and document firm level retail pricing decisions that hold prices constant across markets within firm. Similarly, there is evidence that firms pay somewhat uniform wages across labor markets within

[6]As discussed in Berry, Levinsohn and Pakes (1999), Reynaert and Verboven (2014) and Gandhi and Houde (2017), various non-linear functions of rival firms' characteristics may better approximate optimal instruments. Because we have other instruments available in our context, we do not explore these functions.

the US (Chen, 2021; Hazell, Patterson and Sarsons, 2021), and even across countries (Hjort, Li and Sarsons, 2020). Of course, the empirical relevance of other-market within-firm wages can be tested in the data.

We adapt this idea to instrument a job vacancy's wage by using the average wage for job vacancies posted by the same firm in a given week in all other (CZ $\times$ SOC) markets. We also construct a variant of the instrument excluding from the calculation of the average any markets that are in the same CZ (but other SOCs) or the same SOC (but other CZs). Excluding the same CZ or same SOC makes the instrument somewhat more plausibly exogenous.

Our first version of Hausman instruments can easily be criticized on the grounds that firm level wage decisions across locations may involve simultaneous changes to unobserved benefits and working conditions. If so, a firm's wages in other locations may reflect the unobserved quality of the job in this location. We therefore use a set of instruments that go one step further, by considering not the average wage of the firm in other markets, but the average of the underlying determinants of the wage of the firm in other markets. To implement this strategy, we first obtain predicted wages for each market by running a regression of wages on CZ-SOC fixed effects and year-week fixed effects and then obtaining the corresponding predicted values for the wages. We then take averages of the predicted wages across vacancies posted by the same firm in other markets. As with the Hausman instruments, we calculate two versions: one using the average predicted wage for vacancies by the same firm in all other CZ $\times$ SOC markets, and one—plausibly more exogenous—excluding markets that are in the same CZ or the same SOC from the average predicted wage calculation. Intuitively, this third set of instruments amounts to saying that if a firm faces high-wage competition in other markets, then it also pays higher wages in the current market. In a version of this instrument, we also exclude adjacent commuting zones, to avoid endogeneity due to geographically correlated shocks; as we will see, the results are almost the same when excluding these CZs.

Our preferred specification uses the instrument based on the average *predicted* wage for vacancies by the same firm in all other CZ $\times$ SOC markets excluding markets that are in the same CZ or the same SOC from the average predicted wage calculation. We also run a version of this specification with job title fixed effects, which improves the wage prediction, but also leads to very low first-stage F stats when allowing for heterogeneity in the wage coefficients (see Table 9).

One important caveat about the instruments based on wages in other markets is that some types of firms, which hire some classes of occupations, may engage in across-location wage-setting, but in other cases firms may set wages only based on own-market conditions. Thus, our Hausman-like instruments may work better in some occupational markets than in others, a possibility that suggests further research focusing on subsets of firms and occupations where instruments can be more closely tailored to specific conditions.

Once we obtain an estimate of the wage coefficient, we use this wage coefficient α, the estimated nesting parameter λ_m, and the predicted probabilities of application such as S_{ijmt} to calculate the wage elasticity at the vacancy, market and firm level. The formulas for these elasticities are given in Appendix C.

3 Results

3.1 Nested logit results: job differentiation

Our bottom level nested logit analysis gives us the utility coefficient on the log of distance from the applicant to the job, as well as a set of job fixed effects. The distance coefficients are estimated separately for each market. Table 3 summarizes these coefficients. The distance coefficients are typically negative, as expected. Out of 822 markets, in only one case do we find a distance coefficient that is positive and significantly different from zero at the 5% level.

Table 3. Summary statistics for the coefficient on $\ln(dist)$ in the bottom level logit

There are 822 markets in which we estimate a distance coefficient. Of these, 48 are positive with one significant at the 5% level and an additional 3 coefficients at the 10% level. The table gives the mean, standard deviation and quartiles for the estimated coefficients and for the standard errors and t-stats associated with those coefficients.

	Mean	Sd	25%	50%	75%
Estimate of γ	-0.558	1.083	-0.834	-0.544	-0.301
Standard Error	0.200	0.510	0.054	0.109	0.194
T-stat	-9.621	14.894	-11.133	-4.851	-2.076

Figure 1 shows the relationship between the estimated distaste for distance (the negative of the distance coefficients) and log population in the home commuting zone of each market. The pattern here is clear and is economically interesting. Workers in more densely populated commuting zones are less likely to apply to jobs far away from their zip code of residence than workers in less densely popu-

Table 4. Variance decomposition for the bottom level logit (equation (4))

In the bottom panel, each variance is given as a proportion of the total variance of utility given in the top panel. The variance decomposition in each market sums to one, and therefore the mean column in the bottom panel also sums to one.

	N	Mean	Sd	Min	25%	50%	75%	Max
Var(Utility)	822	0.074	0.299	0.022	0.037	0.044	0.053	7.234
Proportions								
Var(δ)	822	0.335	0.166	0.000	0.221	0.331	0.429	0.985
γ^2Var(ln dist)	822	0.175	0.177	0.000	0.043	0.125	0.247	1.023
λ_m^2Var($\lambda\epsilon$)	822	0.491	0.151	0.003	0.407	0.492	0.586	0.984
γCov(δ, dist)	822	-0.001	0.041	-0.610	-0.010	0.000	0.011	0.298

lated areas. This suggests that within-commuting zone distance may offset some of the apparent job abundance that workers in densely population areas may otherwise appear to enjoy.

Our bottom level logit also recovers the relative job fixed effects within each market. At this stage we can then decompose the utility received by different job applicants, conditional on applying for a job in a given market m. Table 4 shows this variance decomposition. In the utility specification (1), note that the term $\nu_{imt}(\lambda_m)$ is constant within market while $\lambda_m \epsilon_{ijmt}$ is independent of the other terms by assumption. This implies that the variance of within-market utility is decomposed as

$$Var(\delta_j) + \gamma^2 Var(z_{ijm}) + \lambda_m^2 Var(\epsilon_{ijmt}) + \gamma Cov(\delta_j, z_{ijm}) \quad (12)$$

We use our estimated coefficients from the bottom level logit (equation (4)) to calculate, for each market, these variance terms across all the combinations of job/worker within market.

In Table 4, we see that, on average across markets, the job-specific fixed effect δ accounts for 33.5% of the total utility of a job and the covariance of δ_j and applicant distance to a job is low. This means that most of the variance in applicant utility is explained by job/applicant match components. Observable distance between the applicant and the job accounts for 18% of the total variance, while the remainder is accounted for by the unobserved match components.

The results in Table 4 do not rely on any of our later assumptions about instrumental variables or labor market equilibrium. These results are strongly supportive of the idea that jobs are highly differentiated in the eyes of job applicants: less than half of the within-market variation in applicant utility is due to the common vertical component of job desirability, with the rest due to observed and unobserved

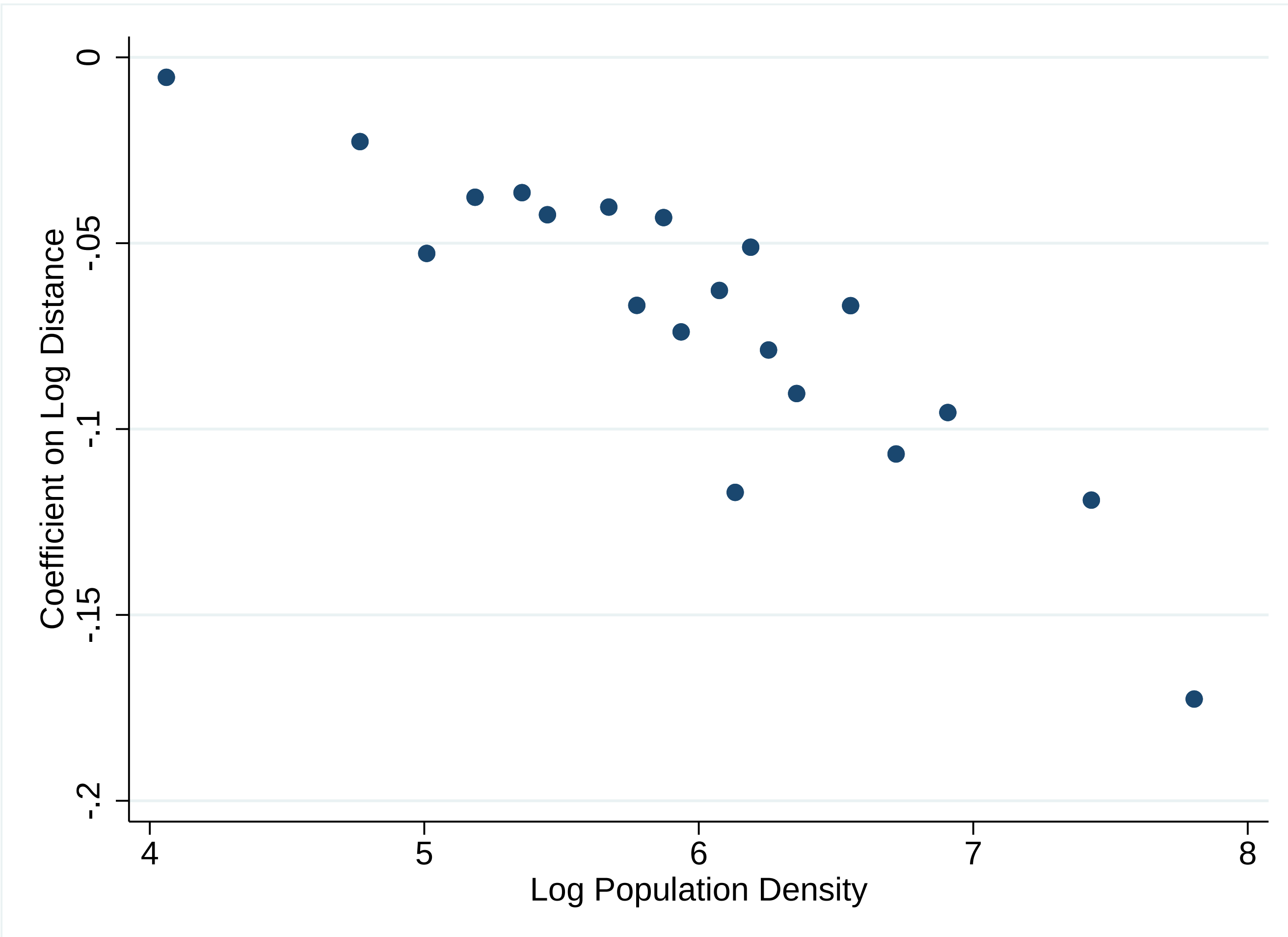

Figure 1. Distance coefficient by population density This figure shows a binned scatter of the median distance coefficient (which varies by CZ × SOC market) by log population density. The distance coefficients are calculated using the nesting parameters from the detailed model, as the coefficients obtained from estimating the multinomial logit models in equation (3) for each market, times the corresponding nesting parameter based on the estimation of equation (4) using the detailed (i.e. most flexible) model.

worker/job interactions.

We now turn to the results of the top level of the nested logit. This step estimates the nested parameters, λ_m, that control substitution in and out of our markets. Smaller values of the parameter indicate less substitutability with jobs outside of the market. Table 5 describes the estimated nesting parameters for the homogeneous and heterogeneous models. Our preferred specification is the heterogenous model, where the nesting parameter is allowed to vary by four market types (low/high wage occupation by rural/urban commuting zone).

We see in the heterogeneous specification of Table 5 that the estimated λ parameters are all in the required range of zero to one, which is not guaranteed by the method. Thus, the nested logit model is not rejected by these values. The estimated parameters are small, and in each case we can strongly reject the logit value of $\lambda = 1$. The pattern of λ coefficients in the heterogeneous model suggests less substitution outside of markets in high skilled occupations and in rural areas.

These results provide clear evidence of strong substitution within our 6-digit SOC by CZ markets, with limited substitution outside of our markets. This has implications for work that uses pure logit models of job differentiation as well as for work that uses broader definitions of labor markets. These models may be imposing, via a functional form restriction, more substitution across CZ/SOC-6 markets than is suggested by our results.

In both specifications of Table 5, we can also reject the extreme case of $\lambda = 0$, which would imply no substitution outside of our markets. The coefficient θ, which captures the "home commuting zone" effect, is positive as expected and is precisely estimated.

Table 5. Summary statistics for estimated top level parameters, θ and λ, for the homogeneous and heterogeneous models

The sample includes jobs in 822 CZ×SOC labor markets over the period between April and June of 2012. The results are from a top level nested logit model, with the nest on in/out of market choices for participants active in this market. λ is the nesting parameter and θ is the coefficient on within-communting zone applications by active applicants to a market.
Data source: CareerBuilder.com

	Homogeneous	**Heterogeneous**			
Estimated θ	0.137	0.128			
Standard Error	0.003	0.003			
		Low Skilled		High-Skilled	
		Urban	Rural	Urban	Rural
Estimated λ	0.120	0.159	0.146	0.123	0.097
Standard Error	0.001	0.002	0.002	0.001	0.001

3.2 Wage elasticities: homogeneous model

In this section, we estimate a wage coefficient and combine it with the output of the nested logit model to calculate wage elasticities of applications. Tables 6 and 7 show estimates from the homogeneous model, with a single wage coefficient and a single nesting parameter across markets. In Table 6, we first report the impact of wages on the job-specific utility δ_j using OLS. We control flexibly for the firm size (number of employees) since jobs offered by larger companies may be systematically different. For example, they may offer better benefits. We also control for the duration of the job listing.

In the OLS specification, the coefficient on the log of wage in job utility is estimated to be negative and significantly different from zero (column 1). This counterintutive result is likely explained by a negative correlation between the unobserved job characteristics and the wage. This could reflect compensating differentials. Marinescu and Wolthoff (2016) suggest that it may reflect that some jobs within an SOC6 may be both high-paying and harder to obtain, and thus unattractive to job applicants who are unlikely to be hired. For example, in the accountant and auditors occupation, "senior accountant" job titles pay more but receive fewer applications than "junior accountant" job titles. Therefore, in column 2, we control for job title fixed effects, which restores the expected positive relationship between wages and the utility of a job.

However, these job titles may not capture all of the relevant variation in unobserved perceived job-vacancy quality. Therefore, in the rest of Table 6, we instrument the wage with a series of different BLP style instruments, instrumenting the wage with characteristics of competing jobs. In columns 3 and 4 (without and with job title fixed effects), we instrument the wage with the number of vacancies in the market posted by competitor firms. This yields much larger wage coefficients than the OLS estimates and suggests that OLS suffers from significant downward bias. In columns 5 and 6, we add to the instrument list: instead of just the number of vacancies posted by competitors in the market, we also include the sum of the log number of employees of competitor firms, and the sum of square of the log number of employees of competitor firms. In these specifications, the wage coefficient is smaller but still much bigger than the OLS estimate. It is possible that the very high wage coefficients found when instrumenting with the number of vacancies alone are biased by the endogeneity of the number of vacancies: indeed, unlike the number of product varieties in a market, the number of vacancies can be adjusted at high frequency and is thus more likely to be endogenous. We then instrument the wage

Table 6. Impact of wages on the utility derived from a job vacancy in the homogeneous model: OLS, BLP-style, and Hausman-style instruments

Estimation is by OLS in the first two columns, and by 2SLS in columns (3) to (10). The sample includes jobs in 822 CZ×SOC labor markets over the period between April and June of 2012. The job-specific utilities are estimated using a nested logit model. The elasticity numbers represent medians across all observations at the job × year-week level. Standard errors are clustered by CZ × SOC.
Data source: CareerBuilder.com

	Dependent variable: δ_j, job-specific utility									
	OLS		IV: Number of Vacancies		IV: Within market BLP Instruments		IV: Average Wage of Same Firm in Other Markets		IV: Average Wage of Same Firm in Other Markets (Excluding Same CZ and Same SOC)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Log Wage	-0.0170***	0.0201***	1.153***	1.470**	0.515***	0.136	0.115***	0.198***	0.149***	0.211***
	(0.00387)	(0.00614)	(0.322)	(0.581)	(0.140)	(0.154)	(0.0181)	(0.0356)	(0.0310)	(0.0523)
Log Employees	0.00155	0.00108	-0.0958***	-0.111**	-0.0427***	-0.00784	-0.0126***	-0.0172***	-0.0217***	-0.0242***
	(0.00159)	(0.00210)	(0.0266)	(0.0430)	(0.0121)	(0.0121)	(0.00255)	(0.00399)	(0.00424)	(0.00618)
(Log Employees) ^{2}	-0.000715***	-0.000801***	0.00623***	0.00672**	0.00244***	-0.000202	0.000312	0.000465	0.000969***	0.000972**
	(0.000127)	(0.000165)	(0.00191)	(0.00289)	(0.000868)	(0.000824)	(0.000192)	(0.000288)	(0.000299)	(0.000416)
Duration	-0.00231***	-0.00178***	-0.000690	3.05e-05	-0.00157***	-0.00164***	-0.00301***	-0.00226***	-0.00345***	-0.00310***
	(0.000300)	(0.000362)	(0.000765)	(0.00101)	(0.000453)	(0.000412)	(0.000350)	(0.000394)	(0.000395)	(0.000448)
CZ × SOC FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Job Title FE		✓		✓		✓		✓		✓
Observations	15,284	11,241	15,284	11,241	15,284	11,241	12,764	9,515	10,757	8,077
Median Market Level Elasticity	-0.0140	0.0166	0.949	1.211	0.424	0.112	0.0944	0.163	0.123	0.174
Median Firm Level Elasticity	-0.135	0.160	9.176	11.71	4.098	1.080	0.912	1.576	1.187	1.682
Median Vacancy-Level Elasticity	-0.138	0.164	9.376	11.96	4.188	1.103	0.932	1.610	1.213	1.719
Kleibergen-Paap F-stat	-	-	19.93	9.867	14.36	11.41	478.9	153.3	208.3	72.06
Anderson-Rubin χ^2-stat	-	-	48.79	35.50	69.67	56.21	48.34	43.46	28.78	22.83

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

with a series of different Hausman-like instruments. Instrumenting the wage by the average wage of the firm in other markets leads to a positive estimate of the wage effect (column 7), while further controlling for job titles increases the magnitude of the estimate (column 8), just like in OLS. We then (col. 9-10) instrument the wage with the average wage of the firm in other markets, but excluding the same SOC6 and the same commuting zone. This instrument is slightly less relevant than the wages of the same firm in all other markets, but still has a high F-stat (compare columns 9-10 vs. 7-8). The wage estimates with this instrument are also positive and slightly higher in magnitude than in columns 7-8.

In Table 7, we use Hausman-style instruments that are likely to be more exogenous. Instead of the actual wages posted by the firm itself in other markets, we use as instrument the predicted wage for the firm in other markets, either including the same CZ and same SOC (Table 7, columns 1-2) or excluding these (columns 3-4). This strategy yields higher wage coefficients than the Hausman-style instruments in Table 6 columns 7-10, but typically smaller than for the BLP style instruments in Table 6, columns

Table 7. Impact of wages on the utility derived from a job vacancy in the homogeneous model: instruments based on average predicted wage of the same firm in other markets

Estimation is by two stage least squares. The sample includes jobs in 822 CZ×SOC labor markets over the period between April and June of 2012. The job-specific utilities are estimated using a nested logit model. The elasticity numbers represent medians across all observations at the job × year-week level. Standard errors are clustered by CZ×SOC.
Data source: CareerBuilder.com

	Dependent variable: δ_j, job-specific utility							
	IV: Average Predicted Wage of Same Firm in Other Markets		IV: Average Predicted Wage of Same Firm in Other Markets (Excluding Same CZ and Same SOC)		IV: Average Predicted Wage of Same Firm in Other Markets (Excluding Adjacent CZ)		IV: Average Predicted Wage of Same Firm in Other Markets (Excluding Same or Adjacent CZ and Same SOC)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log Wage	0.258***	0.526***	0.324***	0.567***	0.261***	0.585***	0.296***	0.611***
	(0.0364)	(0.0851)	(0.0552)	(0.119)	(0.0417)	(0.110)	(0.0522)	(0.136)
Log Employees	-0.0265***	-0.0465***	-0.0413***	-0.0599***	-0.0344***	-0.0607***	-0.0397***	-0.0664***
	(0.00414)	(0.00804)	(0.00672)	(0.0123)	(0.00525)	(0.0114)	(0.00658)	(0.0143)
(Log Employees)^2	0.00128***	0.00238***	0.00225***	0.00319***	0.00184***	0.00325***	0.00219***	0.00364***
	(0.000296)	(0.000547)	(0.000461)	(0.000791)	(0.000360)	(0.000734)	(0.000448)	(0.000910)
Duration	-0.00278***	-0.00165***	-0.00319***	-0.00261***	-0.00351***	-0.00256***	-0.00348***	-0.00274***
	(0.000370)	(0.000484)	(0.000442)	(0.000569)	(0.000424)	(0.000578)	(0.000467)	(0.000632)
CZ × SOC FE	✓	✓	✓	✓	✓	✓	✓	✓
Job Title FE		✓		✓		✓		✓
Observations	12,762	9,514	10,754	8,076	10,912	8,196	10,329	7,746
Median Market Level Elasticity	0.212	0.434	0.267	0.467	0.215	0.482	0.244	0.503
Median Firm Level Elasticity	2.052	4.190	2.580	4.513	2.078	4.655	2.355	4.863
Median Vacancy-Level Elasticity	2.096	4.281	2.636	4.611	2.124	4.757	2.406	4.969
Kleibergen-Paap F-stat	211.6	78.93	145.8	47.32	186.6	51.23	135.5	42.08

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

3-6. Some unobserved variables may be correlated across neighboring commuting zones. Therefore, in columns 5-6, we use predicted wages, but exclude adjacent CZs. In column 7-8, we exclude both adjacent CZs and the same SOC. The wage coefficients from specifications excluding adjacent CZs are essentially the same as from the specifications that exclude the same CZ and same SOC (col. 3-4).

Using the structure of the nested logit, we can derive the market level application elasticity, the firm level elasticity and the vacancy-level elasticity. The medians of these elasticities are all reported at the bottom of Tables 6 and 7; the median is reported because means are driven by outliers (distributions of estimates are reported for the "detailed" model in Figures A.3 and A.4). In all cases, the firm level elasticity is only slightly lower than the vacancy level elasticity:this is because most firms do not post multiple vacancies in the same week in the same SOC6 by commuting zone labor market. The OLS estimates in Table 6 lead to implausibly low elasticities. The IV estimates lead to a median market level elasticity between 0.09 and 1.2, and a firm level elasticity between 0.9 and 11.7. Generally, including job titles yields higher elasticity estimates, and within-market BLP instruments yield higher elasticities than Hausman-style instruments.

3.3 Wage elasticities: heterogeneity

We now allow the wage coefficients and the nesting parameters to vary across labor markets. Otherwise, the estimation strategy stays the same.

Table 8. Impact of wages on the utility derived from a job vacancy in the "heterogeneous" model: OLS, BLP-style, and Hausman-style instruments

Estimation is by OLS in the first two columns, and by 2SLS in columns (3) to (6). The sample includes jobs in 822 CZ×SOC labor markets over the period between April and June of 2012. The job-specific utilities are estimated using a nested logit model. The elasticity numbers represent medians across all observations at the job × year-week level. Standard errors are clustered by CZ × SOC. Data source: CareerBuilder.com

	Dependent variable: δ_j, job-specific utility									
	OLS		IV: Number of Vacancies		IV: Within Market BLP Instruments		IV: Average Wage of Same Firm in Other Markets		IV: Average Wage of Same Firm in Other Markets (Excluding Same CZ and Same SOC)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Log Wage × Rural CZ × Low-Skill SOC	-0.0186*	0.0196	1.418***	2.026**	0.481***	-0.0964	0.0866**	0.113**	0.147***	0.158**
	(0.0110)	(0.0182)	(0.354)	(0.953)	(0.186)	(0.386)	(0.0358)	(0.0541)	(0.0554)	(0.0751)
Log Wage × Urban CZ × Low-Skill SOC	-0.0167	0.0304	3.710*	6.704	1.166	-0.0649	0.223***	0.371***	0.257***	0.407***
	(0.0134)	(0.0194)	(2.065)	(5.759)	(0.708)	(0.851)	(0.0753)	(0.130)	(0.0896)	(0.145)
Log Wage × Rural CZ × High-Skill SOC	-0.0147**	0.0230***	0.764***	1.243*	0.418***	0.271	0.0891***	0.156***	0.142***	0.203***
	(0.00581)	(0.00833)	(0.255)	(0.741)	(0.153)	(0.222)	(0.0176)	(0.0319)	(0.0271)	(0.0492)
Log Wage × Urban CZ × High-Skill SOC	-0.0172***	0.0169***	2.374**	5.246	1.745**	2.099	0.133***	0.262***	0.163***	0.251***
	(0.00583)	(0.00644)	(1.090)	(3.707)	(0.831)	(1.721)	(0.0327)	(0.0628)	(0.0481)	(0.0807)
Log Employees	0.000931	0.000869	-0.138***	-0.224*	-0.0678***	-0.0341	-0.0135***	-0.0165***	-0.0245***	-0.0260***
	(0.00167)	(0.00227)	(0.0465)	(0.126)	(0.0249)	(0.0407)	(0.00280)	(0.00445)	(0.00468)	(0.00679)
(Log Employees)^2	-0.000710***	-0.000840***	0.00916***	0.0143*	0.00429**	0.00163	0.000340	0.000375	0.00113***	0.00105**
	(0.000134)	(0.000180)	(0.00330)	(0.00844)	(0.00183)	(0.00280)	(0.000210)	(0.000324)	(0.000327)	(0.000457)
Duration	-0.00254***	-0.00209***	0.000410	0.00183	-0.00111	-0.00207*	-0.00325***	-0.00255***	-0.00383***	-0.00355***
	(0.000325)	(0.000407)	(0.00140)	(0.00366)	(0.000931)	(0.00108)	(0.000384)	(0.000429)	(0.000454)	(0.000510)
CZ × SOC FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Job Title FE		✓		✓		✓		✓		✓
Observations	15,291	11,245	15,291	11,245	15,291	11,245	12,775	9,526	10,764	8,089
Median Market Level Elasticity	-0.0134	0.0168	1.323	1.890	0.449	0.227	0.0840	0.148	0.128	0.183
Median Firm Level Elasticity	-0.127	0.136	9.708	13.88	4.298	2.580	0.907	1.591	1.285	1.956
Median Vacancy-Level Elasticity	-0.132	0.137	9.730	13.90	4.307	2.667	0.916	1.601	1.306	2
Kleibergen-Paap F-stat	-	-	1.603	0.661	0.727	0.344	43.97	20.94	45.12	17
Anderson-Rubin χ^2-stat	-	-	130.2	99.14	219.2	236.2	67.72	95.35	38.99	46.31

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

In Tables 8 and 9, we report estimates of the heterogeneous model, which allows for different wage coefficients and nesting parameters for low-skill and high-skill occupations and for urban and rural commuting zones. As before, OLS yields elasticities that are implausibly low. For the heterogeneous model, the within-market BLP style instruments have limited relevance, especially when also including job title fixed effects (see F-stat in Table 8). As noted, this may reflect the possibility that firms do not finely tune their wages to local and short-term variations in workers choice sets (a possibility that also seems relevant to the competition tests in Roussille and Scuderi (2022)).) The Hausman style instruments (Table 9, col. 7-10 and Table 9) are more relevant, but the F-stats are perhaps troubling for specifications with job title fixed effects. In terms of the magnitudes of the elasticity estimates, the Hausman style instruments yield similar magnitudes to those in Table 6, col. 7-10, and 7.

Our preferred estimates of the market and firm level elasticities of job specific-utilities with respect to wages are to be found in column 7 of Table 9, instrumenting the wage with the average predicted wage of the same firm in other markets, and excluding same or adjacent CZ and same SOC. For our preferred estimates, the median market level elasticity is 0.265 and the median firm level elasticity is 2.396. These results allow the flexibility of our heterogeneous model, while avoiding the possible problems suggested by the relatively low F-stat of the column 8 results with job fixed effects.

How do elasticities differ between low and high skill occupations and between urban and rural commuting zones? Figures 2 and 3 report elasticities from our preferred specification. It is clear that rural commuting zones have lower market and firm level elasticities than urban commuting zones, both for low and high skilled occupations. These lower elasticities may reflect lower job opportunities in less densely populated areas and is consistent with reduced-form elasticity estimates in Azar, Marinescu and Steinbaum (2019). On the other hand, differences in elasticities between low and high skilled occupations are very small for firm level elasticities, while low skill occupations have higher market level elasticities than high skill occupations.

Based on Figures 2 and 3, we conclude that rural commuting zones have lower elasticities than urban commuting zones. Low and high skill workers have similar elasticities. We cannot blindly assume that low skill workers can more easily move to other jobs because specific skills do not matter. Therefore, there is no strong reason to believe that a SOC-6 by commuting zone market definition is decidedly too narrow for low skill as opposed to high skill workers (as we will see, using the "detailed" model with even more flexible parameter estimates leads to lower market level elasticities for low skill jobs in appendix Figure A.1).

Table 9. Impact of wages on the utility derived from a job vacancy in the "heterogeneous" model: instruments based on average predicted wage of the same firm in other markets

Estimation is by 2SLS. The sample includes jobs in 822 CZ×SOC labor markets over the period between April and June of 2012. The job-specific utilities are estimated using a nested logit model. The elasticity numbers represent medians across all observations at the job × year-week level. Standard errors are clustered by CZ×SOC.
Data source: CareerBuilder.com

	Dependent variable: δ_j, job-specific utility							
	IV: Average Predicted Wage of Same Firm in Other Markets		IV: Average Predicted Wage of Same Firm in Other Markets (Excluding Same CZ and Same SOC)		IV: Average Predicted Wage of Same Firm in Other Markets (Excluding Adjacent CZ)		IV: Average Predicted Wage of Same Firm in Other Markets (Excluding Same or Adjacent CZ and Same SOC)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log Wage × Rural CZ × Low-Skill SOC	0.263***	0.382***	0.368***	0.479***	0.293***	0.459***	0.350***	0.531***
	(0.0604)	(0.121)	(0.0785)	(0.127)	(0.0737)	(0.133)	(0.0778)	(0.148)
Log Wage × Urban CZ × Low-Skill SOC	0.722***	1.230***	0.526***	0.833***	0.573***	0.973***	0.470***	0.846***
	(0.209)	(0.466)	(0.145)	(0.242)	(0.194)	(0.321)	(0.148)	(0.259)
Log Wage × Rural CZ × High-Skill SOC	0.162***	0.392***	0.236***	0.520***	0.192***	0.476***	0.236***	0.627***
	(0.0288)	(0.0801)	(0.0422)	(0.130)	(0.0332)	(0.111)	(0.0444)	(0.182)
Log Wage × Urban CZ × High-Skill SOC	0.270***	0.585***	0.391***	0.771***	0.283***	0.797***	0.331***	1.016***
	(0.0652)	(0.123)	(0.118)	(0.294)	(0.0740)	(0.166)	(0.0976)	(0.303)
Log Employees	-0.0298***	-0.0457***	-0.0453***	-0.0636***	-0.0384***	-0.0613***	-0.0441***	-0.0762***
	(0.00466)	(0.00906)	(0.00712)	(0.0146)	(0.00614)	(0.0128)	(0.00719)	(0.0186)
(Log Employees)^2	0.00142***	0.00225***	0.00248***	0.00340***	0.00203***	0.00325***	0.00243***	0.00423***
	(0.000328)	(0.000607)	(0.000493)	(0.000952)	(0.000414)	(0.000828)	(0.000489)	(0.00118)
Duration	-0.00284***	-0.00174***	-0.00346***	-0.00298***	-0.00375***	-0.00286***	-0.00384***	-0.00303***
	(0.000430)	(0.000587)	(0.000514)	(0.000670)	(0.000492)	(0.000706)	(0.000539)	(0.000795)
CZ × SOC FE	✓	✓	✓	✓	✓	✓	✓	✓
Job Title FE		✓		✓		✓		✓
Observations	12,773	9,525	10,762	8,089	10,916	8,208	10,335	7,761
Median Market Level Elasticity	0.210	0.370	0.301	0.489	0.225	0.454	0.265	0.581
Median Firm Level Elasticity	1.789	3.990	2.499	5.115	1.980	4.859	2.396	5.866
Median Vacancy-Level Elasticity	1.804	4.029	2.522	5.219	2.006	4.900	2.422	6.142
Kleibergen-Paap F-stat	8.287	3.480	13.47	3.635	16.18	11.45	15.87	4.776
Anderson-Rubin χ^2-stat	114.6	155.3	78.75	85.90	67.66	70.94	63.01	74.27

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

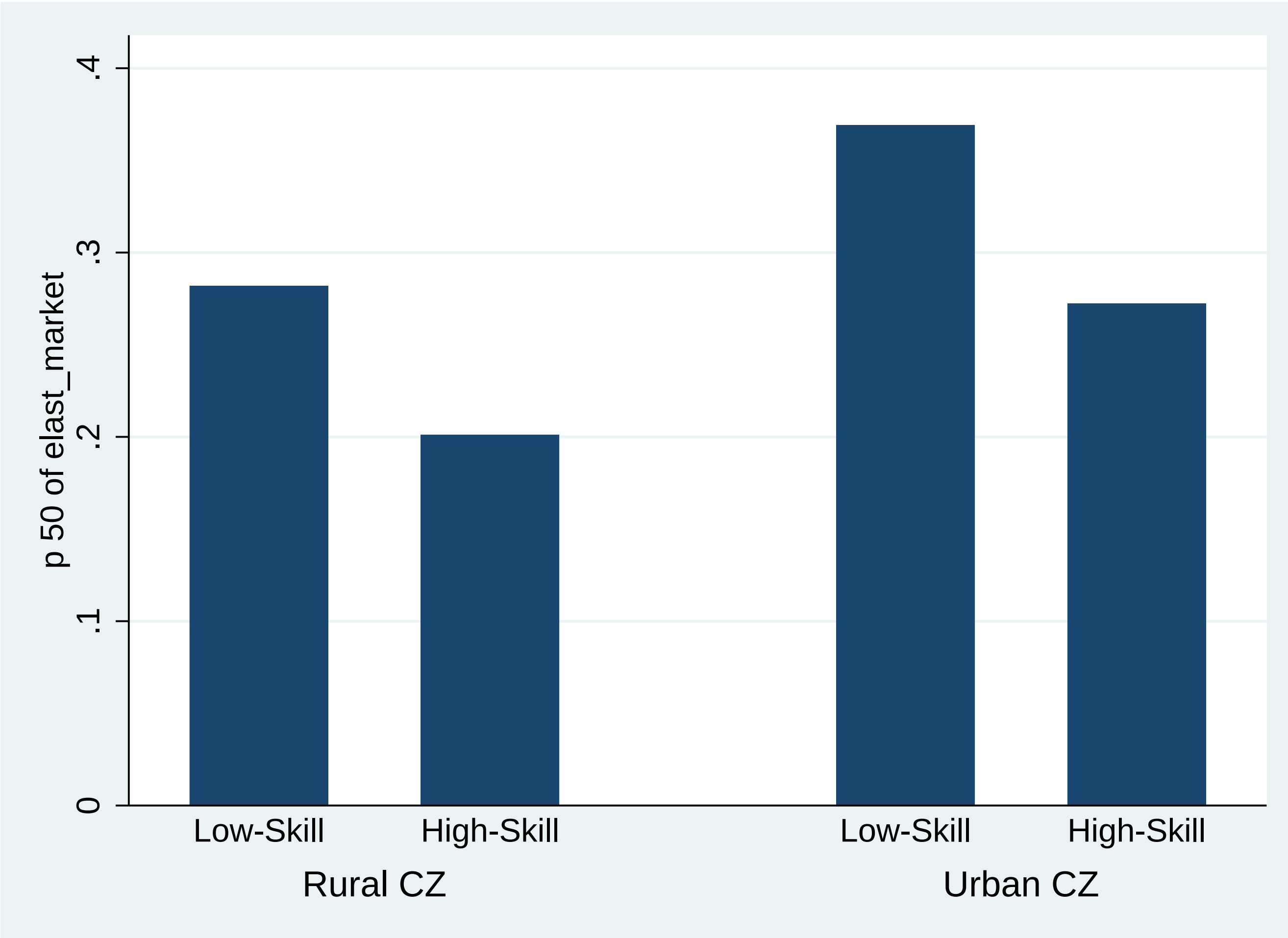

Figure 2. Distribution of Market Level Elasticities by Rural-Urban and Skill Classification This figure shows the median market level elasticity of applications by low/high skill level, and by urban-rural classification for our "Heterogeneous Model". The heterogeneous model allows for heterogeneity in the wage and nesting parameters by low/high skill level, and by urban-rural classification. The results are for the specification that includes only CZ $\times$ SOC fixed effects, and instruments the wage using the average predicted wage of the same firm in other markets (excluding the same CZ, adjacent CZ, and same SOC). The interactions of the wage are instrumented using interactions of the average predicted wage for the same firm in other markets, interacted with the corresponding variables.

3.4 Robustness tests and additional results

3.4.1 Robustness

In our main analysis, we included distance between the job seeker and the job in two ways: as a determinant of job choice within a market (bottom level), and as a determinant of market choice in the form of a "same CZ" dummy (top level). Removing the within-market distance (appendix Tables A.1 and A.2), or both the within market and the "same CZ" dummy (appendix Tables A.3 and A.4) does not materially affect the median elasticities of applications with respect to wages in the heterogenous

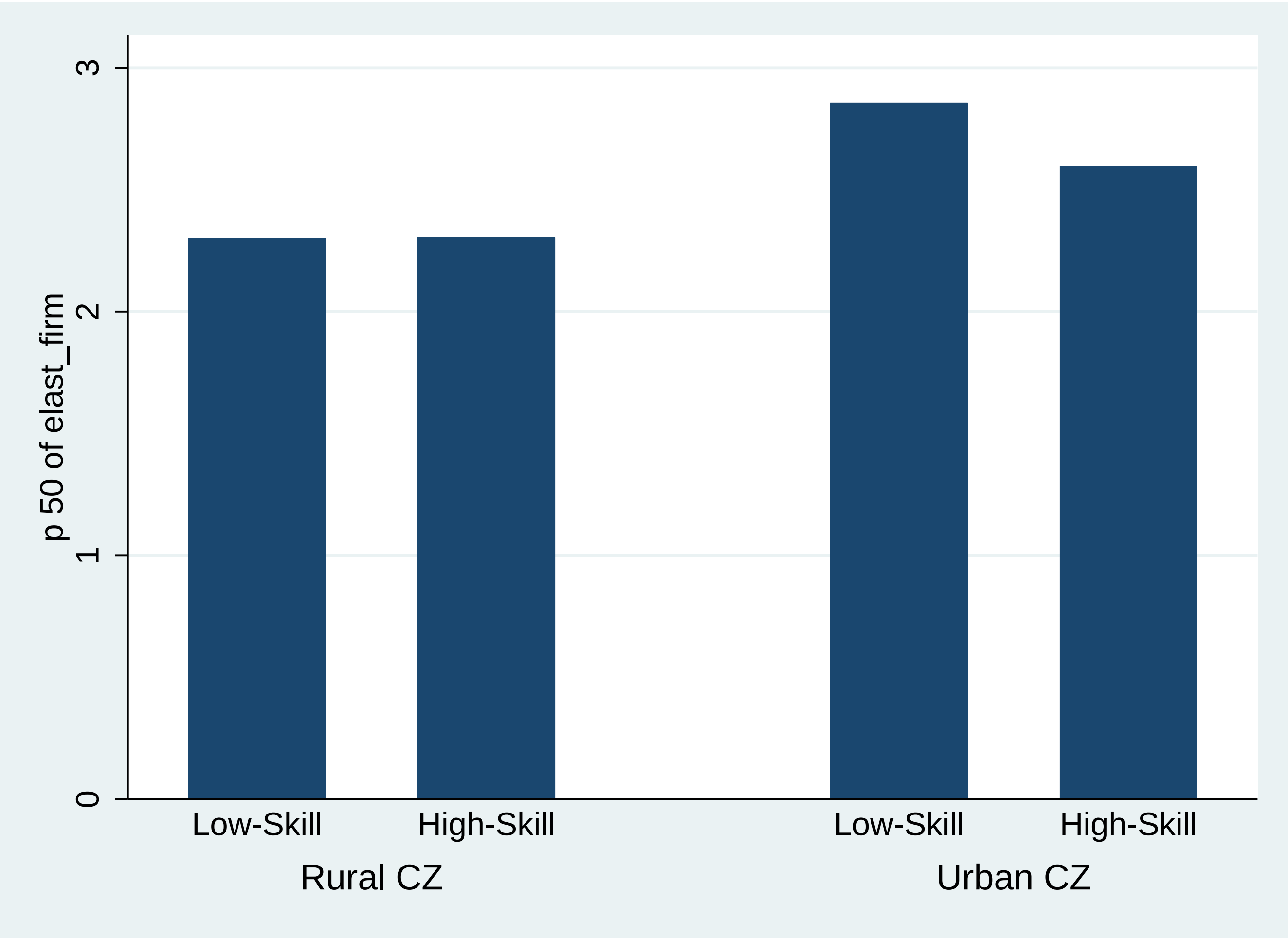

Figure 3. Distribution of Firm Level Elasticities by Rural-Urban and Skill Classification This figure shows the median firm level elasticity of applications by low/high skill level, and by urban-rural classification for our "Heterogeneous Model". The heterogeneous model allows for heterogeneity in the wage and nesting parameters by low/high skill level, and by urban-rural classification. The results are for the specification that includes only CZ $\times$ SOC fixed effects, and instruments the wage using the average predicted wage of the same firm in other markets (excluding the same CZ, adjacent CZ, and same SOC). The interactions of the wage are instrumented using interactions of the average predicted wage for the same firm in other markets, interacted with the corresponding variables.

model, especially when focusing on our preferred instrument, i.e. the average predicted wage of same firm in other markets (excluding same or adjacent CZ and same SOC).

In appendix Table A.5, we perform a series of robustness tests using variations on our baseline preferred specification (Table 9, col. 7). As a reminder, our baseline specifications allows for different wage coefficients for low and high skill, and for urban and rural. The instrument for the wage is always the average predicted wage of the same firm in other markets (excluding the same CZ, adjacent CZ, and same SOC).

First, we investigate the robustness of our results to controlling for log (employment), i.e. firm size. Our dependent variable, the job specific utility, is a rescaling of job applications through our nested logit model, and job applications are related to the *change* in employment. Therefore, including a control for the *level* of employment seems reasonable, and may help pick up differences in e.g. working conditions across firms. Nevertheless, for completeness, we check the robustness of our results to different ways of controlling for firm size. If we include a linear control for firm employment (size) (Table A.5, col. 2) instead of a quadratic, the elasticities are a bit smaller, but in the same ballpark as in our baseline specification. The coefficient on firm size is negative and significant, suggesting that, conditional on the wage, large firms are less desirable places to work at. If we remove any control for firm size (col. 3), estimates of the elasticities are much smaller: the market level elasticity is 0.2 instead of 0.27, and the firm level elasticity is 1.74 instead of 2.4. The smaller estimate for the elasticity makes sense from a statistical perspective: since larger firms pay more and are less desirable, not controlling for firm size reduces the coefficient on the wage, and therefore the elasticities. Since there is no decisive argument for or against including log employment as a control, we decided to include it in our baseline specification, which gives a more conservative estimate (higher elasticity) for the amount of monopsony power.

Second, we investigate robustness to restricting the sample to jobs that receive a minimum of five applications, which was necessary to allow for a meaningful estimation of job fixed effects. If we instead restrict to jobs that receive at least three applications (Table A.5, col. 4), the sample size increases by 36%, and the elasticities decline somewhat. If instead we use a more restrictive criterion of eight applications (col. 5), the elasticities are almost the same if a bit larger than at baseline. Overall, results are fairly robust to different thresholds for the number of job applications required for sample inclusion. Relative to a lower threshold of three, our choice of five applications leads to relatively more conservative estimates (higher elasticities) for the extent of monopsony power.

3.4.2 Additional results: more heterogeneity with the detailed model

In our analysis so far, in the heterogeneous model, we have allowed for different elasticities for rural and urban, and for high and low skill jobs. We now show additional results from an even more flexible model, the "detailed" model, which allows for different wage coefficients and nesting parameters by SOC-6 occupation and by (a quadratic in) population density. This model allows for more detailed results, but at the cost of a lack of power that leads to extreme elasticity estimates for some markets (appendix Table A.6).

At the top level of the nested logit estimation, the detailed model produces results that are quite similar to Table 5. The predicted nesting parameters, λ_m, from this specification have a mean very close to the simpler specifications, with a mean of 0.145 and a standard deviation across markets of 0.08. A few predicted λ_m values are slightly below zero, with a minimum of -0.057. The maximum predicted λ is 0.428. The coefficient on within commuting zone applications, θ, in this specification is also very similar to the θ estimated in the simpler specifications. We regard these results as good evidence of robustness to greater heterogeneity in estimates of λ_m.

Turning to the results of the wage regression, the median elasticity estimates of the detailed model are very close to the median elasticity estimates of the heterogeneous model. With the detailed model like with the heterogeneous model, rural commuting zones have lower elasticities than urban commuting zones (appendix Figures A.1 and A.2). One difference between the detailed and the heterogeneous model is that, in the detailed model, there is almost no difference in the market level elasticities of low and high skill SOCs in urban areas, while in the heterogenous model high skill SOCs had a lower elasticity than low skill SOCs. Therefore, the differences between low and high skill markets may in fact be fairly small.

In appendix Figures A.3 and A.4, we show the range of elasticity estimates for each SOC-6 for the detailed model (see appendix Tables A.7 and A.8 for summary statistics on the elasticities by occupation). The Figures exclude two outlier occupations—"Light Truck or Delivery Service Drivers" and "other" small occupations. The estimated light truck elasticity is extremely negative while the "other" elasticity is extremely positive. These outliers speak against using the detailed model for any serious counterfactuals.

Broadly, in the detailed model most occupations have positive median elasticities, but there are a few occupations with negative median elasticities. While a negative elasticity is implausible, such negative estimates are likely to occur when we slice the data finely; for example, Farber (2015) finds negative labor supply elasticities for some individual taxi drivers. Rankings of occupations by market level elasticities are similar but not identical to rankings by firm level elasticities. For market level elasticities (Figure A.3), sales, wholesale, and manufacturing related jobs have the highest elasticity, with a median slightly above 0.5. Registered nurses have a low elasticity, suggesting there are few suitable job substitutes for registered nurses in other labor markets (other occupation and/or other commuting zone). For firm level elasticities (Figure A.4), administrative assistant types of occupations occupy the top three spots for the most elastic, suggesting that these types of jobs tend to be more substitutes for each other within their market than other types of jobs. At the bottom of the firm elasticity scale are industrial engineers, who also had the second lowest market level elasticity.

In appendix Figure A.5, we plot the median market level elasticity from the detailed model as a function of the population density. Market-level elasticities increase with population density, especially when log population density is above 6.5, i.e. population density is above 665 per square mile; remember that the density threshold that is part of the definition of an urbanized commuting zone is 1000. So the median market level elasticity increases particularly fast with population density once we move into more urbanized commuting zones. Still, even in the most densely populated commuting zones, the market level elasticity is only 1.2.

4 Implications for the labor supply elasticity and antitrust policy

4.1 From the application elasticity to the labor supply elasticity

Our econometric model gives us an estimate of the elasticity of job application with respect to wages. How does that translate into an elasticity of firm employment with respect to wages, i.e. a labor supply elasticity? We will use two approximations to calculate the labor supply elasticity based on our estimated application elasticity: (i) the labor supply elasticity is roughly equal twice the recruitment elasticity (increase in hires in response to an increase in wages), and (ii) the application elasticity is roughly equal to the recruitment elasticity.

The first assumption, that the labor supply elasticity is roughly equal twice the recruitment elasticity is discussed in Manning (2011). Let $R(w)$ be the number of new hires (recruitment) as a function of the wage, and let $s(w)$ be the number of separations as a function of the wage. If a firm's employment level $N(w)$ does not change (steady state), we must have $N(w) = R(w)/s(w)$, and this implies that the labor supply elasticity ϵ is $\epsilon = \epsilon_{Rw} - \epsilon_{sw}$, where ϵ_{Rw} is the recruitment elasticity and ϵ_{sw} is the separation elasticity. If $\epsilon_{Rw} \approx -\epsilon_{sw}$, then $\epsilon \approx 2\epsilon_{Rw}$. This rough equality between the recruitment and the separation elasticity is supported by empirical evidence: Dube et al. (2020) use their own estimates and other estimates from the literature to show that the recruitment elasticity (Horton, Rand and Zeckhauser, 2011) and the separation elasticity (Ho et al., 2016; Hsieh and Kocielnik, 2016; Yin, Suri and Gray, 2018) are very close to each other.

The second assumption – that the wage elasticity of applications is the same as the wage elasticity of hiring – cannot be checked directly in our data. An increase in the offered wage for a given job might attract more qualified applicants and so increase the application rate of qualified applicants. This suggests that the hiring elasticity might be higher than the application elasticity. On the other hand, a higher wage might attract a broader pool of less qualified applicants who decide that the higher wage offsets a low probability of a job offer. By itself, this effect leads to a wage elasticity that is lower than the application elasticity.

While our data cannot speak directly to this issue, we can compare existing estimates of the application elasticity with estimates of the hiring elasticity. Dube et al. (2020) and Manning (2011) report estimates of the recruitment and the separation elasticities, and they are typically between 0 and 2, which is consistent with our application elasticity estimates as well as those of Marinescu and Wolthoff (2016). In Dal Bó, Finan and Rossi (2013), the application elasticity is 0.8, and it is close to the conversion elasticity (i.e. the increase in the probability that the person initially offered the job accepts it), which is 1.07.

Overall, while the evidence is not overwhelming, it seems reasonable for illustrative purposes to assume that the application elasticity is roughly equal to the hiring elasticity, which is equal to half of the labor supply elasticity. Under these assumptions, we can calculate the labor supply elasticity by multiplying our estimated application elasticities by two.

Under this assumption, we can calculate the markdown using our estimates of the wage elasticity of applications. Based on our preferred specification 7 from Table 9, the median markdown is 0.21, implying that workers' marginal productivity is about 21% higher than their wages. Overall, our results show that, even in the largest occupations and therefore arguably most competitive labor markets, wage markdowns are substantial, with a median of 21%.

4.2 From labor supply elasticities to market definition

As a further illustrative exercise, we discuss the implications of our estimates for labor market definition. We first summarize here the critical elasticity test as applied to labor markets, borrowing from (Azar et al., 2020). Since 1982, the horizontal merger guidelines have included the hypothetical monopolist test to determine whether a product market could be profitably monopolized. The idea of the hypothetical monopolist test is to use as the relevant antitrust market the smallest market for which a hypothetical monopolist that controlled that market would find it profitable to implement a "small significant non-transitory increase in price" (SSNIP).

In the 1982 horizontal merger guidelines, there were no specific instructions about how this SSNIP test could be applied, but an influential paper soon defined a methodology (Harris and Simons, 1991): critical loss analysis. Analogously, the hypothetical monopsonist test would suggest as the relevant antitrust market the smallest labor market for which a hypothetical monopsonist that controlled that labor market would find profitable to implement "small significant non-transitory reduction in wages" (SSNRW).

Consider a simple model of monopsony, with a constant value of marginal product of labor given by a, a wage w which depends on the employment level of the monopsonist L. The profits of the monopsonist are

$$\pi(L) = (a - w)L.$$

If the monopsonist changes wages by Δw, and this generates a change in labor supply ΔL, the change in profits is

$$\Delta\pi = \Delta L \times (a - w - \Delta w) - \Delta w \times L.$$

Thus, the SSNRW is profitable for the monopsonist if and only if

$$\Delta L \times (a - w - \Delta w) > \Delta w \times L.$$

Dividing on both sides by wL, we obtain

$$\frac{\Delta L}{L} \times \left(\underbrace{\frac{a - w}{w}}_{\text{Markdown } \mu} - \frac{\Delta w}{w} \right) > \frac{\Delta w}{w}.$$

Rearranging terms (and taking into account that the change in wage is negative, which changes the direction of the inequality):

$$\frac{\Delta L / L}{\Delta w / w} < \frac{1}{\mu - \Delta w / w}.$$

Since the left-hand side is approximately the elasticity of labor supply, which we denote η, we have that the critical elasticity (see Harris and Simons (1991) for the corresponding concept in the product market) for the wage reduction to increase profits is:

$$\eta \approx \frac{1}{\mu - \Delta w / w}.$$

The antitrust practice typically considers a 5% increase in price (for at least a year) as the SSNIP. Therefore, we will consider a 5% "small significant non-transitory reduction in wages" (SSNRW). The market is too broad if the actual labor supply elasticity is less than the critical elasticity. This ends our summary of the SSNRW; we now discuss how it applies to our estimates.

If we have data on the firm level and the market level elasticity, then the inverse firm level elasticity can be used to estimate μ (by the Lerner rule), and the market level elasticity can be used to estimate η. It is clear that the hypothetical monopsonist would face the market level elasticity. But is it incoherent then to estimate μ from the firm level elasticity of a non-monopsonist? It would be if we were talking about the monopsony profit-maximizing, because then the markdown should be $1/\eta$. However, we are merely asking if profit would increase from the status quo of the non-monopsonist.

Based on our estimates in Figure A.3, we can perform the hypothetical monopsonist test for each occupation. We calculate the median market level labor supply elasticity as $2 *$ median market level elasticity.

The market level elasticity is smaller than the critical elasticity for all occupations, indicating that the hypothetical monopsonist in the median CZ times SOC6 market would find it profitable to decrease wages by 5%.

5 Conclusion

Using data from a large online job board, we estimate the wage elasticity of applications at the vacancy-level, firm level, and at the market level where a labor market is defined by a SOC-6 occupation and a commuting zone. We estimate workers' choice among differentiated jobs using a nested logit model.

Our results provide some of the first direct evidence on the nature and extent of job differentiation across a wide range of occupations and locales.

Our nested logit estimates show that jobs are significantly differentiated both within and across SOC6 by CZ labor markets. The geographic distance between the job and the job seeker plays an important role in job differentiation, as workers are less likely to apply to far away jobs within their commuting zone, and much less so to jobs outside their commuting zone. We can decisively reject pure logit models of job differentiation. A variance decomposition shows that the majority of within-market variance in job applicant utility is driven by horizontal factors, as opposed to vertical job quality (including the wage).

Our results show the importance of accounting for the econometric endogeneity of wages. Results that do not account for endogeneity imply application supply curves that are flat or even downward sloping in wages. A series of instrumental variable estimators yield fairly consistent results. Our preferred specification uses as an instrument the competitive effect of predicted wages paid by other firms in other markets. In these results, the firm level application elasticity is 2.4, which is only slightly lower than the vacancy-level elasticity. The market level application elasticity is 0.26. Multiplying these elasticities by two, we obtain a rough estimate of the labor supply elasticity. Our elasticity estimates also allow us to determine that a hypothetical monopsonist would find it profitable to decrease wages by 5% is most markets, implying that most occupations at the SOC-6 level are relevant antitrust markets. Under some assumptions on wage setting and on the relationship between vacancy elasticities and worker supply elasticities, our findings imply that the median wage markdown is 0.21, meaning that workers' productivity is 21% greater than their wages, indicating substantial employer market power.

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Appendix for Online Publication

A Appendix Figures and Tables

Table A.1. Impact of wages on the utility derived from a job vacancy in the "heterogeneous" model, no distance control in bottom level: OLS, BLP-style, and Hausman-style instruments

Estimation is by OLS in the first two columns, and by 2SLS in columns (3) to (6). The sample includes jobs in 822 CZ×SOC labor markets over the period between April and June of 2012. The job-specific utilities are estimated using a nested logit model. The elasticity numbers represent medians across all observations at the job × year-week level. Standard errors are clustered by CZ × SOC.
Data source: CareerBuilder.com

	Dependent variable: δ_j, job-specific utility									
	OLS		IV: Number of Vacancies		IV: BLP Instruments		IV: Average Wage of Same Firm in Other Markets		IV: Average Wage of Same Firm in Other Markets (Excluding Same CZ and Same SOC)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Log Wage × Rural CZ × Low-Skill SOC	-0.0186	0.0144	1.496***	2.297*	0.568***	-0.115	0.0840**	0.114**	0.144**	0.157**
	(0.0114)	(0.0188)	(0.392)	(1.325)	(0.211)	(0.414)	(0.0356)	(0.0513)	(0.0581)	(0.0736)
Log Wage × Urban CZ × Low-Skill SOC	-0.0118	0.0314*	3.988*	7.217	1.258	-0.326	0.230***	0.373***	0.272***	0.424***
	(0.0142)	(0.0189)	(2.338)	(7.306)	(0.797)	(0.927)	(0.0724)	(0.128)	(0.0892)	(0.148)
Log Wage × Rural CZ × High-Skill SOC	-0.0144**	0.0238***	0.818***	1.557	0.462***	0.257	0.0889***	0.154***	0.142***	0.202***
	(0.00619)	(0.00866)	(0.290)	(1.101)	(0.178)	(0.287)	(0.0176)	(0.0331)	(0.0272)	(0.0512)
Log Wage × Urban CZ × High-Skill SOC	-0.0167***	0.0179***	2.913**	9.315	2.169*	2.438	0.140***	0.269***	0.163***	0.250***
	(0.00601)	(0.00691)	(1.457)	(9.290)	(1.119)	(2.744)	(0.0339)	(0.0660)	(0.0483)	(0.0819)
Log Employees	0.000916	0.000219	-0.155***	-0.312	-0.0803**	-0.0379	-0.0134***	-0.0174***	-0.0247***	-0.0271***
	(0.00168)	(0.00225)	(0.0557)	(0.217)	(0.0314)	(0.0586)	(0.00282)	(0.00443)	(0.00471)	(0.00676)
(Log Employees)^2	-0.000700***	-0.000770***	0.0104***	0.0203	0.00521**	0.00193	0.000335	0.000448	0.00115***	0.00114**
	(0.000136)	(0.000179)	(0.00396)	(0.0147)	(0.00232)	(0.00406)	(0.000214)	(0.000322)	(0.000331)	(0.000455)
Duration	-0.00263***	-0.00220***	0.000191	0.000857	-0.00125	-0.00259**	-0.00337***	-0.00271***	-0.00392***	-0.00364***
	(0.000328)	(0.000400)	(0.00158)	(0.00573)	(0.00106)	(0.00125)	(0.000387)	(0.000425)	(0.000454)	(0.000503)
CZ × SOC FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Job Title FE		✓		✓		✓		✓		✓
Observations	15,286	11,236	15,286	11,236	15,286	11,236	12,766	9,516	10,760	8,083
Median Market Level Elasticity	-0.0129	0.0162	1.396	2.143	0.530	0.216	0.0845	0.147	0.127	0.182
Median Firm Level Elasticity	-0.124	0.141	9.967	15.61	4.625	2.408	0.886	1.536	1.269	1.912
Median Vacancy-Level Elasticity	-0.127	0.141	9.984	15.64	4.634	2.480	0.891	1.544	1.285	1.950
Kleibergen-Paap F-stat	-	-	1.252	0.266	0.695	0.292	40.48	18.58	46.03	17.45
Anderson-Rubin χ^2-stat	-	-	137.2	103.1	241.3	259.3	71.40	87.65	39.82	43.37

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table A.2. Impact of wages on the utility derived from a job vacancy in the "heterogeneous" model, no distance control in bottom level: Instruments based on average predicted wage of the same firm in other markets

Estimation is by 2SLS. The sample includes jobs in 822 CZ×SOC labor markets over the period between April and June of 2012. The job-specific utilities are estimated using a nested logit model. The elasticity numbers represent medians across all observations at the job × year-week level. Standard errors are clustered by CZ×SOC.
Data source: CareerBuilder.com

	Dependent variable: δ_j, job-specific utility							
	IV: Average Wage of Same Firm in Other Markets		IV: Average Wage of Same Firm in Other Markets (Excluding Same CZ and Same SOC)		IV: Average Predicted Wage of Same Firm in Other Markets		IV: Average Predicted Wage of Same Firm in Other Markets (Excluding Same CZ and Same SOC)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log Wage × Rural CZ × Low-Skill SOC	0.267***	0.386***	0.367***	0.475***	0.296***	0.470***	0.351***	0.531***
	(0.0604)	(0.118)	(0.0821)	(0.125)	(0.0758)	(0.127)	(0.0817)	(0.146)
Log Wage × Urban CZ × Low-Skill SOC	0.713***	1.209***	0.548***	0.862***	0.619***	1.053***	0.504***	0.885***
	(0.196)	(0.455)	(0.141)	(0.248)	(0.196)	(0.354)	(0.149)	(0.272)
Log Wage × Rural CZ × High-Skill SOC	0.158***	0.385***	0.236***	0.516***	0.195***	0.487***	0.239***	0.632***
	(0.0286)	(0.0859)	(0.0421)	(0.133)	(0.0336)	(0.117)	(0.0450)	(0.189)
Log Wage × Urban CZ × High-Skill SOC	0.277***	0.596***	0.389***	0.764**	0.286***	0.807***	0.340***	1.029***
	(0.0670)	(0.128)	(0.118)	(0.296)	(0.0740)	(0.165)	(0.0974)	(0.302)
Log Employees	-0.0296***	-0.0463***	-0.0457***	-0.0647***	-0.0394***	-0.0641***	-0.0452***	-0.0785***
	(0.00466)	(0.00901)	(0.00722)	(0.0147)	(0.00622)	(0.0130)	(0.00735)	(0.0187)
(Log Employees)^2	0.00141***	0.00230***	0.00251***	0.00349***	0.00210***	0.00344***	0.00251***	0.00440***
	(0.000331)	(0.000604)	(0.000500)	(0.000961)	(0.000421)	(0.000834)	(0.000500)	(0.00119)
Duration	-0.00299***	-0.00192***	-0.00357***	-0.00308***	-0.00387***	-0.00293***	-0.00394***	-0.00314***
	(0.000431)	(0.000578)	(0.000517)	(0.000670)	(0.000504)	(0.000716)	(0.000547)	(0.000801)
CZ × SOC FE	✓	✓	✓	✓	✓	✓	✓	✓
Job Title FE		✓		✓		✓		✓
Observations	12,764	9,515	10,758	8,083	10,913	8,202	10,332	7,755
Median Market Level Elasticity	0.215	0.367	0.300	0.485	0.228	0.464	0.271	0.591
Median Firm Level Elasticity	1.767	3.839	2.430	5.100	1.955	4.856	2.369	5.990
Median Vacancy-Level Elasticity	1.778	3.864	2.445	5.164	1.975	4.884	2.395	6.075
Kleibergen-Paap F-stat	8.138	3.192	13.98	3.657	12.16	10.93	16.83	4.927
Anderson-Rubin χ^2-stat	120.7	147.6	80.14	85.87	71.10	74.03	65.31	78.70

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A.3. Impact of wages on the utility derived from a job vacancy in the "heterogeneous" model, no distance control in bottom level, no same CZ control in top level: OLS, BLP-style, and Hausman-style instruments

Estimation is by OLS in the first two columns, and by 2SLS in columns (3) to (6). The sample includes jobs in 822 CZ×SOC labor markets over the period between April and June of 2012. The job-specific utilities are estimated using a nested logit model. The elasticity numbers represent medians across all observations at the job × year-week level. Standard errors are clustered by CZ × SOC.
Data source: CareerBuilder.com

	Dependent variable: δ_j, job-specific utility									
	OLS		IV: Number of Vacancies		IV: BLP Instruments		IV: Average Wage of Same Firm in Other Markets		IV: Average Wage of Same Firm in Other Markets (Excluding Same CZ and Same SOC)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Log Wage × Rural CZ × Low-Skill SOC	-0.0181	0.0149	1.484***	2.298*	0.571***	-0.108	0.0819**	0.111**	0.143**	0.156**
	(0.0111)	(0.0183)	(0.390)	(1.329)	(0.208)	(0.408)	(0.0352)	(0.0508)	(0.0574)	(0.0727)
Log Wage × Urban CZ × Low-Skill SOC	-0.0114	0.0313*	3.929*	7.158	1.248	-0.313	0.227***	0.368***	0.269***	0.419***
	(0.0139)	(0.0186)	(2.299)	(7.224)	(0.786)	(0.914)	(0.0711)	(0.126)	(0.0877)	(0.145)
Log Wage × Rural CZ × High-Skill SOC	-0.0144**	0.0232***	0.811***	1.568	0.460***	0.255	0.0877***	0.151***	0.141***	0.200***
	(0.00613)	(0.00857)	(0.288)	(1.116)	(0.177)	(0.286)	(0.0174)	(0.0328)	(0.0269)	(0.0506)
Log Wage × Urban CZ × High-Skill SOC	-0.0169***	0.0171**	2.895**	9.315	2.159*	2.363	0.139***	0.265***	0.162***	0.248***
	(0.00596)	(0.00681)	(1.449)	(9.380)	(1.114)	(2.685)	(0.0337)	(0.0656)	(0.0479)	(0.0813)
Log Employees	0.00103	0.000349	-0.154***	-0.312	-0.0799**	-0.0368	-0.0131***	-0.0170***	-0.0245***	-0.0268***
	(0.00167)	(0.00222)	(0.0551)	(0.219)	(0.0313)	(0.0578)	(0.00279)	(0.00438)	(0.00466)	(0.00668)
(Log Employees)^2	-0.000703***	-0.000774***	0.0103***	0.0203	0.00519**	0.00186	0.000322	0.000430	0.00114***	0.00113**
	(0.000135)	(0.000177)	(0.00392)	(0.0149)	(0.00231)	(0.00400)	(0.000212)	(0.000318)	(0.000327)	(0.000450)
Duration	-0.00261***	-0.00217***	0.000208	0.000960	-0.00122	-0.00252**	-0.00333***	-0.00267***	-0.00387***	-0.00359***
	(0.000323)	(0.000393)	(0.00157)	(0.00569)	(0.00106)	(0.00121)	(0.000383)	(0.000420)	(0.000448)	(0.000497)
CZ × SOC FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Job Title FE		✓		✓		✓		✓		✓
Observations	15,288	11,238	15,288	11,238	15,288	11,238	12,767	9,517	10,761	8,084
Median Market Level Elasticity	-0.0129	0.0156	1.386	2.146	0.533	0.214	0.0835	0.145	0.126	0.180
Median Firm Level Elasticity	-0.123	0.136	10.01	15.86	4.650	2.406	0.882	1.525	1.268	1.911
Median Vacancy-Level Elasticity	-0.129	0.136	10.02	15.88	4.659	2.479	0.888	1.532	1.284	1.948
Kleibergen-Paap F-stat	-	-	1.247	0.261	0.694	0.293	40.67	18.82	46.03	17.45
Anderson-Rubin χ^2-stat	-	-	139.2	104.4	241.3	258.4	71.21	87.10	39.93	43.47

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A.4. Impact of wages on the utility derived from a job vacancy in the "heterogeneous" model, no distance control in bottom level, no same CZ control in top level: instruments based on average predicted wage of the same firm in other markets

Estimation is by 2SLS. The sample includes jobs in 822 CZ×SOC labor markets over the period between April and June of 2012. The job-specific utilities are estimated using a nested logit model. The elasticity numbers represent medians across all observations at the job × year-week level. Standard errors are clustered by CZ×SOC.
Data source: CareerBuilder.com

	Dependent variable: δ_j, job-specific utility							
	IV: Average Wage of Same Firm in Other Markets		IV: Average Wage of Same Firm in Other Markets (Excluding Same CZ and Same SOC)		IV: Average Predicted Wage of Same Firm in Other Markets		IV: Average Predicted Wage of Same Firm in Other Markets (Excluding Same CZ and Same SOC)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log Wage × Rural CZ × Low-Skill SOC	0.261***	0.378***	0.363***	0.470***	0.290***	0.462***	0.347***	0.526***
	(0.0597)	(0.116)	(0.0811)	(0.123)	(0.0748)	(0.125)	(0.0807)	(0.145)
Log Wage × Urban CZ × Low-Skill SOC	0.702***	1.189***	0.540***	0.850***	0.610***	1.038***	0.498***	0.874***
	(0.193)	(0.447)	(0.138)	(0.243)	(0.193)	(0.347)	(0.146)	(0.267)
Log Wage × Rural CZ × High-Skill SOC	0.156***	0.381***	0.234***	0.511***	0.192***	0.481***	0.237***	0.627***
	(0.0283)	(0.0850)	(0.0417)	(0.132)	(0.0332)	(0.116)	(0.0446)	(0.187)
Log Wage × Urban CZ × High-Skill SOC	0.276***	0.593***	0.387***	0.759**	0.284***	0.800***	0.338***	1.021***
	(0.0666)	(0.127)	(0.117)	(0.294)	(0.0735)	(0.164)	(0.0967)	(0.299)
Log Employees	-0.0291***	-0.0456***	-0.0452***	-0.0640***	-0.0388***	-0.0632***	-0.0447***	-0.0778***
	(0.00461)	(0.00890)	(0.00714)	(0.0146)	(0.00615)	(0.0128)	(0.00727)	(0.0186)
(Log Employees)^2	0.00138***	0.00226***	0.00248***	0.00346***	0.00207***	0.00339***	0.00249***	0.00436***
	(0.000327)	(0.000597)	(0.000495)	(0.000952)	(0.000416)	(0.000826)	(0.000495)	(0.00118)
Duration	-0.00296***	-0.00190***	-0.00353***	-0.00304***	-0.00383***	-0.00289***	-0.00389***	-0.00310***
	(0.000425)	(0.000571)	(0.000510)	(0.000662)	(0.000497)	(0.000708)	(0.000541)	(0.000793)
CZ × SOC FE	✓	✓	✓	✓	✓	✓	✓	✓
Job Title FE		✓		✓		✓		✓
Observations	12,765	9,516	10,759	8,084	10,915	8,204	10,333	7,756
Median Market Level Elasticity	0.213	0.362	0.298	0.481	0.226	0.459	0.269	0.585
Median Firm Level Elasticity	1.751	3.828	2.432	5.099	1.943	4.844	2.368	6.006
Median Vacancy-Level Elasticity	1.762	3.853	2.448	5.163	1.956	4.871	2.394	6.076
Kleibergen-Paap F-stat	8.143	3.199	13.97	3.654	12.21	10.95	16.81	4.925
Anderson-Rubin χ^2-stat	120.4	147.4	80.40	86.38	70.92	74.20	65.53	79.13

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A.5. Impact of wages on the utility derived from a job vacancy in the "heterogeneous" model: robustness checks

Estimation is by 2SLS. The sample includes jobs in CZ×SOC labor markets over the period between April and June of 2012. The job-specific utilities are estimated using a nested logit model. The elasticity numbers represent medians across all observations at the job × year-week level. Standard errors are clustered by CZ×SOC. The results are for the specification that includes only CZ × SOC fixed effects, and instruments the wage using the average predicted wage of the same firm in other markets (excluding the same CZ, adjacent CZ, and same SOC). The interactions of the wage are instrumented using interactions of the average predicted wage for the same firm in other markets, interacted with the corresponding variables.
Data source: CareerBuilder.com

	Dependent variable: δ_j, job-specific utility					
	Baseline (1)	Weighted by Inverse SE (2)	Linear Firm Size (3)	No Firm Size (4)	Min Applications per Vacancy: 3 (5)	Min Applications per Vacancy: 8
Log Wage × Rural CZ × Low-Skill SOC	0.350***	0.453***	0.259***	0.0861	0.232***	0.454***
	(0.0778)	(0.0865)	(0.0677)	(0.0652)	(0.0623)	(0.0927)
Log Wage × Urban CZ × Low-Skill SOC	0.470***	0.510***	0.400***	0.312**	0.299**	0.646***
	(0.148)	(0.158)	(0.139)	(0.133)	(0.142)	(0.161)
Log Wage × Rural CZ × High-Skill SOC	0.236***	0.274***	0.142***	0.0554**	0.155***	0.294***
	(0.0444)	(0.0539)	(0.0282)	(0.0251)	(0.0345)	(0.0575)
Log Wage × Urban CZ × High-Skill SOC	0.331***	0.345***	0.242***	0.222***	0.269***	0.409***
	(0.0976)	(0.108)	(0.0805)	(0.0761)	(0.0849)	(0.103)
Log Employees	-0.0441***	-0.0529***	-0.0126***		-0.0316***	-0.0548***
	(0.00719)	(0.00893)	(0.00122)		(0.00591)	(0.00869)
(Log Employees)^2	0.00243***	0.00294***			0.00168***	0.00306***
	(0.000489)	(0.000601)			(0.000411)	(0.000572)
Duration	-0.00384***	-0.00306***	-0.00371***	-0.00357***	-0.00373***	-0.00412***
	(0.000539)	(0.000626)	(0.000506)	(0.000492)	(0.000453)	(0.000596)
CZ × SOC FE	✓	✓	✓	✓	✓	✓
Observations	10,335	10,236	10,335	10,530	14,059	7,468
Median Market Level Elasticity	0.265	0.292	0.195	0.0802	0.167	0.270
Median Firm Level Elasticity	2.396	2.751	1.738	0.590	1.540	2.744
Median Vacancy-Level Elasticity	2.422	2.785	1.771	0.591	1.588	2.838
Kleibergen-Paap F-stat	15.87	21.08	11.21	10.23	10.05	18.68
Anderson-Rubin χ^2-stat	64.25	60.23	63.01	35.30	38.67	80.43

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A.6. Summary statistics for application elasticities with respect to job-specific utility δ_j.
The sample includes jobs in 822 CZ×SOC labor markets over the period between April and June of 2012. The elasticities are estimated using a nested logit model.
Data source: CareerBuilder.com

	count	mean	sd	min	p25	p50	p75	max
More Heterogeneity Model								
Vacancy Level	188181	0.979	64.257	-3833.865	1.869	2.530	4.033	275.909
Firm Level	183850	1.018	57.570	-3833.865	1.769	2.432	3.862	275.909
Market Level	10244	-0.722	5.463	-31.192	0.203	0.378	0.527	1.347

Table A.7. Distribution of market level elasticities by 6-digit SOC: detailed model

This table shows the market level elasticity of applications by 6-digit SOC. The detailed model allows the wage and nesting coefficients to vary for each 6-digit occupation, as well as a quadratic polynomial in log population density. The results are for the specification that includes only CZ $\times$ SOC fixed effects, and instruments the wage using the average predicted wage of the same firm in other markets (excluding the same CZ, adjacent CZ, and same SOC). The interactions of the wage are instrumented using interactions of the average predicted wage for the same firm in other markets, interacted with the corresponding variables.

	mean	sd	min	p25	p50	p75	max
Accountants and Auditors	0.344	0.123	0.219	0.265	0.310	0.358	0.865
Bookkeeping, accounting, auditing clerks	0.453	0.133	0.319	0.367	0.410	0.471	1.053
Computer support specialists	0.274	0.128	0.164	0.199	0.220	0.298	0.845
Customer service representatives	0.393	0.119	0.246	0.313	0.367	0.412	1.010
Executive secretaries and administrative	0.614	0.124	0.445	0.531	0.586	0.638	1.240
Financial Analysts	0.493	0.158	0.335	0.372	0.429	0.619	0.974
First-line managers of production/workers	-0.029	0.101	-0.111	-0.086	-0.074	0.000	0.532
Industrial engineers	-0.059	0.108	-0.150	-0.121	-0.106	-0.036	0.493
Legal Secretaries	0.142	0.182	0.001	0.012	0.038	0.149	0.625
Light Truck or Delivery Services Drivers	-27.571	1.387	-31.192	-28.505	-27.394	-26.555	-24.443
Medical secretaries	0.559	0.134	0.398	0.488	0.514	0.592	1.166
Other	0.740	0.124	0.592	0.660	0.702	0.789	1.347
Registered nurses	-0.107	0.151	-0.221	-0.190	-0.179	-0.078	0.418
Sales, wholesale and manufacturing	0.682	0.150	0.560	0.590	0.631	0.689	1.257
Secretaries and Administrative Assistant	0.452	0.126	0.334	0.373	0.410	0.470	1.035
Telemarketers	0.278	0.160	0.170	0.198	0.210	0.327	0.848
Truck drivers, heavy and tractor-trailer	0.344	0.119	0.247	0.270	0.294	0.373	0.925

Table A.8. Distribution of firm level elasticities by 6-digit SOC: detailed model

This table shows the firm level elasticity of applications by 6-digit SOC. The detailed model allows the wage and nesting coefficients to vary for each 6-digit occupation, as well as a quadratic polynomial in log population density. The results are for the specification that includes only CZ $\times$ SOC fixed effects, and instruments the wage using the average predicted wage of the same firm in other markets (excluding the same CZ, adjacent CZ, and same SOC). The interactions of the wage are instrumented using interactions of the average predicted wage for the same firm in other markets, interacted with the corresponding variables.

	mean	sd	min	p25	p50	p75	max
Accountants and Auditors	2.535	1.120	0.251	2.088	2.197	2.618	16.882
Bookkeeping, accounting, auditing clerks	3.783	2.577	0.221	3.219	3.405	3.689	52.334
Computer support specialists	1.618	0.852	0.221	1.264	1.343	1.741	11.317
Customer service representatives	2.492	0.997	0.310	2.166	2.240	2.534	12.572
Executive secretaries and administrative	6.680	10.933	0.361	5.366	5.584	6.065	275.909
Financial Analysts	2.512	0.783	0.354	2.076	2.216	2.617	8.242
First-line managers of production/workers	-0.246	1.144	-1.001	-0.756	-0.598	-0.009	14.412
Industrial engineers	-1.173	1.377	-3.777	-2.047	-1.554	-0.393	3.896
Legal Secretaries	1.342	1.623	0.008	0.246	0.543	1.710	5.248
Light Truck or Delivery Services Drivers	-73.268	11.547	-94.407	-81.168	-75.928	-68.843	-26.613
Medical secretaries	8.319	4.159	-25.624	6.894	7.851	9.196	28.317
Other	-79.454	512.987	-3833.865	8.890	22.244	42.558	149.435
Registered nurses	-0.391	0.515	-0.833	-0.705	-0.617	-0.235	1.338
Sales, wholesale and manufacturing	2.969	0.577	0.675	2.705	2.967	3.213	4.677
Secretaries and Administrative Assistant	4.789	8.483	0.415	3.559	3.900	4.197	109.233
Telemarketers	0.953	0.440	0.210	0.737	0.849	0.994	2.639
Truck drivers, heavy and tractor-trailer	2.680	2.653	0.295	2.123	2.522	2.808	41.671

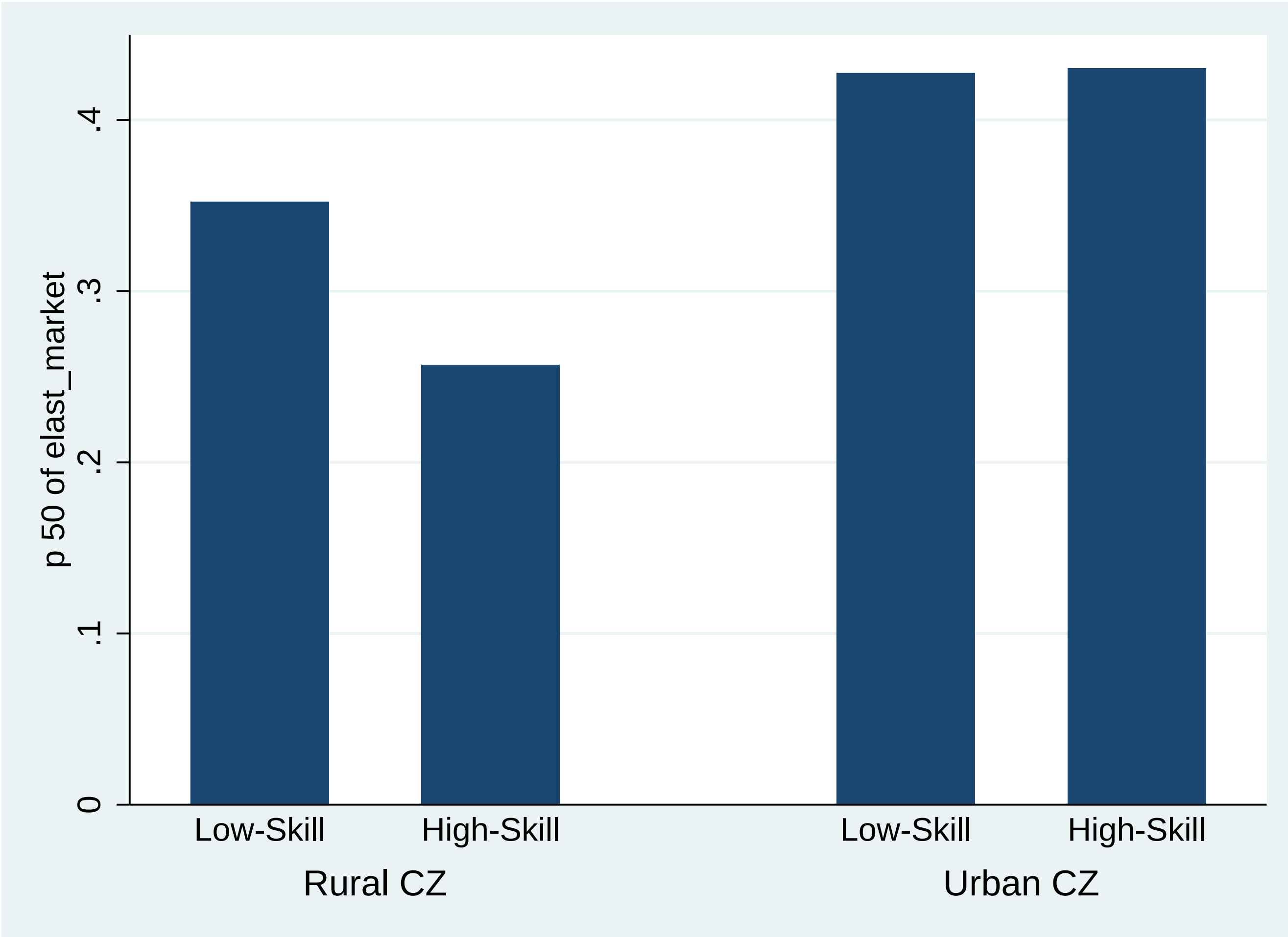

Figure A.1. Distribution of market level elasticities by rural-urban and skill classification: detailed model This figure shows the median market level elasticity of applications by low/high skill level, and by urban-rural classification. The detailed model is more flexible and allows the wage and nesting coefficients to vary for each 6-digit occupation, as well as a quadratic polynomial in log population density. The results are for the specification that includes only CZ $\times$ SOC fixed effects, and instruments the wage using the average predicted wage of the same firm in other markets (excluding the same CZ, adjacent CZ, and same SOC). The interactions of the wage are instrumented using interactions of the average predicted wage for the same firm in other markets, interacted with the corresponding variables.

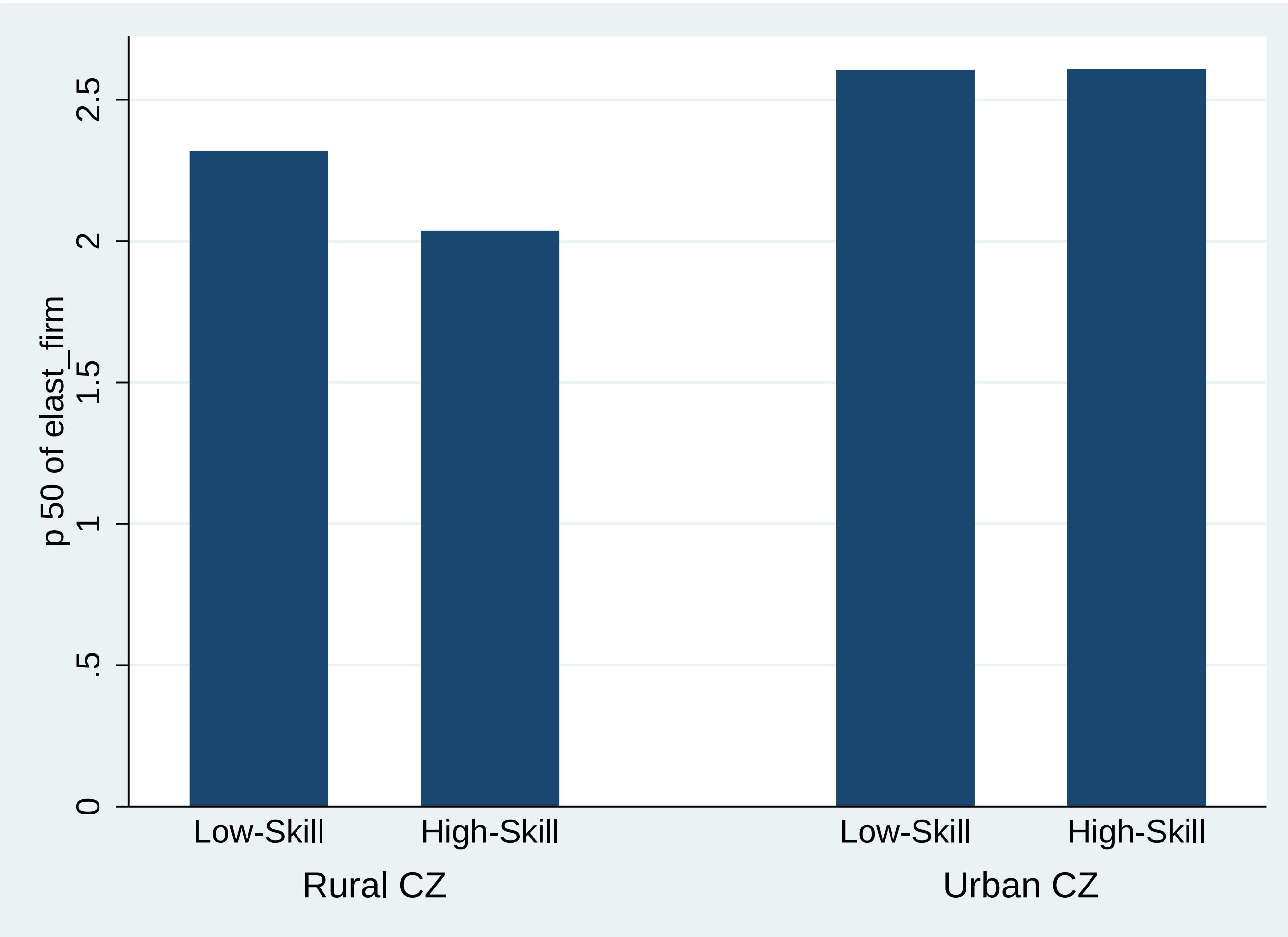

Figure A.2. Distribution of firm level elasticities by rural-urban and skill classification: detailed model This figure shows the median firm level elasticity of applications by low/high skill level, and by urban-rural classification. The detailed model is more flexible and allows the wage and nesting coefficients to vary for each 6-digit occupation, as well as a quadratic polynomial in log population density. The results are for the specification that includes only CZ × SOC fixed effects, and instruments the wage using the average predicted wage of the same firm in other markets (excluding the same CZ, adjacent CZ, and same SOC). The interactions of the wage are instrumented using interactions of the average predicted wage for the same firm in other markets, interacted with the corresponding variables.

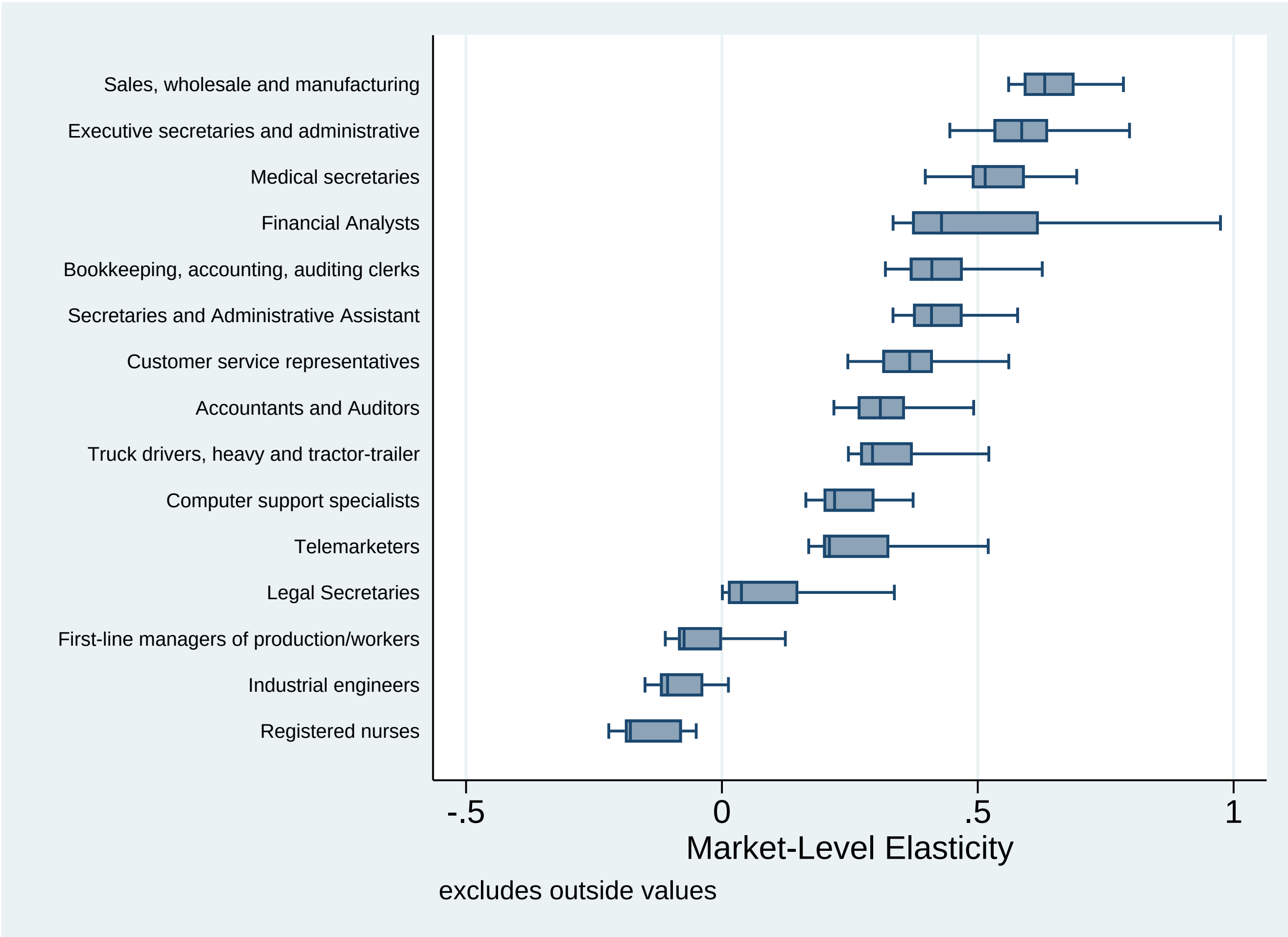

Figure A.3. Distribution of market level elasticities by 6-digit SOC: detailed model This figure shows the median market level elasticity of applications by 6-digit SOC. The detailed model allows the wage and nesting coefficients to vary for each 6-digit occupation, as well as a quadratic polynomial in log population density. The results are for the specification that includes only CZ $\times$ SOC fixed effects, and instruments the wage using the average predicted wage of the same firm in other markets (excluding the same CZ, adjacent CZ, and same SOC). The interactions of the wage are instrumented using interactions of the average predicted wage for the same firm in other markets, interacted with the corresponding variables. The figure excludes "Light Truck or Delivery Service Drivers" and the "Other SOCs" category (grouping SOCs with less than 100,000 observations at the application level) because the range of elasticities was too wide for visualization. Graphs with these categories are included in the appendix.

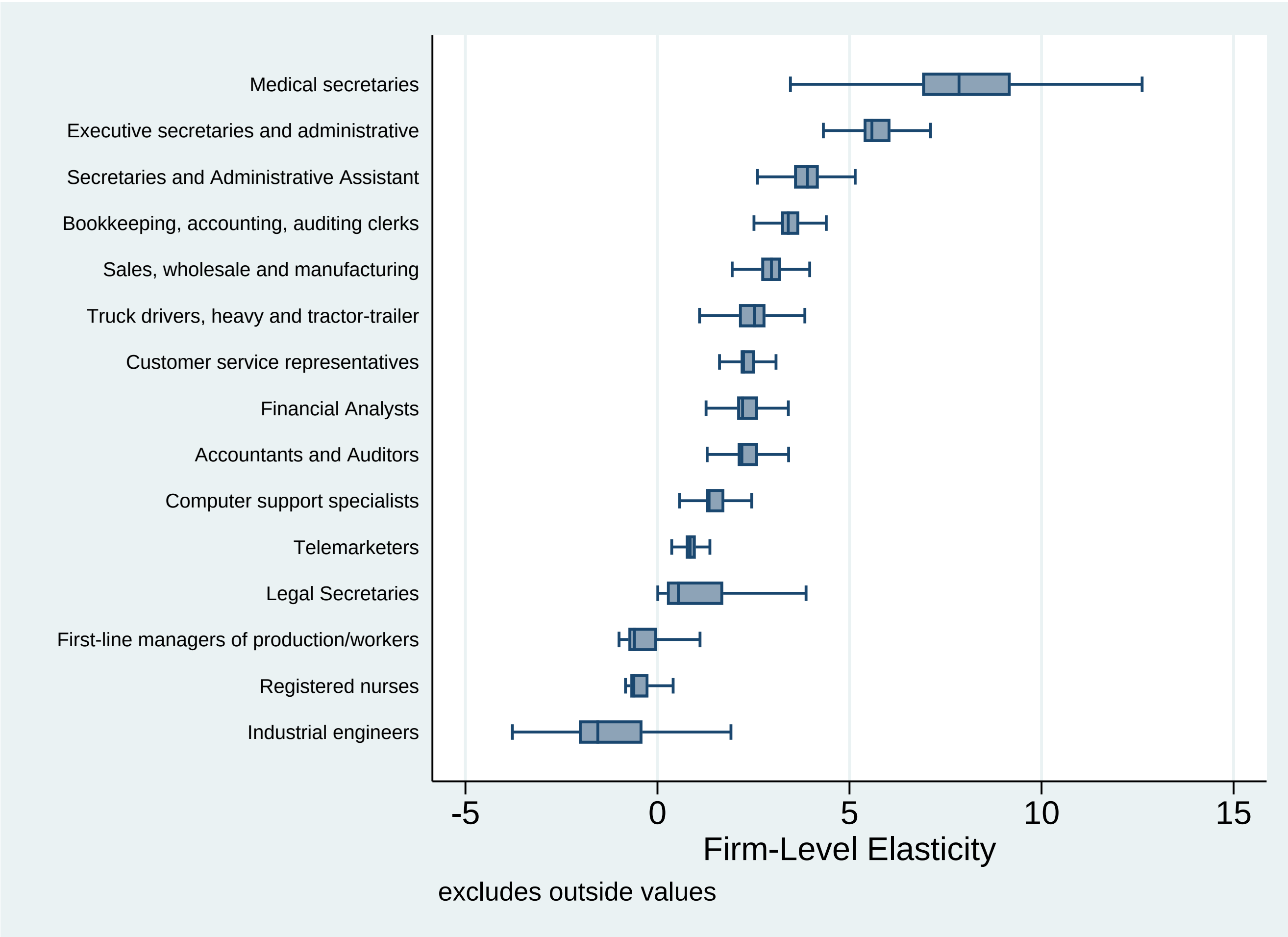

Figure A.4. Distribution of firm level elasticities by 6-digit SOC: detailed model This figure shows the median firm level elasticity of applications by 6-digit SOC. The detailed model allows the wage and nesting coefficients to vary for each 6-digit occupation, as well as a quadratic polynomial in log population density. The results are for the specification that includes only CZ × SOC fixed effects, and instruments the wage using the average predicted wage of the same firm in other markets (excluding the same CZ, adjacent CZ, and same SOC). The interactions of the wage are instrumented using interactions of the average predicted wage for the same firm in other markets, interacted with the corresponding variables. The figure excludes "Light Truck or Delivery Service Drivers" and the "Other SOCs" category (grouping SOCs with less than 100,000 observations at the application level) because the range of elasticities was too wide for visualization. Graphs with these categories are included in the appendix.

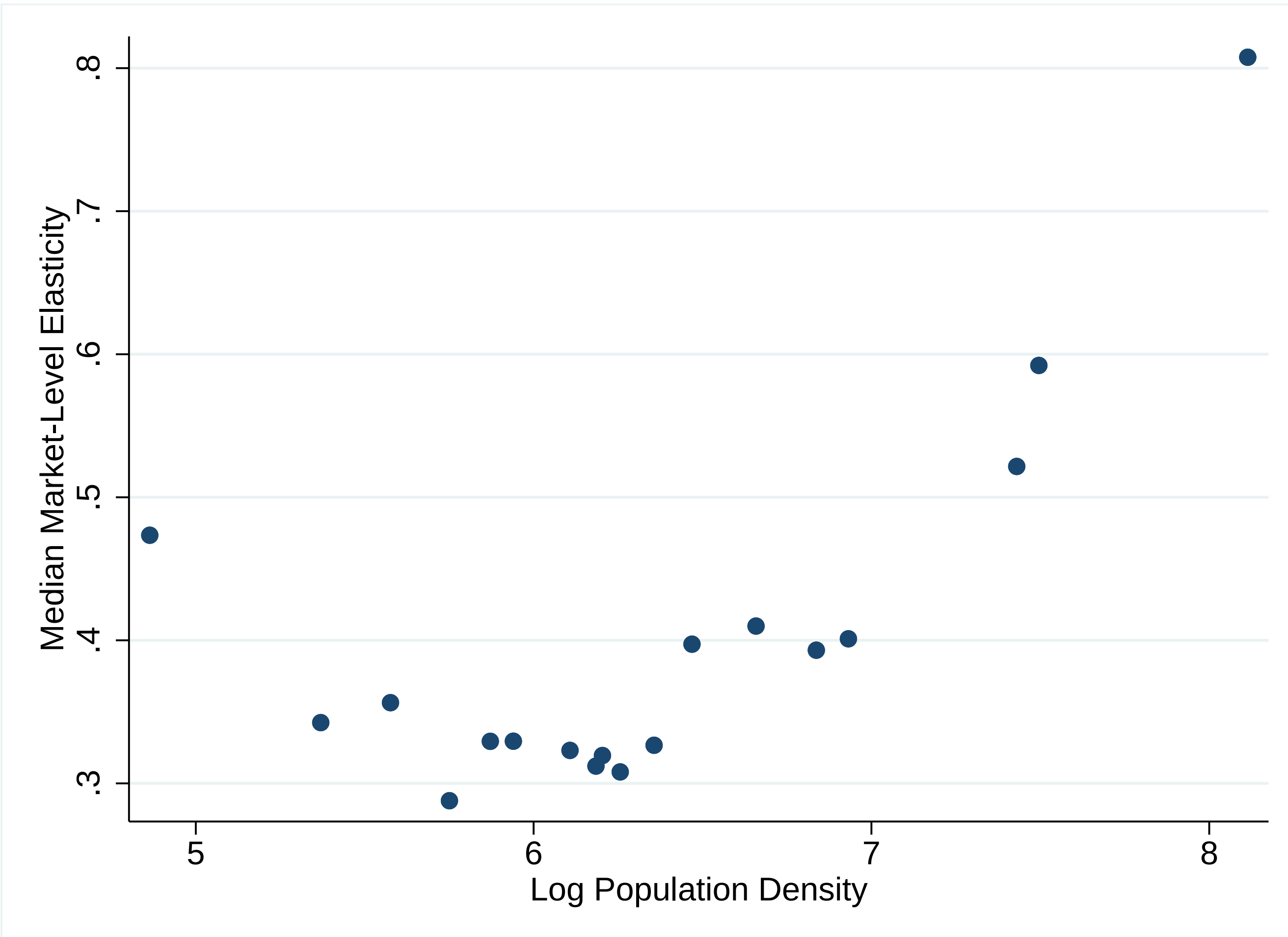

Figure A.5. Median market level elasticities by population density: detailed model This figure shows the median market level elasticity of applications by population density. The detailed model allows the wage and nesting coefficients to vary for each 6-digit occupation, as well as a quadratic polynomial in log population density. The results are for the specification that includes only CZ $\times$ SOC fixed effects, and instruments the wage using the average predicted wage of the same firm in other markets (excluding the same CZ, adjacent CZ, and same SOC). The interactions of the wage are instrumented using interactions of the average predicted wage for the same firm in other markets, interacted with the corresponding variables.

B The Reference Job

In this appendix we outline the proof that we can use the bottom level logit to identify $(\delta_k - \delta_{r(m)})/\lambda_m$ for jobs appearing in all weeks of the data, even if the reference job $r(m)$ and job k are not both active in the same week. We need to assume that, in every week, some job persists from week t to $t+1$. We call this the "persistent job assumption." The "job that persists" can be different for each pair of adjacent weeks in the data. This assumption is satisfied in our data for almost all markets.

Assume WLOG that the reference job $r(m)$ is present in the first week of the data. If we used only that first week in our analysis, as long as there is variation in z_{ik} across jobs, we can then identify γ/λ_m plus $(\delta_k - \delta_j)/\lambda_m$ for every job $k \neq r(m)$ that is posted in market m in week 1. Now let us consider identification of the δ_k/λ_m for jobs that appear in week 2 but not week 1. Critically, assume that at least one job persists from week 1 into week 2. For purposes of identification, we can hold this persistent job's value of $(\delta_j - \delta_{r(m)})/\lambda_m$ fixed at the value we identified from the week one data. All other week 2 values of $(\delta_k - \delta_{r(m)})/\lambda_m$ can then be identified. The argument of this paragraph can then be repeated for each pair of adjacent weeks in the data.

We have now shown that each $(\delta_k - \delta_{r(m)})/\lambda_m$ can be identified under the "persistent jobs assumption." This assumption allows us to measure all job effects δ_k/λ_m relative to a single job's $\delta_{r(m)}/\lambda_m$. In contrast, if no job ever persisted across weeks we could only identify $(\delta_k - \delta_j)/\lambda_m$ for a different j in each week.

Note that in our estimation procedure, we do not use the exact analog of this identification result. Given that the overlapping jobs condition is met, it is more efficient to use all weeks of data to estimate all the (relative) job fixed effects in the market.

C Elasticity Formulas

We use the estimated nesting parameter λ_m, wage coefficient α, and the predicted probabilities of application such as S_{ijmt} to calculate the wage elasticity at the vacancy, market and firm level.

Vacancy-Level Elasticities The slope of the probability that user i applies to job vacancy j in week t with respect to the utility of job vacancy j is

$$\frac{\partial s_{ijmt}}{\partial \delta_j} = s_{ijmt}\left(\frac{1}{\lambda_m} - \frac{1-\lambda_m}{\lambda_m} s_{ijmt|g} - s_{ijmt}\right). \tag{C.1}$$

The slope of the probability that user i applies to job vacancy j in week t with respect to the utility of job vacancy $k \neq j$ is

$$\frac{\partial s_{ijmt}}{\partial \delta_k} = -s_{ijmt}\left(\frac{1-\lambda_m}{\lambda_m} s_{ikmt|g} + s_{ikmt}\right). \tag{C.2}$$

The slopes of the expected shares are the averages of the slopes across users:

$$\frac{\partial s_{jmt}}{\partial \delta_k} = \frac{1}{N_m}\sum_{i=1}^{N_m} \frac{\partial s_{ijmt}}{\partial \delta_k}. \tag{C.3}$$

The general formula for the elasticity of the share of job vacancy j in week t with respect to vacancy k's (where $k = j$ or $k \neq j$) wage is:

$$\frac{\partial \log s_{jmt}}{\partial \log w_k} = \frac{\alpha}{s_{jmt}} \cdot \frac{\partial s_{jmt}}{\partial \delta_k}. \tag{C.4}$$

The elasticity of the share of job vacancy j in week t with respect to vacancy j's own wage is

$$\frac{\partial \log s_{jmt}}{\partial \log w_k} = \frac{\alpha}{s_{jmt}} \cdot \frac{1}{N_m}\sum_{i=1}^{N_m} s_{ijmt}\left(\frac{1}{\lambda_m} - \frac{1-\lambda_m}{\lambda_m} s_{ijmt|g} - s_{ijmt}\right) \tag{C.5}$$

The elasticity of the share of job vacancy j in week t with respect to vacancy $k, k \neq j$'s wage is

$$\frac{\partial \log s_{jmt}}{\partial \log w_k} = \frac{\alpha}{s_{jmt}} \cdot \frac{1}{N_m}\sum_{i=1}^{N_m} -s_{ijmt}\left(\frac{1-\lambda_m}{\lambda_m} s_{ikmt|g} + s_{ikmt}\right) \tag{C.6}$$

Market Level Elasticities The slope of the probability that user i applies to nest $g = 1$ in week t with respect to the inclusive value is

$$\frac{\partial s_{igmt}}{\partial I_{imt}} = \lambda_m s_{igmt}(1 - s_{igmt}). \tag{C.7}$$

The slope of the inclusive value with respect to the log wage of job vacancy k is

$$\frac{\partial I_{imt}}{\partial \log w_k} = \frac{\alpha}{\lambda_m} s_{ikmt|g}. \tag{C.8}$$

Combining the last two equations, the slope of the probability that user i applies to nest $g = 1$ with respect to the log wage of job vacancy k is

$$\frac{\partial s_{igmt}}{\partial \log w_k} = \alpha s_{ikmt}(1 - s_{igmt}). \tag{C.9}$$

The total slope of user i's probability of applying to the inside nest with respect to the log wage of all vacancies inside the market is

$$\sum_{k \in J_{mt}} \frac{\partial s_{igmt}}{\partial \log w_k} = \alpha s_{igmt}(1 - s_{igmt}). \tag{C.10}$$

The total slope of the expected share of the inside nest with respect to the log wage of all vacancies inside the market is

$$\sum_{k \in J_{mt}} \frac{\partial s_{gmt}}{\partial \log w_k} = \alpha \frac{1}{N_m} \sum_{i=1}^{N_m} s_{igmt}(1 - s_{igmt}). \tag{C.11}$$

The total elasticity of the expected share with respect to the wages of all vacancies in the market is

$$\frac{1}{s_{gmt}} \sum_{k \in J_{mt}} \frac{\partial s_{gmt}}{\partial \log w_k} = \frac{\alpha}{s_{gmt}} \frac{1}{N_m} \sum_{i=1}^{N_m} s_{igmt}(1 - s_{igmt}). \tag{C.12}$$

Firm level Elasticities There are F firms. Firm f posts a subset $\mathcal{F}_f$ of the job vacancies in market m in week t (which might also be just one vacancy, or no vacancies). Note that firm f could also post jobs in other CZ $\times$ SOC markets, but we do not take this into account in our analysis because our model treats any application outside the market as part of the outside option. The probability that user i applies to a job posted by firm f in market m in week t is

$$s_{ifmt} = \sum_{j \in \mathcal{F}_f} s_{ijmt}. \tag{C.13}$$

The slope of the probability that user i applies to a job vacancy posted by firm f with respect to the log wage of job k posted by firm f is a sum of own-wage elasticities and cross-wage elasticities:

$$\frac{\partial s_{ifmt}}{\partial \log w_k} = \sum_{j \in \mathcal{F}_f} \frac{\partial s_{ijmt}}{\partial \log w_k}. \tag{C.14}$$

The slope of the expected share of firm f with respect to the log wage of job k posted by firm f is a sum of own-wage elasticities and cross-wage elasticities:

$$\frac{\partial s_{fmt}}{\partial \log w_k} = \sum_{j \in \mathcal{F}_f} \frac{\partial s_{jmt}}{\partial \log w_k}. \tag{C.15}$$

The total slope of the expected share of firm f with respect to a simultaneous change in the log wage for all of its own vacancies is

$$\sum_{k \in \mathcal{F}_f} \frac{\partial s_{fmt}}{\partial \log w_k} = \sum_{k \in \mathcal{F}_f} \sum_{j \in \mathcal{F}_f} \frac{\partial s_{jmt}}{\partial \log w_k}. \tag{C.16}$$

The total elasticity of the expected share of firm f with respect to a simultaneous increase in the wage for all of its own vacancies is obtained by dividing the last equation by the expected share of firm f in market m in week t:

$$\frac{1}{s_{fmt}} \sum_{k \in \mathcal{F}_f} \frac{\partial s_{fmt}}{\partial \log w_k} = \frac{1}{s_{fmt}} \sum_{k \in \mathcal{F}_f} \sum_{j \in \mathcal{F}_f} \frac{\partial s_{jmt}}{\partial \log w_k} \tag{C.17}$$

$\frac{\partial s_{jmt}}{\partial \log w_k}$ can be found in equation C.5 multiplied by s_{jmt} for the own elasticity, and equation C.6 multiplied by s_{jmt} for the cross elasticity.