Opening the Black Box of the Matching Function: the Power of Words

Online Appendix

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A Model Details

It follows directly from the results in Shimer (2005) that the equilibrium in each of these cases is constrained efficient and that workers' expected payoffs equal their marginal contribution. We exploit this fact to simplify the equilibrium derivation. In particular, we characterize equilibrium queue lengths using the planner's problem before considering decentralization to obtain the equilibrium wages.

A.1 Skill Homogeneity

Proposition 1. *Consider the model with skill homogeneity and $y_B x_H < y_A e^{2(\mu_0+\mu_1)}$. The equilibrium queue lengths satisfy*

$$\lambda_{jk} = \mu_0 + \mu_1 + \left(\mathbb{1}_{\{j=B\}} - \frac{1}{2}\right)(\log y_B - \log y_A) + \left(\mathbb{1}_{\{k=H\}} - \frac{1}{2}\right)\log x_H. \tag{1}$$

The equilibrium wages satisfy

$$w_{jk} = \frac{\lambda_{jk} e^{-\lambda_{jk}}}{1 - e^{-\lambda_{jk}}} y_j x_k. \tag{2}$$

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Proof. The problem of a planner who wants to maximize expected output can be written as

$$\max_{\lambda_{Ak},\lambda_{Bk}} \frac{1}{4}\sum_j \sum_k \left(1-e^{-\lambda_{jk}}\right) y_j x_k$$

subject to $\frac{1}{4}\sum_j \sum_k \lambda_{jk} = \mu_0 + \mu_1$, which represents the constraint imposed by the availability of workers. Using ξ to denote the multiplier on the resource constraint, the first-order conditions of the Lagrangian are

$$e^{-\lambda_{jk}} y_j x_k = \xi \tag{3}$$

for $j \in \{A,B\}$ and $k \in \{L,H\}$. These four first-order conditions and the resource constraint together form a system of five equations with five unknowns (λ_{jk}, ξ).

Given $x_L = 1$, evaluation of the first-order condition (3) for different values of k yields $\lambda_{jH} = \lambda_{jL} + \log x_H$. Similarly, evaluation of the first-order condition (3) for different values of j gives $\lambda_{BL} = \lambda_{AL} + \log y_B - \log y_A$. Substitution of these results into the resource constraint implies (1).

For this interior allocation to indeed be optimal, we need to verify that the shortest queue length remains positive. That is, $\lambda_{AL} > 0$, which by equation (1) is satisfied if and only if $y_B x_H < y_A e^{2(\mu_0+\mu_1)}$.

As mentioned above, efficiency of the equilibrium requires that workers' expected payoff equals their marginal contribution to surplus, which is equal to ξ_i. A worker's expected payoff is the product of his matching probability and the wage that he would be paid. A firm of type (j,k) matches as long as at least one worker applies, which happens with probability $1-e^{-\lambda_{jk}}$. Since there are on average λ_{jk} of such workers applying to the firm, the matching probability of a worker is $\left(1-e^{-\lambda_{jk}}\right)/\lambda_{jk}$. Dividing ξ by this matching probabilities yields (2). □

A.2 Horizontal Differentiation of Skills

Proposition 2. *Consider the model with horizontal differentiation and $\tau = 0$. The equilibrium queue lengths are $\lambda_{1Ak} = \lambda_{0Bk} = 0$,*

$$\lambda_{0Ak} = \mu_0 + \left(\mathbb{1}_{\{k=H\}} - \frac{1}{2}\right)\log x_H \qquad \textit{and} \qquad \lambda_{1Bk} = 2\mu_1 + \left(\mathbb{1}_{\{k=H\}} - \frac{1}{2}\right)\log x_H. \tag{4}$$

The equilibrium wages are

$$w_{0Ak} = \frac{\lambda_{0Ak}e^{-\lambda_{0Ak}}}{1-e^{-\lambda_{0Ak}}} y_{0A} x_k \qquad \textit{and} \qquad w_{1Bk} = \frac{\lambda_{1Bk}e^{-\lambda_{1Bk}}}{1-e^{-\lambda_{0Bk}}} y_{1B} x_k. \tag{5}$$

Proof. For τ sufficiently small, the problem of a planner who wants to maximize output can be written as

$$\max_{\lambda_{0Ak},\lambda_{1Bk}} \frac{1}{4}\sum_k \left(1-e^{-\lambda_{0Ak}}\right) y_{0A}x_k + \frac{1}{4}\sum_k \left(1-e^{-\lambda_{1Bk}}\right) x_k$$

subject to $\frac{1}{4}\sum_k \lambda_{0Ak} = \mu_0$ and $\frac{1}{4}\sum_k \lambda_{1Bk} = \mu_1$, which represent the constraint imposed by the availability of workers of either type. Using ξ_i to denote the multiplier on the resource constraint for type i, the first-order conditions of the Lagrangian are

$$e^{-\lambda_{0Ak}} y_{0A} x_k = \xi_0 \tag{6}$$

$$e^{-\lambda_{1Bk}} y_{1B} x_k = \xi_1 \tag{7}$$

for $k \in \{L,H\}$. These four first-order conditions and the two resource constraints together form a system of six equations with six unknowns (λ_{0Ak}, λ_{1Bk}, ξ_0, ξ_1). Given $x_L = 1$, evaluation of the FOCs for the two different values of k yields $\lambda_{0AH} = \lambda_{0AL} + \log x_H$ and $\lambda_{1BH} = \lambda_{1BL} + \log x_H$. Substituting this into the resource constraints then implies (4).

As in the proof of proposition 1, we derive the wages by dividing workers' marginal contribution to surplus ξ_i by their matching probability. Using the same logic as in that proof, the relevant matching probabilities are $\left(1-e^{-\lambda_{0Ak}}\right)/\lambda_{0Ak}$ and $\left(1-e^{-\lambda_{1Bk}}\right)/\lambda_{1Bk}$. Hence, we obtain (5). □

A.3 Vertical Differentiation of Skills

Proposition 3. *Consider the model with vertical differentiation, satisfying* $\theta \in \left(\frac{y_{0B}}{y_{0A}}e^{-2\mu_0}, \frac{y_{0B}}{y_{0A}}e^{2\mu_0}\right)$ *and* $\theta \in \left(x_H e^{-2\mu_1}, \frac{1}{x_H}e^{2\mu_1}\right)$. *The equilibrium queue lengths are*

$$\lambda_{0jk} \equiv \lambda_{0j} = \mu_0 + \left(\mathbb{1}_{\{j=B\}} - \frac{1}{2}\right)(\log y_{0B} - \log y_{0A} - \log\theta) \tag{8}$$

$$\lambda_{1jk} = \mu_1 + \left(\mathbb{1}_{\{j=B\}} - \frac{1}{2}\right)\log\theta + \left(\mathbb{1}_{\{k=H\}} - \frac{1}{2}\right)\log x_H. \tag{9}$$

The equilibrium wages are

$$w_{0jk} = \frac{\lambda_{0j}e^{-\lambda_{0j}}}{1-e^{-\lambda_{0j}}} y_{0j}x_k \qquad \text{and} \qquad w_{1jk} = \frac{\lambda_{1jk}e^{-\lambda_{1jk}}}{1-e^{-\lambda_{1jk}}}\left[y_{1j} - \left(1-e^{-\lambda_{0j}}\right)y_{0j}\right]x_k. \tag{10}$$

Proof. The planner's problem is

$$\max_{\lambda_{ijk}} \frac{1}{4} \sum_j \sum_k \left[\left(1 - e^{-\lambda_{1jk}}\right) y_{1j} + e^{-\lambda_{1jk}} \left(1 - e^{-\lambda_{0jk}}\right) y_{0j} \right] x_k,$$

subject to the resource constraint based on the number of workers of each type $\frac{1}{4} \sum_j \sum_k \lambda_{ijk} = \mu_i$ for $i \in \{0, 1\}$. Using ξ_i to denote the multiplier on the resource constraint for type i, the first-order conditions of the Lagrangian are

$$e^{-\lambda_{1jk}} e^{-\lambda_{0jk}} y_{0j} x_k = \xi_0 \tag{11}$$

and

$$e^{-\lambda_{1jk}} \left[y_{1j} - \left(1 - e^{-\lambda_{0jk}}\right) y_{0j} \right] x_k = \xi_1, \tag{12}$$

for $j \in \{A, B\}$ and $k \in \{L, H\}$. These eight first-order conditions and the two resource constraints together form a system of ten equations with ten unknowns $(\lambda_{ijk}, \xi_0, \xi_1)$.

We first consider the queues of type-0 workers. Dividing (12) by (11) gives

$$e^{\lambda_{0jk}} \frac{y_{1j} - y_{0j}}{y_{0j}} + 1 = \frac{\xi_1}{\xi_0},$$

for $j \in \{A, B\}$ and $k \in \{L, H\}$. This immediately reveals that λ_{0jk} is independent of k, i.e. $\lambda_{0jL} = \lambda_{0jH} \equiv \lambda_{0j}$. Further, it implies that $\lambda_{0Bk} = \lambda_{0Ak} + \log y_{0B} - \log y_{0A} - \log \theta$. Together with the resource constraint for $i = 0$, this gives (8).

Next, consider the queues of type-1 workers. Using $x_L = 1$ as well as the solutions for λ_{0jk}, evaluation of the first-order condition (11) for different values of k yields $\lambda_{1jH} = \lambda_{1jL} + \log x_H$ for $j \in \{A, B\}$. Similarly, evaluation of (11) for different values of j gives $\lambda_{1Bk} = \lambda_{1Ak} + \log \theta$ for $k \in \{L, H\}$. Together with the resource constraint for $i = 1$, these results imply (9).

For this interior allocation to indeed be optimal, we need to verify that each λ_{ijk} is indeed non-negative. Solving (8) and (9) for θ shows that this is the case if $\theta \in \left(\frac{y_{0B}}{y_{0A}} e^{-2\mu_0}, \frac{y_{0B}}{y_{0A}} e^{2\mu_0} \right)$ and $\theta \in \left(x_H e^{-2\mu_1}, \frac{1}{x_H} e^{2\mu_1} \right)$.

As in the proof of proposition 1 and 2, we derive the wages by dividing workers' marginal contribution to surplus ξ_i by their matching probability. The matching probability of an experienced worker can be derived in a similar fashion as in those proofs and equals $\left(1 - e^{-\lambda_{1jk}}\right) / \lambda_{1jk}$. For an inexperienced worker to match, two events need to take place: i) no experienced applicant shows up, and ii) the worker is chosen among all inexperienced applicants. The joint probability of these events is $e^{-\lambda_{1jk}} \left(1 - e^{-\lambda_{0j}}\right) / \lambda_{0j}$. Dividing (11) and (12) by these matching probabilities yields (10). □

Predictions Across Job Titles. To derive the predictions across job title, it is helpful to analyze the queues and wages of the two types of workers separately. First, consider the experienced workers ($i = 1$). As $\theta \geq 1$, equation (9) implies $\lambda_{1Bk} \geq \lambda_{1Ak}$ for $k \in \{L, H\}$, with equality if and only if $\theta = 1$. That is, sensitive job title $j = B$ attracts (weakly) more experienced applicants than job title $j = A$. Hence, matching is (weakly) harder for an experienced worker in job title B than in job title A. As experienced workers must be indifferent between both job titles in the equilibrium characterized in proposition 3, job title B must pay them (weakly) higher wages than job title A, i.e. $w_{1Bk} \geq w_{1Ak}$ for $k \in \{L, H\}$. In other words, the sensitive job title B attracts a larger number of experienced workers and pays them higher wages than job title A.

Now, consider the inexperienced workers ($i = 0$). We will show that, depending on parameter values, job title B may attract fewer or more of such workers, while paying them higher wages.

First, consider a case in which the sensitive job title B pays inexperienced workers higher wages than job title A and attracts more of them. Equation (8) implies that the sensitive job title B attracts more inexperienced applicants than job title A if and only if $y_{0B}/y_{0A} > \theta$, where $\theta = (y_{1B} - y_{0B})/(y_{1A} - y_{0A}) \geq 1$. This condition means that inexperienced workers are very productive in the sensitive job title B relative to job title A, in the sense that this relative productivity exceeds the sensitivity measure θ. In that case, a similar indifference condition as above implies that job title B must pay higher wages to inexperienced applicants than job title A, i.e. $w_{0Bk} > w_{0Ak}$. With wages and queues of both types of workers being larger in the sensitive job title B, the relation between wages and applications across job title is clearly positive in this case.

Second, we show that there exist parameter combinations for which job title B pays inexperienced workers a higher wage than job title A, but attracts so few of them, that its total queue of applicants (inexperienced or experienced) is shorter. Specifically, taking the sum of equations (8) and (9) reveals that firms with job title $j = B$ receive fewer applications overall (from inexperienced or experienced workers) if $y_{0B} < y_{0A}$, i.e. if inexperienced workers are less productive in job title B. Job title B may however continue to pay higher wages to inexperienced applicants. As in Faberman & Menzio (2017), equation (10) reveals that $w_{0Bk} > w_{0Ak}$ if and only if

$$\frac{\varepsilon\left(\mu_0 - \frac{1}{2}\left(\log y_{0B} - \log y_{0A} - \log\theta\right)\right)}{\varepsilon\left(\mu_0 + \frac{1}{2}\left(\log y_{0B} - \log y_{0A} - \log\theta\right)\right)} < \frac{y_{0B}}{y_{0A}},$$

where $\varepsilon(q) \equiv qe^{-q}/(1-e^{-q})$. The left-hand side of this expression is decreasing in θ, so the inequality holds for any θ larger than some lower bound $\underline{\theta}(y_{0B}/y_{0A})$, satisfying $\underline{\theta}' < 0$ and $\underline{\theta}(1) = 1$.

Hence, if job title *B* is less productive with an inexperienced worker than job title *A* but sufficiently sensitive, then it pays higher wages to both inexperienced and experienced workers, but attracts fewer applicants overall. In this case, the relationship between wages and applications across job titles is clearly negative.

B Omitted Tables and Figures

Table B.1: Words that predict higher or lower experience and education of applicants within an SOC code

Experience +	Experience -	Education +	Education -
manager	rn	director	rn
senior	web	developer	customer
director	center	nurse	services
executive	insurance	it	needed
of	loan	net	warehouse
retail	3	controller	healthcare
management		research	license
supervisor		performance	
controller		desk	
design		agent	
consulting		summer	
dba		vice	
chief		forklift	
asp		distribution	
		hvac	
		chief	

Note: Words that appear at least 10 times and that are significant at the 5% level in explaining the residuals after a regression of the average education or average experience of applicants on SOC codes fixed effects. Words are ordered by frequency and underlined when they appear at least 100 times. Source: CareerBuilder.com.

Figure B.1: Words that predict wages within a given SOC code

Higher Wages:

[0.044;0.060]; [0.077;0.200]; [0.202;1.576] log points

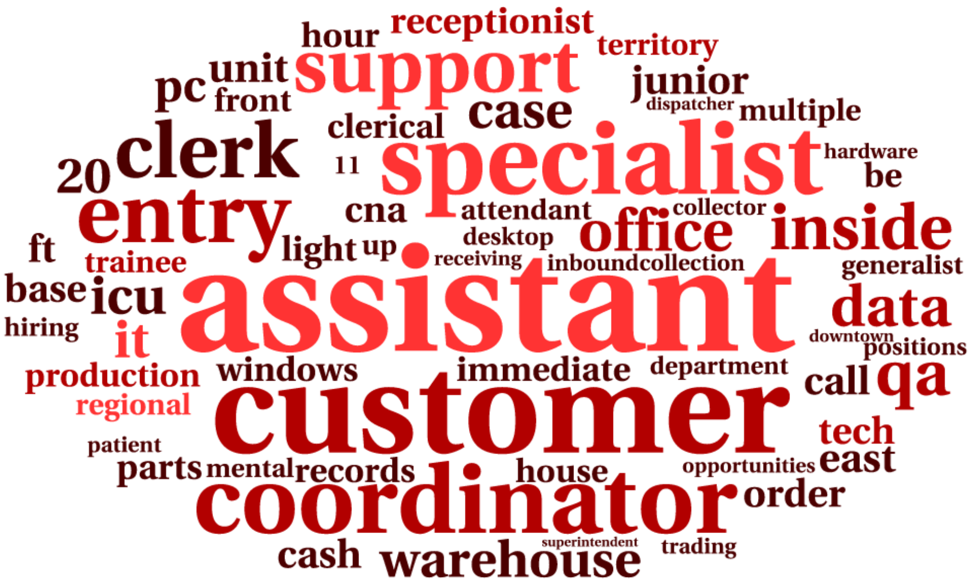
Lower Wages:

[-1.101;-0.169]; [-0.167;-0.104]; [-0.101;-0.063] log points

Note: Words that are significant at the 5% level in explaining the residuals after a regression of the posted wage on SOC codes fixed effects (Table C.5, column II) and appear at least 10 times. The big rectangle is "-", which typically separates the main job title from additional details. Word cloud created using www.tagul.com. The size of a word represents its frequency, while the color represents the tercile of its coefficient, weighted by frequency.
Source: CareerBuilder.com

Figure B.2: Words that predict the number of applicants per view within a given SOC code

Higher Number:



[0.154;0.251]; [0.269;0.482]; [0.517;4.974] appl. per 100 views

Lower Number:

[-3.920;-0.377]; [-0.373;-0.301]; [-0.299;-0.164] appl. per 100 views

Note: Words that are significant at the 5% level in explaining the residuals after a regression of the number of applicants per view on SOC codes fixed effects and appear at least 10 times. The big rectangle is "-", which typically separates the main job title from additional details. Word cloud created using www.tagul.com. The size of a word represents its frequency, while the color represents the tercile of its coefficient, weighted by frequency.
Source: CareerBuilder.com

C Additional Results and Robustness

C.1 Wage Posting

Cross-Sectional Variance. Table C.1 displays our results regarding whether firms post a wage or not. Using a linear probability model, we find that both job titles (column I) and firm fixed effects (column II) have high explanatory power for the decision to post a wage: they each explain around 70% of the variance in wage-posting behavior. Including both simultaneously essentially explains all of the variation in job posting behavior (the R^2 is 0.93 in column III).

Including additional job characteristics improves the model fit only slightly (column IV), although some characteristics have a statistically significant impact on the posting decision. For example, jobs that require a high school degree or a 4-year college degree are significantly more likely (5 and 1 percentage points, respectively) to post a wage than jobs that require a 2-year college degree. On the other hand, jobs that require a graduate degree are significantly less likely (3 percentage points) to post a wage than jobs that require a 2-year college degree. Jobs that do not specify an education requirement are also less likely to post a wage (2 percentage points).[1]

Word Analysis. The words that significantly increase or decrease the probability that a job ad contains a wage are displayed in Figure C.1. Unlike the figure for the wage level, this figure does not show a clear pattern. In particular, both "high-wage" words and "low-wage" words (from Figure B.1) can predict a higher probability of posting a wage. For example, if we consider words indicating seniority, then both "manager" (higher wage) and "junior" (lower wage) increase the probability that a wage is present in the ad, while "chief" (higher wage) and "representative" (lower wage) decrease this probability. If we consider words indicating specialization, then both "web" (higher wage) and "retail" (lower wage) increase the probability of posting a wage, while both "-" (higher wage) and "associate" (lower wage) decrease the probability of posting a wage.

C.2 Wage Variance Results

Effect of Occupations and Job Titles. We investigate the effect of occupational controls on the wage variance in both the CareerBuilder data and the CPS. Although we do not observe job titles in the CPS, we can control for occupations via the SOC codes. The first three columns

[1] Brencic (2012) performs a similar exercise for three different countries. For the US, using data from Monster.com, she finds that jobs requiring a college degree are more likely to post a wage than jobs requiring high school, while jobs requiring a graduate degree are the least likely to post a wage.

of Table C.2 present wage regressions for the CPS with increasingly finer occupation controls, using CPS weights for the outgoing rotation group. In column I, we regress log weekly earnings on the most aggregated classification (*major* occupations), distinguishing 11 different occupations. This explains approximately 15% of the variation in the wages. Column II and III show the specifications with 23 *minor* and 523 *detailed* occupations[2], respectively. This increases the (adjusted) R^2. The most detailed occupational classification available in the CPS explains slightly over a third of the wage variance (column III), leaving about two thirds of the wage variance unexplained.

In columns IV, V, and VI, we use the *posted* wages from the CareerBuilder sample and run the same specifications as in columns I, II, and III. The results in terms of the explained wage variation are strikingly similar to the CPS sample: major occupations explain about 15% of the variance in posted wages and detailed occupations explain slightly over a third of the variance.

While the most detailed SOC codes available in the CPS distinguish between 523 occupations, the CareerBuilder data of course allows us to control for job titles. As column VII shows, this explains more than 90% of the variance in posted wages (column VII). That is, relatively little variation in posted wages remains within a job title.

Robustness. The results in Table C.2 indicate that job title fixed effects can explain most of the cross-sectional variation in wages. A natural concern is that part of this effect is mechanical as our data set contains many different job titles. We explore the robustness of the effect in a number of ways.

First, we perform a permutation test in which we re-estimate the specification with job title fixed effects (column II) 1000 times with randomly re-assigned wages. The average adjusted R^2 is 0 in this case, confirming that our results are not simply the result of the large number of job titles.[3]

Second, we limit the sample to job titles that appear at least two, three or four times. This does not change the results, as can be seen from Table C.3: even when focusing on job titles that appear in at least $n \in \{2,3,4\}$ job postings, we find that job titles explain around 90% of the variance in posted wages.

Third, we explore the explanatory power of the first n words of the job title for various values of n. Table C.4 displays the results. The first word of the job title already has a great

[2]The CareerBuilder data uses the SOC 2000 classification while CPS uses Census occupational codes based on SOC 2010. To address this difference in classification, we converted SOC 2000 to SOC 2010 and then to Census codes. Because SOC 2010 is more detailed than the SOC 2000, a small number of Census codes had to be slightly aggregated. In Table C.2, the same occupational classifications are used for both CareerBuilder and CPS data.

[3]These results are available upon request.

deal of explanatory power: first word fixed effects explain about 60% of the wage variance. Astonishingly, the first word of the job title has greater explanatory power than the most detailed occupational classification that can be used in the CPS (see Table C.2, column VI). Using the first three words of the job title significantly improves the explanatory power of the model, with an R^2 of 0.93. Using the first four words only slightly improves the explanatory power compared to using the first three words. Finally, using all words in the job title essentially does not add any explanatory power compared to using the first four words. These results show that the first four words of the job title convey almost all of the information that is relevant for posted wages, and justify our choice of using the first four words to define the job title.

Fourth, we explore the explanatory power of a small number of frequent words, i.e. those listed in Table 4. In particular, we take the wage residuals after regressing log yearly posted wages on detailed SOC codes fixed effects, and we regress those residuals on fixed effects for each of the frequent words. The results of this exercise are presented in Table C.5. We find that the frequent words already explain 23% of the variation in the wage residuals (column III). More than half of this explanatory power is due to the words indicating seniority (column IV), while the remaining explanatory power is roughly equally divided between words indicating specialties related to computers and other specialties (column V and VI).

Fifth, we explore how sensitive the explanatory power of job titles is to the definition of the wage. Firms often post a wage range rather than a single wage, and we have focused so far on explaining the midpoint of this range. In Table C.6, we show that job titles are just as powerful in explaining the minimum of the range (column I) and the maximum of the range (column III). We also find, again, that SOC codes explain less than 40% of the variance in the minimum or the maximum offered wage (columns II and IV). Finally, we investigate the power of job titles in explaining how large the wage range is. We define the wage range as the maximum minus the minimum divided by the midpoint. We divide the range by the midpoint to adjust for the fact that higher wage jobs may also have larger absolute ranges. This range variable takes the value of zero when only one wage value is posted. Remarkably, we find that job titles have high explanatory power for wage ranges as well: they explain about 80% of the variance in the wage range. By contrast, SOC codes only explain about 20% of the variance in the wage range. We conclude that job titles explain most of the variance in the minimum, the midpoint and the maximum of the posted wage range, as well as in the size of the posted wage range.

Table C.1: Explaining wage posting behavior

VARIABLES	I Posts wage	II Posts wage	III Posts wage	IV Posts wage	V Firm f.e.
Job title f.e.	Yes***		Yes***	Yes***	Yes***
Firm f.e.		Yes***	Yes***	Yes***	
Job characteristics				Yes***	
Observations	61,132	61,135	61,132	61,132	61,132
R^2	0.747	0.697	0.928	0.933	0.765
Adj. R^2	0.619	0.672	0.884	0.892	0.647
AIC	-21,907	-11,056	-93,107	-97,856	-48,551

Note: Linear probability model. In columns I-IV, the dependent variable is log yearly posted wage. In column V, the dependent variable is the firm effect estimated in column I. Stars next to "Yes" show the level of significance of the F-test for the joint significance of that group of controls: $^{***}p < 0.01$, $^{**}\ p < 0.05$, $^{*}\ p < 0.1$. Job characteristics include vacancy duration, a dummy for salary expressed per hour, required education and experience, designated market area, and calendar month.
Source: CareerBuilder.com.

Table C.2: Using SOC codes fixed effects to explain wages: CPS vs CareerBuilder data

	CPS			CareerBuilder			
	Major	Minor	Detailed	Major	Minor	Detailed	Job Titles
	I	II	III	IV	V	VI	VII
Observations	1,587	1,587	1,587	10,465	10,465	10,465	10,465
R^2	0.149	0.195	0.480	0.144	0.167	0.412	0.943
Adj. R^2	0.144	0.184	0.362	0.143	0.166	0.387	0.907
AIC	4,369	4,280	3,587	15,414	15,125	11,487	-12,925

Note: In columns I-III, the dependent variable is log weekly earnings. In columns IV-VII, the dependent variable is log yearly posted wage. Columns II and IV control for major occupation groups fixed effects. Columns II and V control for minor occupation groups fixed effects. Columns III and VI control for detailed occupation groups fixed effects. Column VII controls for job title fixed effects. The specifications in columns IV-VII only use jobs for which an SOC code was present.
Source: Current Population Survey and CareerBuilder.com.

Table C.3: Explaining the variation in posted wages: sample restricted to job titles that appear at least n times

VARIABLES	I $n=1$	II $n=2$	III $n=3$	IV $n=4$	V
Job title f.e.	Yes***	Yes***	Yes***	Yes***	
Observations	11,715	10,467	6,301	5,622	
R^2	0.902	0.937	0.893	0.880	
Adj. R^2	0.840	0.908	0.865	0.853	

Note: The dependent variable is log yearly posted wage. In column V, the dependent variable is the firm effect estimated in column I. Stars next to "Yes" show the level of significance of the F-test for the joint significance of that group of controls: ***$p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Source: CareerBuilder.com.

Table C.4: Posted wages: the explanatory power of job titles and how it varies with truncating the job title after the first *n* words

VARIABLES	I Posted wage	II Posted wage	III Posted wage	IV Posted wage	V Posted wage
Job title f.e.	1 word	2 word	3 words	4 words	All words
Observations	11,715	11,715	11,715	11,715	11,715
R^2	0.610	0.865	0.925	0.944	0.946
Adj. R^2	0.568	0.817	0.885	0.909	0.910
AIC	8,416	-4,010	-10,968	-14,359	-14,726

Note: All columns include job title fixed effects, but the definition of job title is different in each column. In column V, all words in the job title are used to define the job title. In columns I-IV, the first *n* words are used to define the job title.
Source: CareerBuilder.com.

Table C.5: Using words to explain within SOC wage variation

VARIABLES	I Resid.	II Resid.	III Resid.	IV Resid.	V Resid.	VI Resid.
Job title f.e.	Yes					
Words in job title f.e.		Yes				
Frequent words f.e.			Yes			
Frequent words denoting ...						
seniority				Yes		
specialties					Yes	
computer terms						Yes
Observations	11,715	11,715	11,715	11,715	11,715	11,715
R^2	0.871	0.571	0.226	0.136	0.054	0.051
Adj. R^2	0.790	0.490	0.222	0.135	0.052	0.051

Note: The dependent variable is wage residuals after a regression of log yearly posted wage on detailed SOC codes fixed effects. f.e. stands for fixed effects. Frequent words are those listed in Table 4. Frequent words denoting seniority, specialties and computer terms are those in the first, second and third column of Table 4, respectively.
Source: CareerBuilder.com.

Table C.6: Explaining the variation in posted wages: minimum wage offered, maximum wage offered, and wage range

	Min. offered wage		Max. offered wage		Wage range	
	I	II	III	IV	V	VI
Job title f.e.	Yes		Yes		Yes	
SOC f.e.		Yes		Yes		Yes
Observations	11,717	11,717	12,383	12,383	11,898	11,898
R-squared	0.941	0.399	0.943	0.386	0.861	0.236
Adj. R-squared	0.904	0.367	0.908	0.354	0.772	0.196
AIC	-14,347	12,891	-12,721	16,778	-29,113	-8,849

Note: “Wage range” is the maximum offered wage minus the minimum offered wage divided by the midpoint of the range.
Source: CareerBuilder.com.

Figure C.1: Words that predict probability of posting a wage within a given SOC code

Higher Probability:

[0.015;0.042]; [0.046;0.107]; [0.109;0.859] percentage points

Lower Probability:

[-0.720;-0.048]; [-0.046;-0.032]; [-0.027;-0.027] percentage points

Note: The words included are significant at the 5% level in explaining the residuals after a regression of the "Posts wage" dummy on SOC codes fixed effects and appear at least 10 times. The big rectangle is "-", which typically separates the main job title from additional details. Word cloud created using www.tagul.com. The size of a word represents its frequency, while the color represents the tercile of its coefficient, weighted by frequency.
Source: CareerBuilder.com

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