Posted Wage Inequality

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Roadmap

Motivation

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  $\rightarrow$ Worker heterogeneity + Firm heterogeneity + W-F sorting + ...

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- Results from the literature:
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  2. 5-15% firm effect $\rightarrow$ variations in firm wage premiums
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  (Q: *Only available for a limited set of developed countries. Other countries? Alternative ways?*)

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  (Q: *Do we fully understand any of these components? Deep drivers? Heterogeneity?*)

This Paper - New Method

- A new way to study wage determination taking advantage of
  1. Online job vacancy/ads data
  2. Machine learning algorithms

- Key idea: worker $\sim$ job

  As firms document all the job characteristics to attract their ideal candidates, and post wage based on their valuation ▸ vacancy sample

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- Advantage:
    1. Vacancy data is more accessible & up-to-date
       $\rightarrow$ EE data is not always available, e.g. China
    2. Not only alternative but also ideal environment for studying firm effect & sorting
       $\rightarrow$ Pre-bargaining; Pre-mismatch
    3. Estimation is more flexible & parsimonious
       $\rightarrow$ No restriction on connected set or exogenous mobility, less limited mobility bias
    4. Open the black box of worker effect in a data-driven way
       $\rightarrow$ See what are the important skills/tasks contributing to wage differential & sorting

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   1.1 Feature Selection
   1.2 Feature Clustering
   1.3 Dimensional Reduction

   two methods (w/ & w/o human knowledge)

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3. Extensive analysis: Examine potential heterogeneity of skill prices & firm wage premium and the driver of inequality trend

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2. Our approach shows a data-driven skill/task structure featured by different specificity levels
3. For the posted wage variations from job effect and firm-job sorting
   - Occupation-specific skills/tasks account for the major shares, esp. in high-skill occupation; Extensive/Intensive margin (Exp) are equally important
   - Education-related skills/tasks account for more shares in low-skill occupation
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4. Levels of skill prices & of firm wage premiums (& sorting) vary across occupations
5. Increased posted wage variance in our data is largely driven by increased sorting, esp. from those occupation-specific skills/tasks

Roadmap

Data: Basic Info

`Lagou.com`: the largest IT-centered online job board in China (mostly "cognitive jobs")

- Over 6 million vacancies between 2013 and 2020 ▸ vacancy trend
- Mainly jobs in all occupations demanded by IT-producing/using firms: Computer, Design & Media, Business Operation, Financial & Law, Sales, Admin ▸ occupation classification
- Like other vacancy data, biased to young/low-experienced and high education workers/jobs in large cities ▸ details & reliefs
- Vacancy information: job name, posted wage, location, requirements on education and experience, job task or skill description, job benefits, firm name, ... ▸ vacancy sample
- Final Sample after cleaning: 4 million vacancies ▸ sample cleaning ▸ summary statistics

Potential concerns: various data/sample representativeness issues ▸ details & reliefs

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2. Data
3. Econometric Setting
4. Machine Learning Vacancy
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Posted Wage Regression

- Baseline: $\ln w_i = X_i\beta + \psi_j + \iota_t + \epsilon_i$
  - w_i is the mean of the posted wage scope
  - X_i is a vector of job characteristics, denote $\theta_i \equiv X_i\beta$
  - ψ_j is the firm effects
  - ι_t is the year effects

- Estimated β will be the market average prices of the job characteristics

- Estimated ψ_j will be the firm-specific wage premiums/discounts for any reasons

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- Estimated ψ_j will be the firm-specific wage premiums/discounts for any reasons
- $\hat{\beta}$ and $\hat{\psi}_j$ would be biased if $\text{cov}\left(X_i, \epsilon_i\right) \neq 0$ and $\text{cov}\left(\psi_j, \epsilon_i\right) \neq 0$
- $\text{var}\left(\ln w_i\right) = \underbrace{\text{var}\left(\theta_i\right)}_{\text{Job Effect}} + \underbrace{\text{var}\left(\psi_j\right)}_{\text{Firm Effect}} + \underbrace{2\,\text{cov}\left(\theta_i, \psi_j\right)}_{\text{Firm-Job Sorting}} + \text{var}\left(\epsilon_i\right)$

Education, Experience, Occupation $\subset$ {Skills, Tasks}

- One way: $X = \{\text{EDU, EXP, OCC}\}$ ▸ results ▸ compare with $X = \{\text{EDU, EXP}\}$ ▸ bias correction

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- All are different subspaces of the full skill/task space
- In theory, an occupation is a subset in the skill/task space
  - A pre-defined bundle of different skills/tasks
  - Lack of within-occupation skill/task variations
- In practice, occupation info of vacancy data is generated by mapping job title or content to the official categories ▸ occupation classifiction

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- In practice, occupation info of vacancy data is generated by mapping job title or content to the official categories ▸ occupation classifiction
- Below, we directly exploit all information in vacancy texts to create proxy variables for various skills/tasks
  - By doing this, we also show a data-driven skill/task structure

Roadmap

Overview of ML Procedures

▸ Jump to Results

1. Feature Selection: *110,000+* $\rightarrow$ *3100+*
   Transform vacancy documents $\mathbf{D}$ to an indicator matrix $\mathbf{C}$ ($N \times K$), where $K = |V|$;
   Run Lasso regression of $\ln w$ on $\mathbf{C}$ to shrink the entire vacancy text vocabulary set V V to a vocabulary subset V' (and $\mathbf{C}$ to $\mathbf{C}'$)

▸ Lasso detail ▸ Lasso turning by BIC ▸ Lasso inference & sanity check

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2. Feature Clustering: *3100+* $\to$ *8 groups*
   Train a word embedding model (Word2Vec) on vacancy text $\mathbf{D}$ to obtain the embedding space representation for selected features: $\mathbf{U}' \equiv \{\mathbf{u}_k\}$ where $k \in V'$;
   Apply K-Means classifier to $\mathbf{U}'$ generate P $(= 8)$ clusters $\{V'_p\}_{p=1}^{P}$

   ▸ word embedding detail ▸ K-Means detail ▸ a data driven skill & task space ▸ a data driven skill & task space

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   ▸ word embedding detail ▸ K-Means detail ▸ a data driven skill & task space ▸ a data driven skill & task space

3. Dimensional Reduction: *3100+* $\rightarrow$ *8* $\times$ *3 = 24*
   Use PLS to transform each $\mathbf{C'}_p \equiv \{\mathbf{c}_k\}$, $k \in V'_p$ into a low dimensional representation Ξ_p ($N \times Q$; $Q = 3$) and obtain $\{\Xi_p\}_{p=1}^{P}$
   ▸ dimensional reduction detail

Feature Selection: Lasso Regression

▸ Overview

1st step: extract the useful information in vacancy text

- First we transform the vacancy text into an indicator matrix **C** with dimension $N \times K$ where each entry c_{ik} is an indicator of a token (word/phrase) k in vacancy i and the total vocabulary set is V

- Then we use (regularized linear) Lasso regression (L1 penalization):
  $\hat{\zeta} = \underset{\zeta}{\arg\min} \sum_{i=1}^{N} \left(\ln w_i - \sum_{k=1}^{K} c_{ik} \zeta_k \right)^2 + \lambda \sum_{k=1}^{K} |\zeta_k|$

Feature Selection: Tune Lasso ▸ Overview

- Following the suggestion in the literature, we use BIC as the criterion to gauge the hyperparameter λ: $\min \mathrm{BIC}(\lambda) = \frac{\| \ln \mathbf{w} - \mathbf{C}\hat{\zeta}_\lambda \|^2}{\sigma^2} + \widehat{df}_\lambda \log N$
- The estimation results 700-3100 features (V') with nonzero coefficients

	Pooled	Computer	Design_ Media	Admin
λ^*	332.0	190.3	238.5	155.0
MSE	.162	.149	.142	.100
R^2	.566	.494	.461	.418
BIC/N	.446	.527	.561	.613
df	3,144	1,922	929	691
K	109,123	51,602	39,306	24,896
N	3,999,005	1,330,001	561,236	277,932

Feature Selection: Inference and Interpretation on Lasso Results

▸ Overview

- In general, features selected and their coefficients in high-dimensional penalized model are not interpretable due to multicollinearity and flexibility
- Inference via subsampling (10x10) shows that our selected features/tokens are rather robust (small confidence interval) ▸ subsampling results
- Interpretation on coefficients are still forbidden, but now we can inspect important features to see if they make some intuitive sense ▸ top positive tokens ▸ top negative tokens

Feature Clustering: Word Embedding ▸ Overview

2nd step: examine what are these selected features (beyond eyeballing)

- Indicator matrix $\mathbf{C}$ tells nothing about the meaning of the words
- We train a word embedding model, Word2Vec (CBOW), to learn the relationship between tokens
  - it maps each word to a latent vector space (with dimension $H = 100$), which best predicts the probability of a word given the context (adjacent words)
- The result is a $K \times H$ embedding weight matrix $\mathbf{U}$, where each row of the matrix, $\mathbf{u}_k$, is the representation vector of the word k in the latent embedding space
- We only use the part of the selected features: $\mathbf{U}' \equiv \{\mathbf{u}_k\}$ where $k \in V'$

Feature Clustering: K-Means Clustering ‣ Overview

- We now can use unsupervised clustering algorithms to cluster our selected features
- We use K-Means classifier, which finds the centroids for the clusters $\{V'_p\}$ in the embedding space to minimize the sum of within-cluster Euclidean distances:

$$\underset{\{V'_1, V'_2, \ldots, V'_P\}}{\arg\min} \sum_{p=1}^{P} \sum_{k \in V'_p} \left\| \mathbf{u}_k - \frac{1}{|V'_p|} \sum_{j \in V'_p} \mathbf{u}_j \right\|^2$$

- P is the predetermined cluster numbers, and we set $P = 8$ *(arbitrary)*
- Visualization of clustering results in 2D (through t-SNE only for demonstration):

‣ Pooled ‣ Computer ‣ Design & Media ‣ Admin

Feature Clustering: Skill/Task Structure ▸ Overview

A data-driven skill/task structure shows layers of specificity ▸ specificity measure

0. Compensation (V'_c)
1. General skills (V'_g)
   - Cognitive: e.g. logic, self-learning
   - Interpersonal: e.g. communication, extrovert
   - Non-cognitive: e.g. hard working, responsibility
2. Education-related or -extensive skills (V'_e)
   - e.g. education level, college majors, certificates, fundamental occupational skills, basic field experience
3. Occupation-specific skills and tasks ($V'_{s1}, \ldots, V'_{s5}$)
   - e.g. c++, python, graphic design, logistic management, audit, business negotiation, client responding, ...

(way more granular than cognitive/social/... dimension or traditional occ dimension)

Dimension Reduction

▸ Overview

3rd step: further reduce the dimension of these features

- Instead of PCA (unsupervised), we use partial least squares (PLS) (supervised) regression which uses the covariance of the predictive and target variables
- Transform the indicator matrix $\mathbf{C'}_p \equiv \{\mathbf{c}_k\}, k \in V'_p$ of each cluster p into a low dimensional representation Ξ_p; Set reduced dimension $Q = 3$ *(arbitrary)*
- Thus for each occupation, we now have 8 proxy matrices (linear combination) $\Xi_1, \Xi_2, \ldots, \Xi_8$ corresponding to 8 clusters $V'_1, V'_2, \ldots, V'_8$
- OLS regressions show that they preserve over 95% predictive power (R^2) of the Lasso regression

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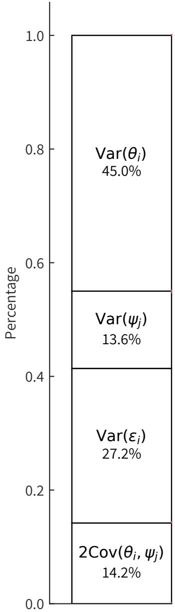
Proxy Variables on Skills & Tasks

- Under our construction, $\{\Xi_g, \Xi_e, \Xi_{s1}, \dots, \Xi_{s5}\}$ proximate to a full set of skills/tasks required in the vacancy that are predictive for posted wage
- Our final specification of job controls: $X = \{X_{ext}, X_{int}\}$
  - $X_{ext} \equiv \{\text{EDU}, \Xi_g, \Xi_e, \Xi_{s1}, \dots, \Xi_{s5}\}$, (extensive margin)
  - $X_{int} \equiv \{\text{EXP}\}$ (intensive margin) ▸ compare R2
- We further split X_{ext} into three groups:
  - Most general group: Ξ_g
  - Medium specific group: $\Xi_m \equiv \{\text{EDU}, \Xi_e\}$
  - Most specific group: $\Xi_s \equiv \{\Xi_{s1}, \dots, \Xi_{s5}\}$

Variance Decomposition



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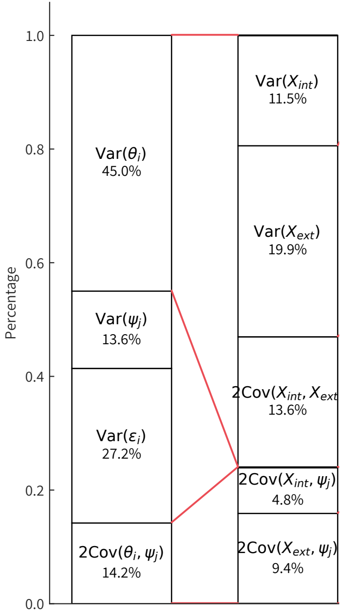

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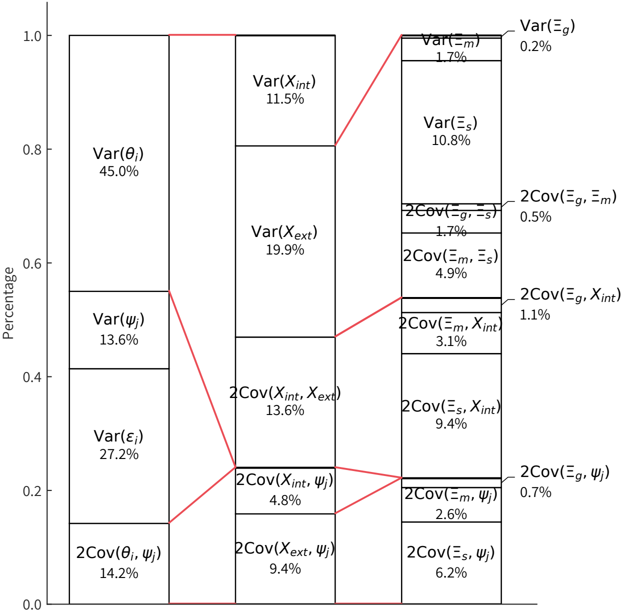


Variance Decomposition: Robustness

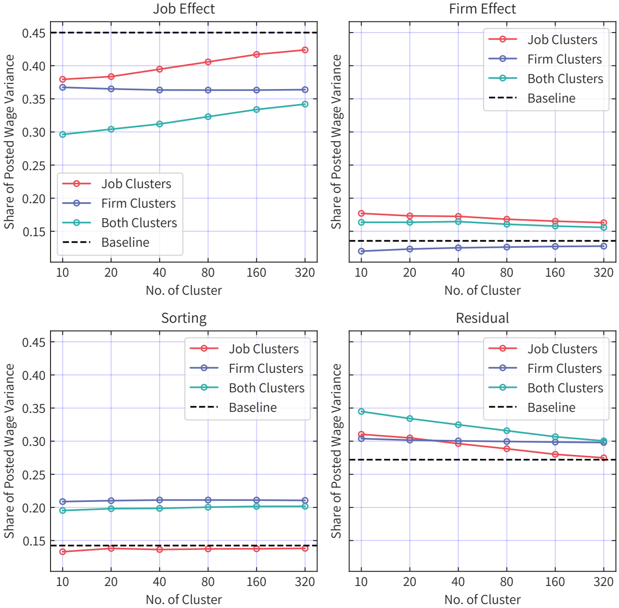
- Limited mobility bias is limited as long as firms have enough number of vacancies
  ▸ bias correction
- Education or Experience composition does not drive our results ▸ conditional on EXP & EDU
- Switching Ξ_4 from Ξ_s to Ξ_m has strongest impact on Admin sample ▸ $\Xi_m \equiv \{\text{EDU}, \Xi_4\}$
- Can still largely replicate the results in Deming and Kahn (2018) ▸ replicate DK ▸ app
- Non-wage compensation terms selected by Lasso largely because they can predict job and firm effects ▸ add Ξ_0 into regression
- Estimated firm wage premium are positively correlated with firm size (conditional on sorting) and accounted by firm location, consistent with the literature ▸ firm FE regression
- Mean residuals by firm-job cells show that the linear (additive separability) assumption seems to be a worse approximation in pooled sample ▸ mean residual distribution

Roadmap

A Shortcut

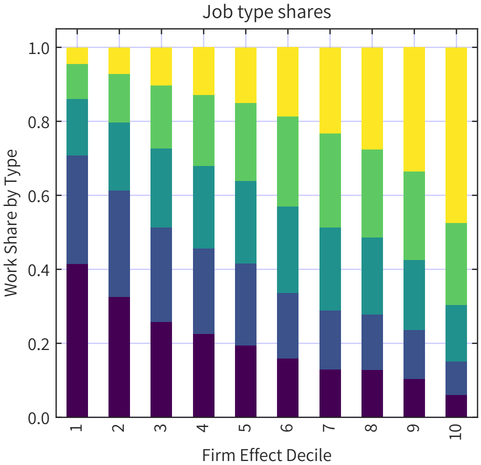
- Occupation is itself a concept born from skill/task specificity, though too coarse
- Bonhomme et al. (2019) suggests another way to solve the finite sample bias: estimating latent firm groups: $\min_{\mathfrak{k}_1,\ldots,\mathfrak{k}_J, H_1,\ldots,H_{\mathfrak{K}}} \sum_{j=1}^{J} n_j \int \left(\widehat{F}_j(y) - H_{\mathfrak{k}_j}(y)\right)^2 d\mu(y)$
- Here we can also use our embedding space representation to classify latent job groups:
  - First, for each vacancy: $\mathbf{z}_i = \sum_{k \in V_i} \mathbf{u}_k = (z_{i1}, \ldots, z_{iH})$
  - Then, $\min_{\{\mathfrak{l}_1,\ldots,\mathfrak{l}_I, G_1,\ldots,G_{\mathfrak{L}}\}} \sum_{i=1}^{I} \sum_{h=1}^{H} \left(z_{ih} - G_{\mathfrak{l}_i}(h)\right)^2$
  - This can be seen as a way to generate occupations with arbitrary number $\mathfrak{L}$

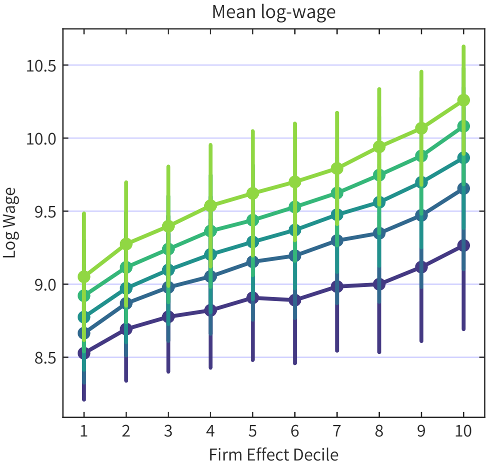
A Shortcut



Job Effect
Firm Effect
Sorting
Residual
Share of Posted Wage Variance
No. of Cluster
0.45
0.40
0.35
0.30
0.25
0.20
0.15
10
20
40
80
160
320
Job Clusters
Firm Clusters
Both Clusters
Baseline

Work Types and Posted Wage by Firm Types





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Firm Wage Premium Varies Across Occupations

- Shares of firm effect and sorting (job effect) are larger (smaller) in high-skill occupation than low skill occupation, despite of more features ‣ compare shares
- We also find for low-skilled occupations have estimated firm effects less consistent with the firm effects estimated in high-skilled occupation ‣ compare firm FE

Occupational Specific Specification

- Allow for firm wage premiums varying across major occupations
  $\ln w_i = X_i\beta + \psi_j^o + \iota_t + \epsilon_i$
  - Also compare with $\ln w_i = X_i\beta + \psi_j + o_i + \iota_t + \epsilon_i$

	Benchmark		$\psi_j \equiv \hat{\psi}_j + \hat{o}_i$		$\psi_j \equiv \hat{\psi}_j^o$	
	Comp.	Share	Comp.	Share	Comp.	Share
$\mathrm{Var}(\ln w)$	.362	-	.362	-	.360	-
$\mathrm{Var}(\theta_i)$	.163	.450	.141	.391	.136	.378
$\mathrm{Var}(\epsilon_i)$	.098	.272	.096	.265	.088	.245
$\mathrm{Var}(\psi_j)$	.049	.136	.056	.156	.065	.182
$2\,\mathrm{Cov}(\theta_i, \psi_j)$	.051	.142	.068	.188	.070	.196
Obs	3998840		3998840		3926231	
Firm	86165		86165		300079	

mean residual distribution

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- Allow for skill prices varying across major occupations
  $\ln w_i = \sum_o \mathbb{1}_{[i\in o]} X_i\beta_o + \psi_j + \iota_t + \epsilon_i$

	Benchmark		$\psi_j \equiv \hat{\psi}_j + \hat{o}_i$		$\psi_j \equiv \hat{\psi}_j^o$		$\theta_i \equiv X\hat{\beta}_o$	
	Comp.	Share	Comp.	Share	Comp.	Share	Comp.	Share
$\mathrm{Var}(\ln w)$	.362	-	.362	-	.360	-	.361	-
$\mathrm{Var}(\theta_i)$	.163	.450	.141	.391	.136	.378	.170	.470
$\mathrm{Var}(\epsilon_i)$	.098	.272	.096	.265	.088	.245	.092	.255
$\mathrm{Var}(\psi_j)$	.049	.136	.056	.156	.065	.182	.049	.136
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▸ mean residual distribution

Shares Across Occupations

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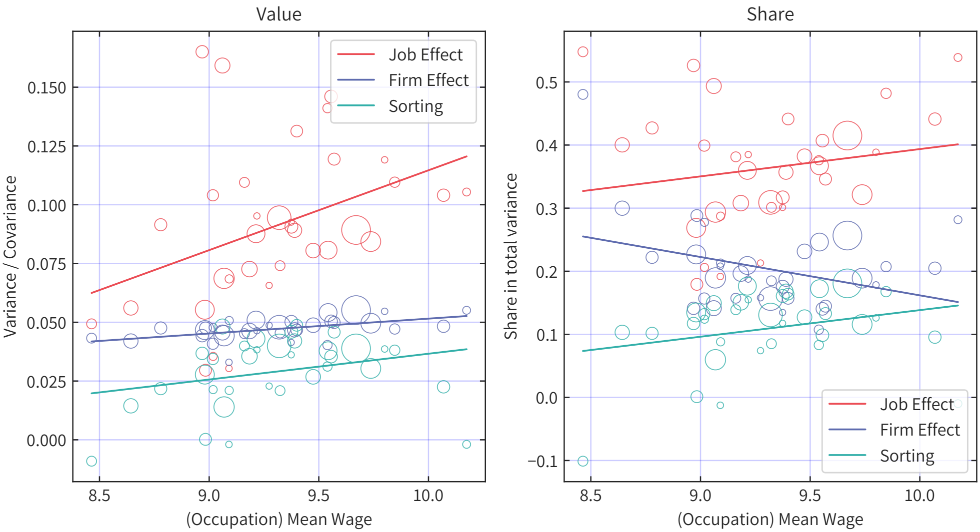

Shares Across Occupations

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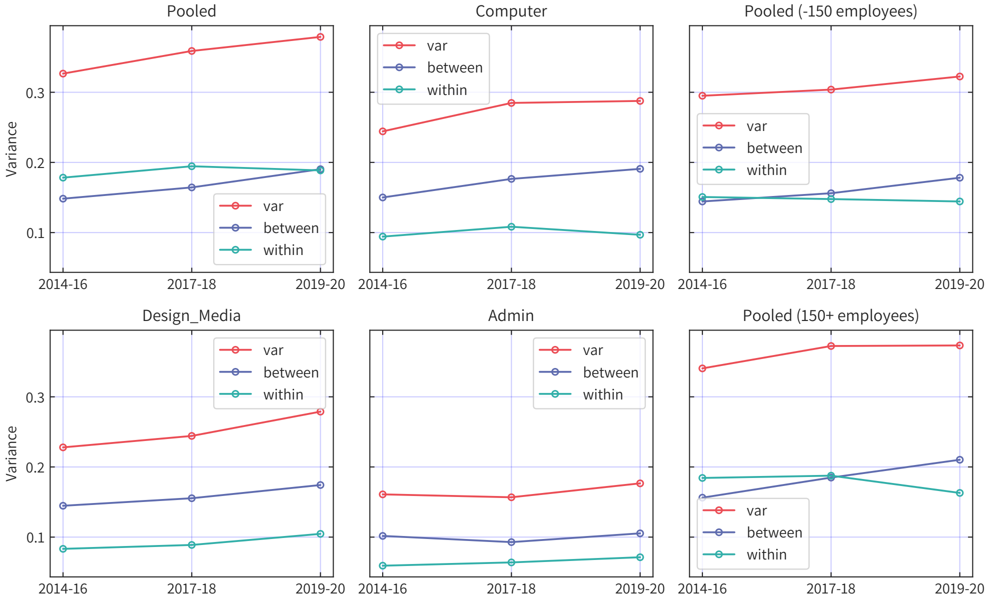
Posted Wage Variance Trend



Posted Wage Variance Trend Drivers

$\psi_j = \hat{\psi}_j^o$ new skills

	2014-2016		2017-2018		2019-2020	
	Comp.	Share	Comp.	Share	Comp.	Share
Var(ln w)	.326	-	.357	-	.377	-
Panel A: $X = \{$**EDU**, **EXP**, $\Xi_2, \ldots, \Xi_8\}$						
Var(θ_i)	.149	.455	.163	.457	.157	.417
Var(ϵ_i)	.096	.294	.092	.258	.094	.249
Var(ψ_j)	.048	.148	.050	.141	.059	.157
2 Cov(θ_i, ψ_j)	.033	.103	.051	.144	.067	.177
Panel B: Decompose θ Terms						
Var(X_{int})	.039	.121	.043	.120	.041	.109
Var(X_{ext})	.069	.212	.071	.198	.068	.180
2 Cov(X_{int}, X_{ext})	.040	.123	.049	.139	.048	.128
2 Cov(X_{int}, ψ_j)	.011	.035	.018	.051	.022	.059
2 Cov(X_{ext}, ψ_j)	.022	.067	.033	.093	.044	.118
Panel C: Further Decompose X_{ext} Terms						
Var(Ξ_g)	.001	.003	.001	.002	.001	.002
Var(Ξ_m)	.005	.016	.006	.017	.006	.015
Var(Ξ_s)	.039	.120	.039	.109	.037	.098
2 Cov(Ξ_g, Ξ_m)	.002	.006	.002	.005	.002	.004
2 Cov(Ξ_g, Ξ_s)	.007	.021	.006	.016	.006	.015
2 Cov(Ξ_m, Ξ_s)	.015	.046	.018	.049	.017	.045
2 Cov(Ξ_g, X_{int})	.004	.011	.004	.010	.004	.010
2 Cov(Ξ_m, X_{int})	.009	.027	.011	.032	.011	.028
2 Cov(Ξ_s, X_{int})	.028	.085	.034	.096	.034	.090
2 Cov(Ξ_g, ψ_j)	.002	.005	.002	.006	.003	.008
2 Cov(Ξ_m, ψ_j)	.007	.020	.010	.027	.011	.030
2 Cov(Ξ_s, ψ_j)	.014	.043	.022	.060	.030	.080
Obs	930149		1494468		1565866	
Firm	41750		62907		53662	

Roadmap

1. Introduction
2. Data
3. Econometric Setting
4. Machine Learning Vacancy
5. Main Results
6. A Short Cut
7. Extensive Analyses
8. Conclusion

Take-Away Message

1. Vacancy data + ML $\sim$ EE data + AKM
2. Specificity is (still) an important dimension to think about multidimensional skill/task space
3. Occ-specific & Exp-related skill/task variations are the most important for wage inequality & firm-worker sorting
4. Firms do pay differently for similar-looking jobs, but also varying across occupations
5. Increased posted wage variances in our data is largely due to increased firm-job sorting

Appendix

Data Concerns & Reliefs

Back Intro Back Data

- Vacancy data may be selective or less representative
  - Vacancy data is incline to young and more educated workers, esp. here
  - Not all jobs on the internet or different post frequency than job composition
  - Ideal match but not real match results
  - Only entry wage thus missing (re-)bargaining, discrimination, promotion, rent-sharing, revealing of worker ability or matching productivity, ...

(Valid issue for all vacancy data; Partially justified in the literature; Extent is an empirical question; Can improve with better data and adjust composition; Better fit liquid labor market; Not all bad for estimation)

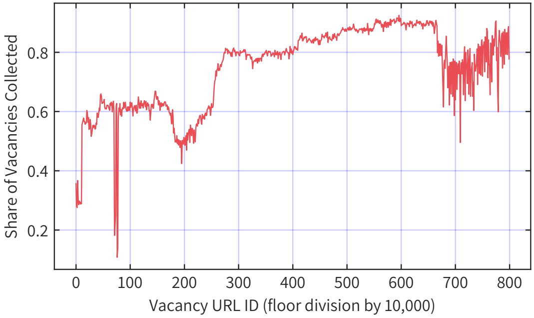
- Our wage measure incorporates variation in hours
  - One might worry that wage variation could be thus over-estimated
  - One might worry that those efficient compensations are solely compensating more working hours

(Often additional pay for overtime hours; Variation is limited comparing to wage; Inequality is often considered on overall compensation level; Need to think hour and wage as a package)

Trends on Collected Vacancies

Back

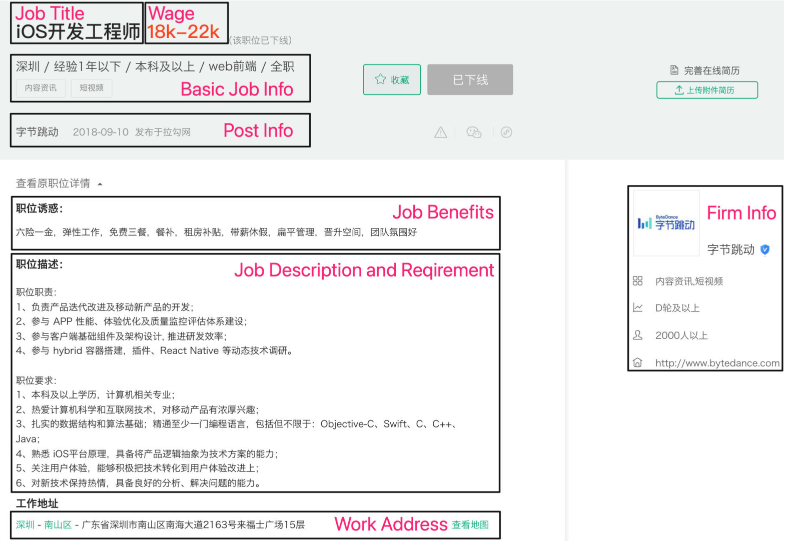
# of Vacancies by Posted Month



% of Vacancies by Post ID Chunks

A Sample Vacancy

◂ Back Intro ◂ Back Data



Job Title
iOS开发工程师

Wage
18k–22k

(该职位已下线)

深圳 / 经验1年以下 / 本科及以上 / web前端 / 全职

内容资讯 短视频

Basic Job Info

收藏 已下线

完善在线简历

上传附件简历

字节跳动 2018-09-10 发布于拉勾网

Post Info

查看原职位详情

职位诱惑：

Job Benefits

六险一金，弹性工作，免费三餐，餐补，租房补贴，带薪休假，扁平管理，晋升空间，团队氛围好

职位描述：

Job Description and Reqirement

职位职责：
1、负责产品迭代改进及移动新产品的开发；
2、参与 APP 性能、体验优化及质量监控评估体系建设；
3、参与客户端基础组件及架构设计，推进研发效率；
4、参与 hybrid 容器搭建，插件、React Native 等动态技术调研。

职位要求：
1、本科及以上学历，计算机相关专业；
2、热爱计算机科学和互联网技术，对移动产品有浓厚兴趣；
3、扎实的数据结构和算法基础；精通至少一门编程语言，包括但不限于：Objective-C、Swift、C、C++、Java；
4、熟悉 iOS平台原理，具备将产品逻辑抽象为技术方案的能力；
5、关注用户体验，能够积极把技术转化到用户体验改进上；
6、对新技术保持热情，具备良好的分析、解决问题的能力。

工作地址

深圳 - 南山区 - 广东省深圳市南山区南海大道2163号来福士广场15层

Work Address 查看地图

Firm Info

ByteDance 字节跳动

字节跳动

内容资讯,短视频

D轮及以上

2000人以上

http://www.bytedance.com

Sample Cleaning

Back

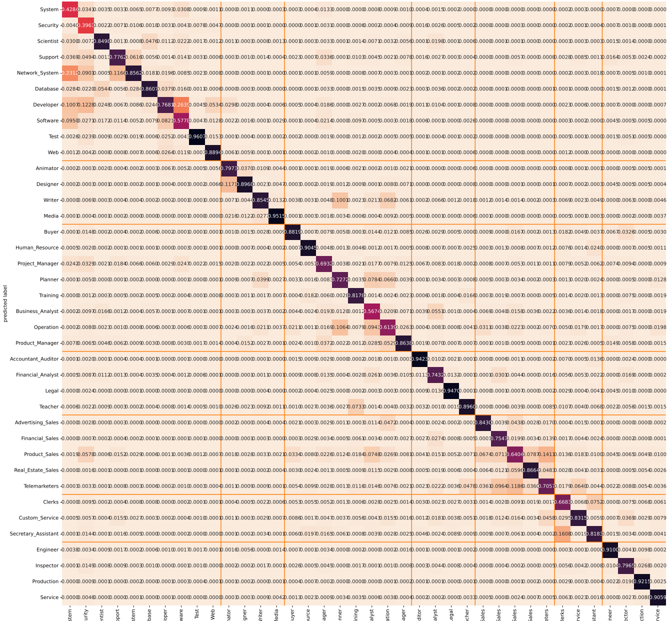
- Drop vacancies with not full-time jobs, outlier wages, job descriptions less than 20 words, nonChinese content
- Drop vacancies in 2013
- Drop vacancies from firms with less than 10 posts and from all the locations that have less than 1000 vacancies
- Drop duplicated vacancies based on job descriptions and education and experience requirements
- Drop vacancies with occupations not in selected major occupations

Data: Occupation Classification Back Data Back Estimation

- No ready-for-use occupation classification
- Match to a set of selected 6-digit occupations (”minor”) in six 2-digit occupations (”major”) in U.S. SOC 2018
- Key idea: an occupation is defined by a bundle of skills and tasks
- 1st step: for each occupation choose several exclusive keywords, and find the set of just-match vacancies as the ”learning” sample
- 2nd step: use the ”learning” group to train a Naive Bayes classifier based on the job titles and job descriptions
- 3rd step: apply the trained classifier to both the ”unknown” sample and the ”learning” sample confusion matrix

Confusion Matrix of Occupation Assignment

Back



Data: Summary Statistics ▸ back

	Pooled	Major Occupation					
	-	Computer	Design_ Media	Business_ Operations	Financial_ Legal	Sales	Admin
Vacancy #	3,999,005	1,330,001	561,236	1,162,404	214,661	452,771	277,932
- share	1.00	.33	.14	.29	.05	.11	.07
Avg # Words	108.91	104.26	103.05	115.60	110.69	120.31	95.09
Wage (1k CNY):							
- Mean	13.64	17.38	10.68	14.19	11.95	10.21	6.32
- SD	9.24	9.79	6.31	9.52	9.19	6.53	3.90
Firm:							
- #	86,330	67,369	68,092	78,244	41,285	58,847	59,016
- Avg Posts	46.32	19.74	8.24	14.86	5.20	7.69	4.71
- Median Posts	20.0	9.0	4.0	6.0	2.0	3.0	2.0
Firm Size (share):							
- -15	.03	.03	.05	.02	.02	.03	.03
- 15-50	.18	.17	.25	.16	.15	.19	.20
- 50-150	.23	.21	.26	.22	.22	.23	.26
- 150-500	.21	.21	.21	.22	.23	.20	.23
- 500-2000	.15	.16	.12	.16	.18	.15	.14
- 2000+	.20	.23	.11	.22	.21	.19	.13
Education (share):							
- Vocational College	.33	.24	.38	.29	.27	.51	.52
- Bachelor	.54	.66	.47	.61	.63	.22	.24
- Master/Doctor	.01	.02	.00	.01	.03	.00	.00
- Not Specified	.12	.08	.15	.09	.07	.27	.23
Experience (share):							
- 0	.22	.12	.21	.16	.25	.48	.50
- 1-3	.37	.33	.48	.37	.36	.31	.38
- 3-5	.31	.41	.25	.33	.26	.16	.10
- 5-10	.11	.14	.05	.14	.13	.05	.03

Data: Summary Statistics ‣ back

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- 150-500	.21	.21	.21	.22	.23	.20	.23
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- 3-5	.31	.41	.25	.33	.26	.16	.10
- 5-10	.11	.14	.05	.14	.13	.05	.03

Variance Decomposition

Back

	Pooled		Computer		Design_Media		Admin	
	Comp.	Share	Comp.	Share	Comp.	Share	Comp.	Share
Var(ln w)	.360	-	.279	-	.251	-	.164	-
Panel A: X={EDU, EXP}								
Var(θ_i)	.102	.283	.052	.188	.053	.212	.050	.307
Within-Firm:								
Var($\theta_i - \bar{\theta}_j$)	.072	.199	.037	.133	.036	.144	.033	.204
Var(ϵ_i)	.132	.367	.089	.318	.078	.310	.061	.371
Between-Firm:								
Var($\bar{\theta}_j$)	.030	.084	.015	.055	.017	.068	.017	.102
Var(ψ_j)	.076	.212	.102	.365	.086	.342	.041	.253
2 Cov($\bar{\theta}_j, \psi_j$)	.049	.137	.036	.130	.034	.136	.011	.069
Panel B: X={EDU, EXP, OCC} (Change from Panel A)								
Var(θ_i)	+.045	+.124	+.012	+.044	+.008	+.031	+.002	+.013
Within-Firm:								
Var($\theta_i - \bar{\theta}_j$)	+.031	+.087	+.012	+.043	+.004	+.015	+.002	+.010
Var(ϵ_i)	−.031	−.087	−.012	−.043	−.004	−.015	−.002	−.010
Between-Firm:								
Var($\bar{\theta}_j$)	+.013	+.037	+.000	+.002	+.004	+.017	+.001	+.005
Var(ψ_j)	−.012	−.033	−.006	−.021	−.007	−.028	−.001	−.008
2 Cov($\bar{\theta}_j, \psi_j$)	−.001	−.003	+.005	+.018	+.003	+.012	+.001	+.005
Obs	3998840		1325260		548808		260364	
Firm	86165		62628		55664		41448	

Variance Bias Correction ◂ Back

	Pooled		Computer		Design_Media		Admin	
	Comp.	Share	Comp.	Share	Comp.	Share	Comp.	Share
Var(ln w)	.360	-	.279	-	.251	-	.164	-
Panel A: Plug-In								
Var(θ_i)	.102	.283	.052	.188	.053	.212	.050	.307
Var(ϵ_i)	.132	.367	.089	.318	.078	.310	.061	.371
Var(ψ_j)	.076	.212	.102	.365	.086	.342	.041	.253
2 Cov(θ_j, ψ_j)	.049	.137	.036	.130	.034	.136	.011	.069
Panel B: Homoscedasticity Correction (Change from Panel A)								
Var(θ_i)	−.000	+.000	+.000	+.000	+.000	+.000	−.000	+.000
Var(ϵ_i)	+.003	+.009	+.004	+.016	+.009	+.035	+.011	+.070
Var(ψ_j)	−.003	−.008	−.004	−.016	−.009	−.035	−.011	−.070
2 Cov(θ_j, ψ_j)	+.000	+.000	−.000	+.000	−.000	+.000	+.000	+.000
Panel C: KSS (Leave-Out) Correction (Change from Panel A)								
Var(θ_i)	−.000	+.000	+.000	+.000	−.000	+.000	−.000	+.000
Var(ϵ_i)	+.003	+.007	+.004	+.014	+.007	+.029	+.010	+.060
Var(ψ_j)	−.003	−.007	−.004	−.015	−.007	−.028	−.010	−.060
2 Cov(θ_j, ψ_j)	+.000	+.001	−.000	+.000	+.000	+.000	−.000	+.000
Obs	3998840		1325260		548808		260364	
Firm	86165		62628		55664		41448	

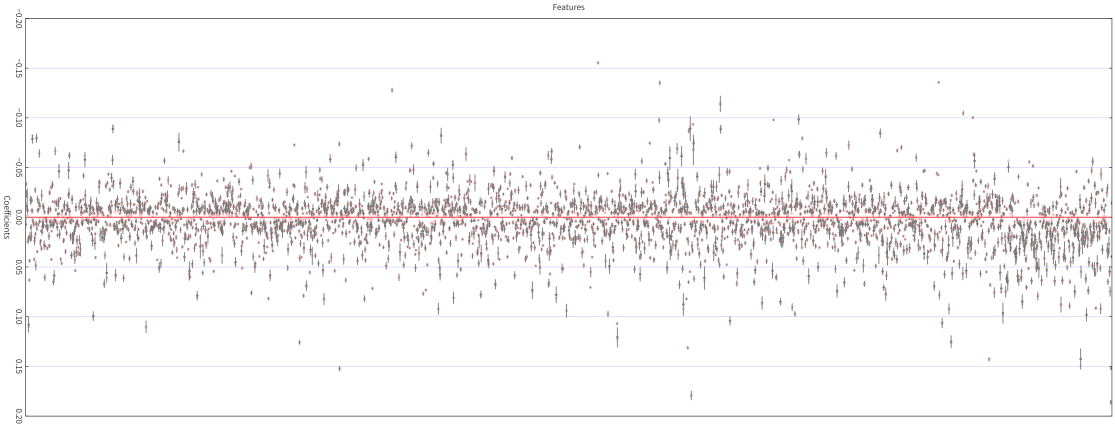
Variance Decomposition

Back

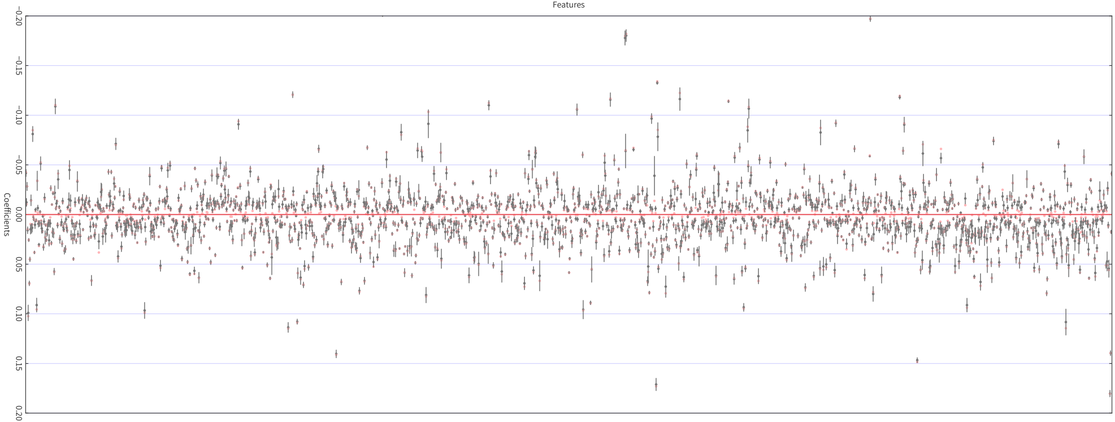
	Pooled		Computer		Design_Media		Admin	
	Comp.	Share	Comp.	Share	Comp.	Share	Comp.	Share
$\mathrm{Var}(\ln w)$	.360	-	.279	-	.251	-	.164	-
Panel A: X={EDU, EXP}								
$\mathrm{Var}(\theta_i)$	.102	.283	.052	.188	.053	.212	.050	.307
Within-Firm:								
$\mathrm{Var}(\theta_i - \bar{\theta}_j)$	.072	.199	.037	.133	.036	.144	.033	.204
$\mathrm{Var}(\epsilon_i)$	.132	.367	.089	.318	.078	.310	.061	.371
Between-Firm:								
$\mathrm{Var}(\bar{\theta}_j)$	.030	.084	.015	.055	.017	.068	.017	.102
$\mathrm{Var}(\psi_j)$	.076	.212	.102	.365	.086	.342	.041	.253
$2\,\mathrm{Cov}(\bar{\theta}_j, \psi_j)$	.049	.137	.036	.130	.034	.136	.011	.069
Panel B: X={EDU, EXP, OCC}								
$\mathrm{Var}(\theta_i)$	.146	.407	.065	.232	.061	.243	.052	.320
Within-Firm:								
$\mathrm{Var}(\theta_i - \bar{\theta}_j)$	.103	.286	.049	.176	.040	.159	.035	.214
$\mathrm{Var}(\epsilon_i)$	.101	.280	.077	.275	.074	.295	.059	.361
Between-Firm:								
$\mathrm{Var}(\bar{\theta}_j)$	.044	.121	.016	.057	.021	.085	.017	.107
$\mathrm{Var}(\psi_j)$	.064	.179	.096	.344	.079	.314	.040	.245
$2\,\mathrm{Cov}(\bar{\theta}_j, \psi_j)$	.048	.134	.041	.148	.037	.148	.012	.074
Obs	3998840		1325260		548808		260364	
Firm	86165		62628		55664		41448	

Confidence Intervals on Lasso Coefficients via Subsampling (Pooled)

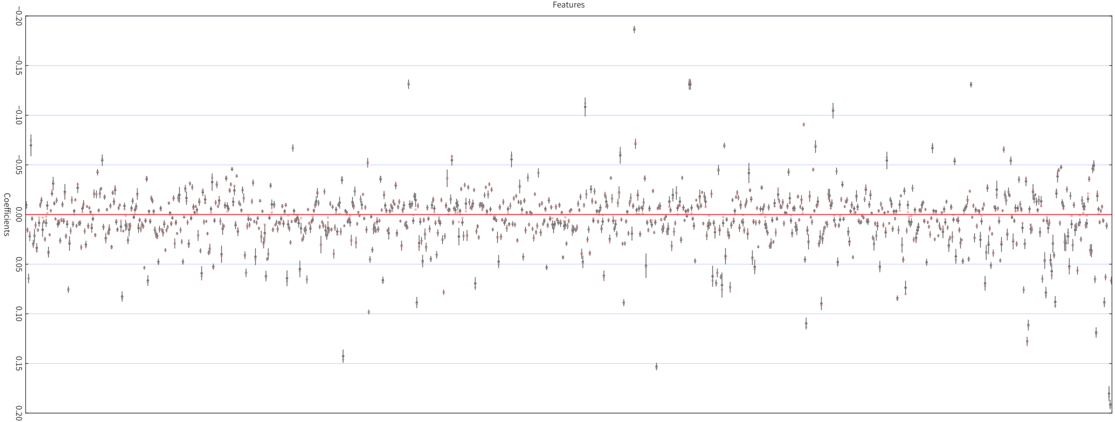
Back



Confidence Intervals on Lasso Coefficients via Subsampling (Computer) ◂ Back

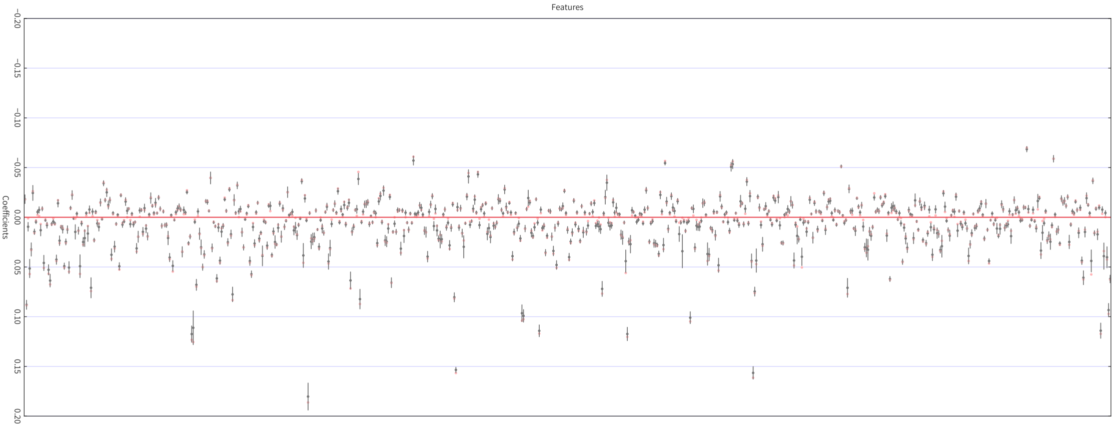


Confidence Intervals on Lasso Coefficients via Subsampling (Design & Media) ◂ Back



Confidence Intervals on Lasso Coefficients via Subsampling (Admin)

Back



Feature Selection: Top Features (Positive) Back

	Pooled			Computer			Design_Media			Admin		
	token	coef	feq	token	coef	feq	token	coef	feq	token	coef	feq
1	14th month pay	.152	.014	15th month pay	.181	.010	14th month pay	.193	.011	undergraduate	.161	.014
2	three meals	.143	.014	three meals	.148	.014	lead	.155	.025	undergraduate	.157	.156
3	large platform	.131	.019	14th month pay	.140	.017	three meals	.129	.015	president	.120	.014
4	master degree	.126	.015	master degree	.109	.027	c++	.121	.017	ceo	.117	.010
5	lead	.107	.041	lead	.089	.038	crisis	.113	.011	build	.117	.016
6	c++	.092	.051	golang	.080	.017	games	.098	.180	lead	.105	.017
7	algorithm	.082	.061	guru	.079	.047	europe & america	.090	.011	government	.103	.030
8	guru	.082	.028	deep learning	.078	.022	engine	.090	.046	high salary	.089	.018
9	famous	.079	.019	famous	.070	.014	4a	.090	.014	translation	.083	.012
10	machine learning	.077	.016	high salary	.070	.018	six insurance & one fund	.086	.046	bachelor degree	.082	.018
11	formation	.076	.013	maestro	.068	.012	finance	.084	.016	strategy	.077	.015
12	undergraduate	.074	.319	overseas	.067	.010	undergraduate	.078	.238	large scale	.076	.030
13	overseas	.072	.026	go	.065	.027	listed company	.076	.021	landing	.070	.018
14	react	.072	.020	c++	.064	.144	finance	.076	.031	project management	.067	.011
15	development	.071	.374	algorithm	.064	.164	outsourcing	.074	.012	overseas	.066	.021
16	undergraduate	.066	.029	react	.064	.061	guru	.070	.022	background	.064	.032
17	high salary	.063	.028	machine learning	.061	.045	overseas	.068	.024	develop	.063	.097
18	landing	.060	.067	landing	.061	.037	journalists	.068	.011	13th month pay	.063	.019
19	strategy	.057	.047	development	.059	.776	13th month pay	.068	.023	unified recruitment	.058	.031
20	live streaming	.056	.014	audio & video	.058	.012	c4d	.066	.021	budget	.057	.021
21	listed company	.055	.027	unified recruitment	.054	.044	famous	.065	.023	major	.055	.019
22	large scale	.055	.072	beijing	.053	.012	unity	.065	.043	decoration	.055	.016
23	responsibilities	.055	.048	live streaming	.052	.011	high salary	.064	.016	resources	.053	.043
24	shuttle	.054	.018	recommend	.052	.023	management	.063	.010	promote	.051	.029
25	finance	.054	.070	management	.051	.016	3d	.063	.106	finance	.051	.036
26	six insurance & one fund	.053	.055	ai	.051	.015	large scale	.063	.043	english	.050	.054
27	python	.052	.066	stock	.049	.025	performance	.063	.016	business negotiations	.048	.010
28	director	.052	.022	undergraduate	.048	.365	unified recruitment	.059	.019	optimization	.046	.079
29	unified recruitment	.051	.042	salary	.048	.049	undergraduate	.059	.023	responsibilities	.046	.035
30	hive	.051	.013	supplementary	.045	.019	ip	.057	.017	integrated planning	.046	.028

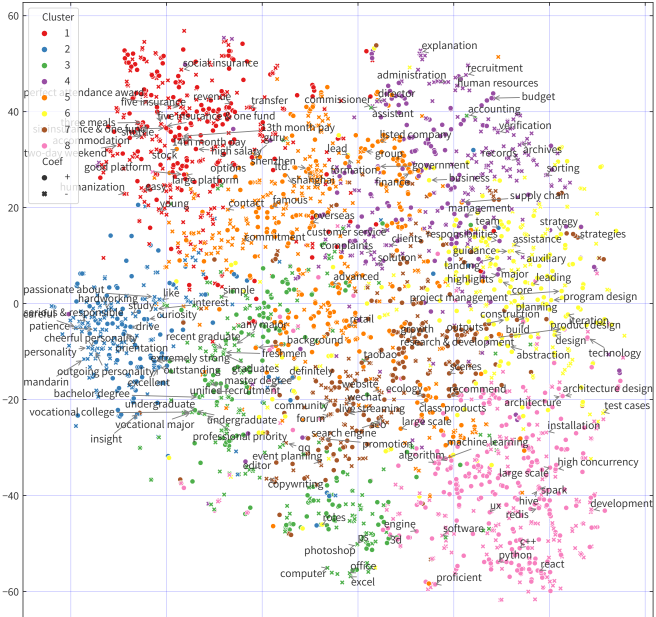
Feature Selection: Top Features (Negative)

Back

	Pooled			Computer			Design_Media			Admin		
	token	coeff	feq	token	coeff	feq	token	coeff	feq	token	coeff	feq
1	freshmen	-.155	.018	graduates	-.205	.013	freshmen	-.188	.017	five insurance	-.070	.052
2	five insurance	-.136	.030	five insurance	-.197	.016	internship	-.133	.011	graduates	-.061	.082
3	graduates	-.128	.033	vocational college	-.134	.072	five insurance	-.132	.033	vocational school	-.059	.038
4	vocational major	-.100	.036	social insurance	-.121	.012	graduates	-.132	.030	freshmen	-.057	.048
5	two-day weekend	-.098	.166	vocational major	-.119	.030	two-day weekend	-.090	.176	internship	-.056	.012
6	vocational college	-.094	.148	two-day weekend	-.115	.147	recent graduate	-.072	.026	interns	-.053	.017
7	assistant	-.079	.011	recent graduate	-.106	.011	vocational college	-.070	.144	two-day weekend	-.051	.214
8	customer service	-.075	.030	test cases	-.067	.068	social insurance	-.068	.023	player	-.046	.024
9	social insurance	-.073	.028	installation	-.067	.048	vocational major	-.066	.041	mandarin	-.046	.172
10	accounting	-.071	.019	th	-.066	.014	ltd.	-.059	.012	women	-.038	.015
11	accommodation	-.067	.016	computer	-.065	.011	any major	-.055	.011	social insurance	-.037	.060
12	administration	-.067	.027	after sales	-.061	.011	humanization	-.055	.019	qq	-.037	.036
13	commissioner	-.063	.011	young	-.060	.013	comics	-.053	.014	easy	-.035	.043
14	taobao	-.059	.015	five insurance & one fund	-.059	.273	cad	-.052	.010	website	-.033	.032
15	assistance	-.058	.164	business trip	-.051	.030	photoshop	-.049	.235	cleaning	-.030	.015
16	ps	-.056	.029	records	-.048	.015	cdr	-.047	.012	health	-.029	.024
17	ltd.	-.056	.012	hardworking	-.048	.015	website	-.047	.180	clerks	-.029	.014
18	installation	-.055	.020	holidays	-.046	.059	assistance	-.046	.131	attendance	-.029	.104
19	photoshop	-.052	.039	clients	-.046	.078	ps	-.045	.142	e-commerce	-.029	.031
20	careful	-.050	.032	easy	-.043	.017	hardworking	-.044	.023	input	-.028	.044
21	hardworking	-.050	.032	software testing	-.043	.047	anime	-.044	.019	shift	-.028	.013
22	verification	-.048	.011	wechat	-.041	.042	easy	-.044	.033	answer the phone	-.027	.101
23	human resources	-.047	.032	.net	-.041	.034	contact	-.042	.011	administration	-.027	.256
24	website	-.047	.090	patience	-.040	.023	editor	-.039	.204	perfect attendance award	-.026	.032
25	any major	-.047	.020	website	-.039	.101	artwork	-.038	.032	apply for the job	-.025	.018
26	humanization	-.046	.012	focused	-.038	.011	forum	-.038	.034	mobile	-.025	.013
27	excel	-.046	.047	network equipment	-.037	.016	taobao	-.038	.024	hardworking	-.025	.055
28	mandarin	-.045	.027	bug	-.036	.053	young	-.038	.034	join	-.024	.041
29	explanation	-.044	.013	works	-.035	.023	commission	-.037	.017	games	-.024	.039
30	young	-.044	.025	holiday	-.034	.037	clients	-.037	.096	front desk	-.023	.088
31	contact	-.044	.010	dividend	-.034	.012	wechat	-.037	.172	department manager	-.023	.014

Feature Clustering: Visualization (Pooled)

◂ Back

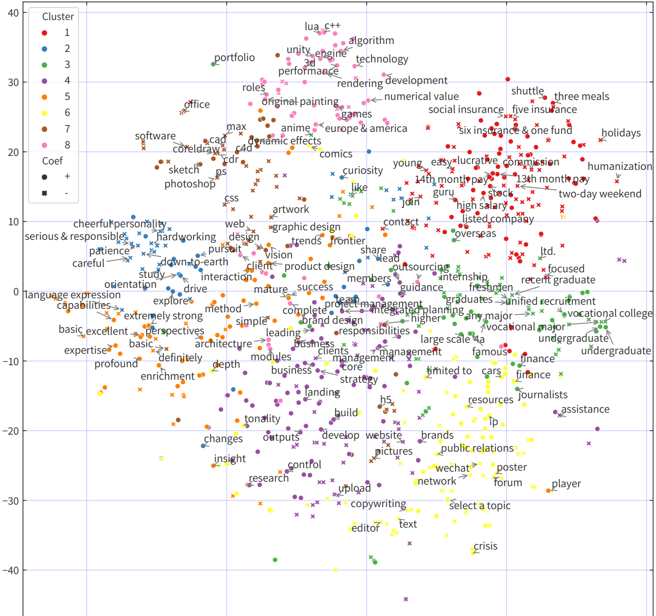


Feature Clustering: Visualization (Computer)

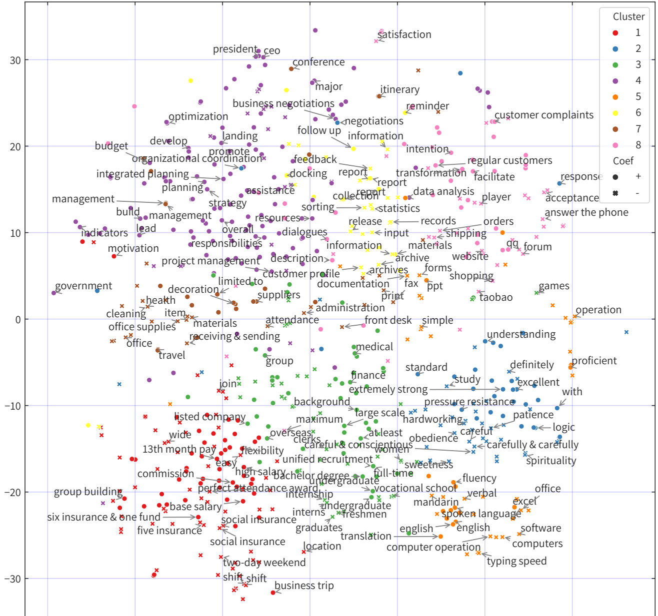
Back

Feature Clustering: Visualization (Design_Media)

Back

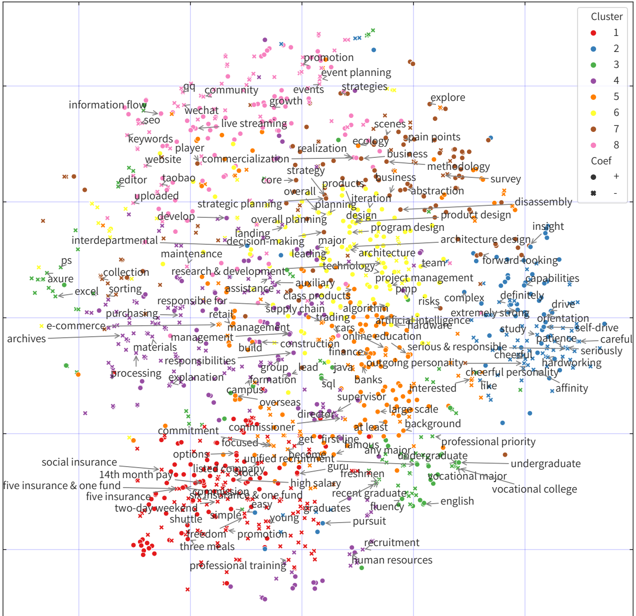


Feature Clustering: Visualization (Admin) ◂ Back



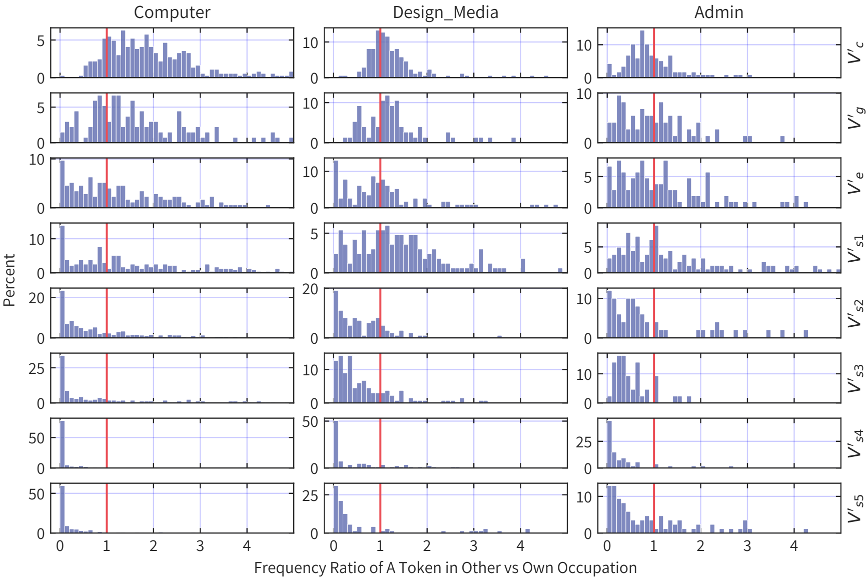
Feature Clustering: Visualization (Business Operation)

◂ Back



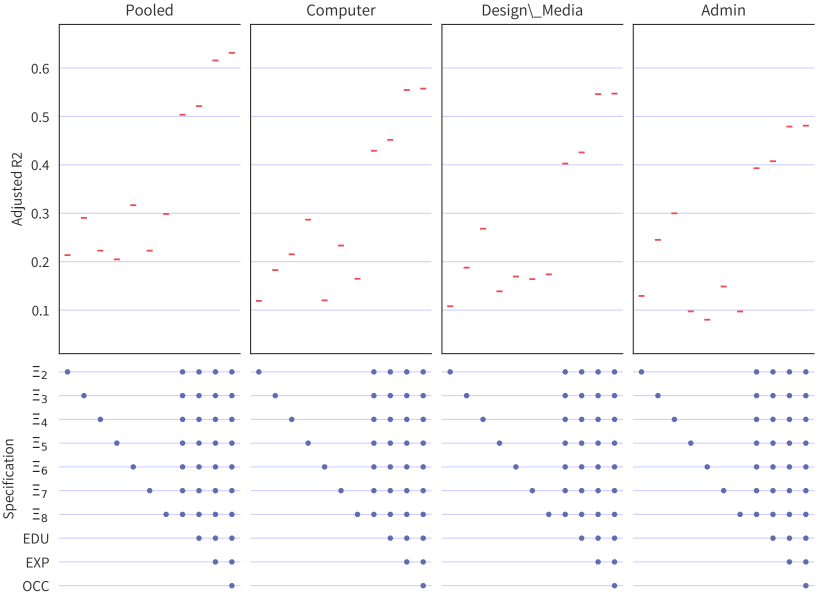
Feature Clustering: General vs Specific

Back



R2 Under Different Specifications

Back



Variance Bias Correction

Back

	Pooled		Computer		Design_Media		Admin	
	Comp.	Share	Comp.	Share	Comp.	Share	Comp.	Share
Var(ln w)	.362	-	.281	-	.253	-	.164	-
Panel A: Plug-In								
Var(θ_i)	.163	.450	.082	.291	.084	.331	.067	.408
Var(ϵ_i)	.096	.267	.071	.252	.065	.255	.050	.304
Var(ψ_j)	.051	.141	.074	.263	.062	.243	.035	.216
2 Cov(θ_i, ψ_j)	.051	.142	.054	.193	.043	.171	.012	.072
Panel B: Homoscedasticity Correction (Change from Panel A)								
Var(θ_i)	$+.000$	$+.000$	$-.000$	$+.000$	$-.000$	$+.000$	$+.000$	$+.001$
Var(ϵ_i)	$+.002$	$+.006$	$+.004$	$+.012$	$+.007$	$+.029$	$+.009$	$+.057$
Var(ψ_j)	$-.002$	$-.006$	$-.004$	$-.012$	$-.007$	$-.029$	$-.009$	$-.057$
2 Cov(θ_i, ψ_j)	$-.000$	$+.000$	$+.000$	$+.001$	$-.000$	$+.000$	$-.000$	$-.002$
Panel C: KSS (Leave-Out) Correction (Change from Panel A)								
Var(θ_i)	$-.000$	$+.000$	$+.000$	$+.000$	$+.000$	$+.000$	$-.000$	$-.001$
Var(ϵ_i)	$+.002$	$+.005$	$+.003$	$+.012$	$+.006$	$+.024$	$+.008$	$+.048$
Var(ψ_j)	$-.002$	$-.005$	$-.003$	$-.012$	$-.006$	$-.024$	$-.008$	$-.048$
2 Cov(θ_i, ψ_j)	$+.000$	$+.000$	$+.000$	$+.001$	$+.000$	$+.002$	$+.000$	$+.001$
Obs	3998840		1325260		548808		260364	
Firm	86165		62628		55664		41448	

Conditional On EXP=0

Back

	Pooled		Computer		Design_Media		Admin	
	Comp.	Share	Comp.	Share	Comp.	Share	Comp.	Share
Var(ln w)	.305	-	.407	-	.226	-	.097	-
Panel A: $X = \{$**EDU**, **EXP**, $\Xi_2, \ldots, \Xi_8\}$								
Var(θ_i)	.079	.258	.069	.169	.036	.159	.014	.146
Var(ϵ_i)	.115	.377	.111	.273	.084	.372	.049	.512
Var(ψ_j)	.068	.222	.138	.339	.075	.333	.029	.298
2 Cov(θ_i, ψ_j)	.044	.143	.089	.219	.033	.145	.005	.047
Panel B: Decompose θ Terms								
Var(X_{int})	.000	.000	.000	.000	.000	.000	.000	.000
Var(X_{ext})	.079	.258	.069	.169	.036	.159	.014	.146
2 Cov(X_{int}, X_{ext})	.000	.000	.000	.000	.000	.000	.000	.000
2 Cov(X_{int}, ψ_j)	.000	.000	.000	.000	.000	.000	.000	.000
2 Cov(X_{ext}, ψ_j)	.044	.143	.089	.219	.033	.145	.005	.047
Panel C: Further Decompose X_{ext} Terms								
Var(Ξ_g)	.001	.004	.001	.003	.001	.005	.000	.002
Var(Ξ_m)	.005	.018	.010	.024	.004	.016	.003	.031
Var(Ξ_s)	.047	.153	.036	.087	.021	.094	.007	.068
2 Cov(Ξ_g, Ξ_m)	.001	.004	.001	.004	.001	.002	.000	.004
2 Cov(Ξ_g, Ξ_s)	.006	.021	.003	.008	.003	.012	.001	.009
2 Cov(Ξ_m, Ξ_s)	.018	.058	.017	.043	.007	.032	.003	.032
2 Cov(Ξ_g, X_{int})	.000	.000	.000	.000	.000	.000	.000	.000
2 Cov(Ξ_m, X_{int})	.000	.000	.000	.000	.000	.000	.000	.000
2 Cov(Ξ_s, X_{int})	.000	.000	.000	.000	.000	.000	.000	.000
2 Cov(Ξ_g, ψ_j)	.003	.010	.005	.013	.002	.008	.000	.002
2 Cov(Ξ_m, ψ_j)	.008	.027	.024	.060	.006	.029	.002	.022
2 Cov(Ξ_s, ψ_j)	.032	.106	.059	.146	.024	.108	.002	.023
Obs	858147		144122		104960		120241	

Conditional On EXP=1-3

Back

	Pooled		Computer		Design_Media		Admin	
	Comp.	Share	Comp.	Share	Comp.	Share	Comp.	Share
$\text{Var}(\ln w)$	.204	-	.195	-	.140	-	.104	-
Panel A: $X = \{$**EDU**, **EXP**, $\Xi_2, \ldots, \Xi_8\}$								
$\text{Var}(\theta_i)$	.062	.302	.034	.174	.022	.158	.027	.259
$\text{Var}(\epsilon_i)$	.081	.396	.064	.331	.057	.407	.049	.468
$\text{Var}(\psi_j)$	.043	.213	.068	.348	.048	.343	.024	.235
$2\,\text{Cov}(\theta_i, \psi_j)$	.018	.088	.029	.147	.013	.095	.004	.036
Panel B: Decompose θ **Terms**								
$\text{Var}(X_{int})$	.000	.000	.000	.000	.000	.000	.000	.000
$\text{Var}(X_{ext})$	.062	.302	.034	.174	.022	.158	.027	.259
$2\,\text{Cov}(X_{int}, X_{ext})$	.000	.000	.000	.000	.000	.000	.000	.000
$2\,\text{Cov}(X_{int}, \psi_j)$	.000	.000	.000	.000	.000	.000	.000	.000
$2\,\text{Cov}(X_{ext}, \psi_j)$	.018	.088	.029	.147	.013	.095	.004	.036
Panel C: Further Decompose X_{ext} **Terms**								
$\text{Var}(\Xi_g)$	.001	.003	.000	.002	.000	.002	.000	.001
$\text{Var}(\Xi_m)$	.005	.024	.004	.020	.002	.013	.005	.051
$\text{Var}(\Xi_s)$	.036	.177	.021	.106	.016	.116	.013	.126
$2\,\text{Cov}(\Xi_g, \Xi_m)$	.001	.006	.000	.002	.000	.001	.000	.005
$2\,\text{Cov}(\Xi_g, \Xi_s)$	.005	.023	.002	.009	.001	.006	.001	.012
$2\,\text{Cov}(\Xi_m, \Xi_s)$	.014	.068	.007	.036	.003	.020	.007	.066
$2\,\text{Cov}(\Xi_g, X_{int})$	.000	.000	.000	.000	.000	.000	.000	.000
$2\,\text{Cov}(\Xi_m, X_{int})$	.000	.000	.000	.000	.000	.000	.000	.000
$2\,\text{Cov}(\Xi_s, X_{int})$	.000	.000	.000	.000	.000	.000	.000	.000
$2\,\text{Cov}(\Xi_g, \psi_j)$	.001	.005	.001	.007	.000	.003	.000	.000
$2\,\text{Cov}(\Xi_m, \psi_j)$	.006	.031	.009	.046	.005	.034	.003	.031
$2\,\text{Cov}(\Xi_s, \psi_j)$	.011	.052	.018	.094	.008	.058	.001	.005
Obs	1457630		432077		254456		88030	

Conditional On EXP=3-5

Back

	Pooled		Computer		Design_Media		Admin	
	Comp.	Share	Comp.	Share	Comp.	Share	Comp.	Share
$\text{Var}(\ln w)$	.202	-	.167	-	.162	-	.192	-
Panel A: $X = \{$**EDU**, **EXP**, $\Xi_2, \ldots, \Xi_8\}$								
$\text{Var}(\theta_i)$	.043	.212	.020	.121	.021	.129	.047	.246
$\text{Var}(\epsilon_i)$	.079	.390	.055	.332	.060	.368	.085	.442
$\text{Var}(\psi_j)$	.054	.266	.065	.392	.061	.374	.049	.254
$2\,\text{Cov}(\theta_i, \psi_j)$	.027	.132	.026	.156	.021	.129	.013	.067
Panel B: Decompose θ Terms								
$\text{Var}(X_{int})$	.000	.000	.000	.000	.000	.000	.000	.000
$\text{Var}(X_{ext})$	.043	.212	.020	.121	.021	.129	.047	.246
$2\,\text{Cov}(X_{int}, X_{ext})$	.000	.000	.000	.000	.000	.000	.000	.000
$2\,\text{Cov}(X_{int}, \psi_j)$	.000	.000	.000	.000	.000	.000	.000	.000
$2\,\text{Cov}(X_{ext}, \psi_j)$	.027	.132	.026	.156	.021	.129	.013	.067
Panel C: Further Decompose X_{ext} Terms								
$\text{Var}(\Xi_g)$	.000	.002	.000	.000	.000	.000	.001	.004
$\text{Var}(\Xi_m)$	.004	.019	.002	.013	.001	.008	.010	.054
$\text{Var}(\Xi_s)$	.026	.129	.013	.080	.016	.096	.024	.125
$2\,\text{Cov}(\Xi_g, \Xi_m)$	.001	.004	.000	.001	.000	.001	.001	.005
$2\,\text{Cov}(\Xi_g, \Xi_s)$	.003	.015	.001	.005	.001	.009	.002	.009
$2\,\text{Cov}(\Xi_m, \Xi_s)$	.009	.044	.004	.023	.002	.014	.011	.056
$2\,\text{Cov}(\Xi_g, X_{int})$	.000	.000	.000	.000	.000	.000	.000	.000
$2\,\text{Cov}(\Xi_m, X_{int})$	.000	.000	.000	.000	.000	.000	.000	.000
$2\,\text{Cov}(\Xi_s, X_{int})$	.000	.000	.000	.000	.000	.000	.000	.000
$2\,\text{Cov}(\Xi_g, \psi_j)$	.001	.007	.001	.006	.001	.007	.000	.000
$2\,\text{Cov}(\Xi_m, \psi_j)$	.007	.035	.007	.041	.005	.030	.007	.038
$2\,\text{Cov}(\Xi_s, \psi_j)$	.018	.090	.018	.109	.015	.092	.006	.029
Obs	1222973		533940		127417		17247	

Conditional On EDU=C

◂ Back

	Pooled		Computer		Design_Media		Admin	
	Comp.	Share	Comp.	Share	Comp.	Share	Comp.	Share
Var(ln w)	.244	-	.211	-	.200	-	.106	-
Panel A: $X = \{$**EDU**, **EXP**, $\Xi_2, \ldots, \Xi_8\}$								
Var(θ_i)	.111	.454	.072	.342	.066	.330	.033	.307
Var(ϵ_i)	.085	.349	.064	.303	.059	.293	.046	.428
Var(ψ_j)	.038	.154	.052	.245	.047	.234	.024	.229
2 Cov(θ_i, ψ_j)	.011	.044	.023	.109	.028	.142	.003	.028
Panel B: Decompose θ **Terms**								
Var(X_{int})	.033	.135	.028	.134	.024	.119	.010	.095
Var(X_{ext})	.046	.188	.026	.122	.024	.121	.013	.122
2 Cov(X_{int}, X_{ext})	.032	.130	.018	.085	.018	.090	.010	.091
2 Cov(X_{int}, ψ_j)	.005	.021	.014	.065	.012	.062	.002	.015
2 Cov(X_{ext}, ψ_j)	.005	.022	.009	.044	.016	.080	.001	.013
Panel C: Further Decompose X_{ext} **Terms**								
Var(Ξ_g)	.001	.004	.000	.002	.000	.001	.000	.003
Var(Ξ_m)	.002	.010	.001	.005	.001	.005	.001	.008
Var(Ξ_s)	.028	.114	.019	.092	.018	.090	.009	.084
2 Cov(Ξ_g, Ξ_m)	.001	.004	.000	.001	.000	.001	.000	.001
2 Cov(Ξ_g, Ξ_s)	.005	.019	.002	.009	.002	.008	.001	.007
2 Cov(Ξ_m, Ξ_s)	.009	.037	.003	.013	.003	.017	.002	.020
2 Cov(Ξ_g, X_{int})	.003	.012	.001	.006	.001	.005	.001	.005
2 Cov(Ξ_m, X_{int})	.005	.022	.002	.011	.003	.013	.002	.014
2 Cov(Ξ_s, X_{int})	.023	.096	.014	.068	.014	.072	.008	.072
2 Cov(Ξ_g, ψ_j)	.001	.003	.001	.004	.001	.003	-.000	.003
2 Cov(Ξ_m, ψ_j)	.001	.005	.002	.010	.002	.011	.001	.008
2 Cov(Ξ_s, ψ_j)	.004	.015	.007	.031	.013	.066	.001	.008
Obs	1302141		308332		198391		127547	

Conditional On EDU=B

Back

	Pooled		Computer		Design_Media		Admin	
	Comp.	Share	Comp.	Share	Comp.	Share	Comp.	Share
Var(ln w)	.313	-	.244	-	.244	-	.223	-
Panel A: $X = \{$**EDU**, **EXP**, $\Xi_2, \ldots, \Xi_8\}$								
$\text{Var}(\theta_i)$	.129	.411	.063	.259	.085	.349	.101	.455
$\text{Var}(\epsilon_i)$	.094	.299	.070	.287	.071	.291	.073	.326
$\text{Var}(\psi_j)$	.052	.166	.070	.286	.054	.220	.037	.166
$2\,\text{Cov}(\theta_i, \psi_j)$	.039	.124	.041	.167	.035	.142	.010	.045
Panel B: Decompose θ Terms								
$\text{Var}(X_{int})$	.043	.138	.027	.113	.036	.145	.036	.160
$\text{Var}(X_{ext})$	.052	.165	.022	.091	.026	.108	.036	.163
$2\,\text{Cov}(X_{int}, X_{ext})$	.034	.108	.014	.056	.023	.095	.030	.133
$2\,\text{Cov}(X_{int}, \psi_j)$	.014	.044	.013	.054	.016	.067	.008	.036
$2\,\text{Cov}(X_{ext}, \psi_j)$	.025	.081	.028	.113	.018	.075	.002	.009
Panel C: Further Decompose X_{ext} Terms								
$\text{Var}(\Xi_g)$	.001	.003	.000	.001	.000	.001	.001	.004
$\text{Var}(\Xi_m)$	.002	.006	.001	.004	.001	.004	.002	.009
$\text{Var}(\Xi_s)$	.034	.110	.017	.069	.020	.080	.025	.112
$2\,\text{Cov}(\Xi_g, \Xi_m)$	.001	.003	.000	.001	.000	.001	.000	.001
$2\,\text{Cov}(\Xi_g, \Xi_s)$	.005	.016	.001	.005	.002	.007	.003	.012
$2\,\text{Cov}(\Xi_m, \Xi_s)$	.009	.027	.003	.011	.003	.014	.005	.023
$2\,\text{Cov}(\Xi_g, X_{int})$	.003	.009	.001	.003	.001	.006	.002	.008
$2\,\text{Cov}(\Xi_m, X_{int})$	.005	.015	.002	.007	.003	.013	.005	.022
$2\,\text{Cov}(\Xi_s, X_{int})$	.026	.084	.011	.045	.019	.077	.023	.103
$2\,\text{Cov}(\Xi_g, \psi_j)$	.002	.006	.001	.005	.001	.005	-.001	.005
$2\,\text{Cov}(\Xi_m, \psi_j)$	.003	.010	.004	.015	.003	.011	.003	.013
$2\,\text{Cov}(\Xi_s, \psi_j)$	.020	.064	.023	.093	.014	.058	.000	.002
Obs	2142593		863523		248143		55786	

If $\Xi_m \equiv \{\text{EDU}, \Xi_3, \Xi_4\}$ Back

	Pooled		Computer		Design_Media		Admin	
	Comp.	Share	Comp.	Share	Comp.	Share	Comp.	Share
Var(ln w)	.362	-	.281	-	.253	-	.164	-
Panel A: $X = \{$**EDU**, **EXP**, $\Xi_2, \ldots, \Xi_8\}$								
Var(θ_i)	.163	.450	.082	.291	.084	.330	.067	.409
Var(ϵ_i)	.098	.272	.074	.264	.071	.279	.058	.353
Var(ψ_j)	.049	.136	.071	.251	.056	.219	.027	.168
2 Cov(θ_i, ψ_j)	.052	.142	.054	.193	.043	.170	.012	.072
Panel B: Decompose θ Terms								
Var(X_{int})	.042	.115	.028	.099	.030	.119	.016	.096
Var(X_{ext})	.072	.199	.035	.126	.030	.117	.030	.184
2 Cov(X_{int}, X_{ext})	.049	.136	.019	.067	.024	.094	.021	.129
2 Cov(X_{int}, ψ_j)	.017	.048	.017	.060	.018	.072	.004	.025
2 Cov(X_{ext}, ψ_j)	.034	.094	.037	.133	.025	.099	.008	.047
Panel C: Further Decompose X_{ext} Terms								
Var(Ξ_g)	.001	.003	.000	.001	.000	.001	.000	.002
Var(Ξ_m)	.017	.048	.007	.026	.006	.025	.018	.109
Var(Ξ_s)	.022	.062	.014	.051	.011	.045	.003	.019
2 Cov(Ξ_g, Ξ_m)	.004	.010	.001	.003	.001	.004	.002	.011
2 Cov(Ξ_g, Ξ_s)	.005	.012	.001	.005	.001	.004	.001	.003
2 Cov(Ξ_m, Ξ_s)	.023	.064	.011	.039	.009	.037	.007	.041
2 Cov(Ξ_g, X_{int})	.004	.011	.001	.004	.001	.005	.001	.006
2 Cov(Ξ_m, X_{int})	.020	.054	.006	.022	.011	.042	.017	.102
2 Cov(Ξ_s, X_{int})	.026	.071	.011	.041	.012	.047	.003	.020
2 Cov(Ξ_g, ψ_j)	.002	.007	.002	.007	.001	.005	.000	.001
2 Cov(Ξ_m, ψ_j)	.014	.040	.015	.052	.012	.048	.007	.040
2 Cov(Ξ_s, ψ_j)	.017	.048	.021	.075	.012	.046	.001	.007
Obs	3998840		1325260		548808		260364	

If $\Xi_m \equiv \{\text{EDU}, \Xi_3, \Xi_4, \Xi_5\}$ ◂ Back

	Pooled		Computer		Design_Media		Admin	
	Comp.	Share	Comp.	Share	Comp.	Share	Comp.	Share
Var(ln w)	.362	-	.281	-	.253	-	.164	-
Panel A: $X = \{$**EDU**, **EXP**, $\Xi_2, \ldots, \Xi_8\}$								
Var(θ_i)	.163	.450	.082	.291	.084	.331	.066	.405
Var(ϵ_i)	.098	.272	.074	.264	.071	.279	.058	.352
Var(ψ_j)	.049	.136	.071	.251	.056	.219	.027	.168
2 Cov(θ_i, ψ_j)	.051	.142	.054	.194	.043	.171	.012	.070
Panel B: Decompose θ Terms								
Var(X_{int})	.042	.115	.028	.099	.030	.119	.016	.096
Var(X_{ext})	.072	.199	.035	.125	.030	.118	.029	.180
2 Cov(X_{int}, X_{ext})	.049	.136	.019	.067	.024	.094	.021	.129
2 Cov(X_{int}, ψ_j)	.017	.048	.017	.060	.018	.072	.004	.025
2 Cov(X_{ext}, ψ_j)	.034	.094	.038	.134	.025	.099	.007	.046
Panel C: Further Decompose X_{ext} Terms								
Var(Ξ_g)	.001	.002	.000	.001	.000	.001	.000	.001
Var(Ξ_m)	.021	.057	.015	.055	.008	.033	.020	.122
Var(Ξ_s)	.018	.051	.007	.024	.010	.038	.002	.011
2 Cov(Ξ_g, Ξ_m)	.004	.011	.002	.005	.001	.005	.002	.012
2 Cov(Ξ_g, Ξ_s)	.004	.011	.001	.003	.001	.004	.000	.002
2 Cov(Ξ_m, Ξ_s)	.024	.066	.010	.037	.010	.038	.005	.032
2 Cov(Ξ_g, X_{int})	.004	.011	.001	.004	.001	.005	.001	.006
2 Cov(Ξ_m, X_{int})	.022	.062	.012	.041	.013	.050	.018	.109
2 Cov(Ξ_s, X_{int})	.023	.063	.006	.022	.010	.039	.002	.014
2 Cov(Ξ_g, ψ_j)	.002	.007	.002	.007	.001	.005	.000	.001
2 Cov(Ξ_m, ψ_j)	.017	.047	.025	.089	.014	.053	.007	.041
2 Cov(Ξ_s, ψ_j)	.015	.041	.011	.038	.010	.041	.001	.003
Obs	3998840		1325260		548808		260364	

Compensation Explain Wage Variance Through Job and Firm Effects

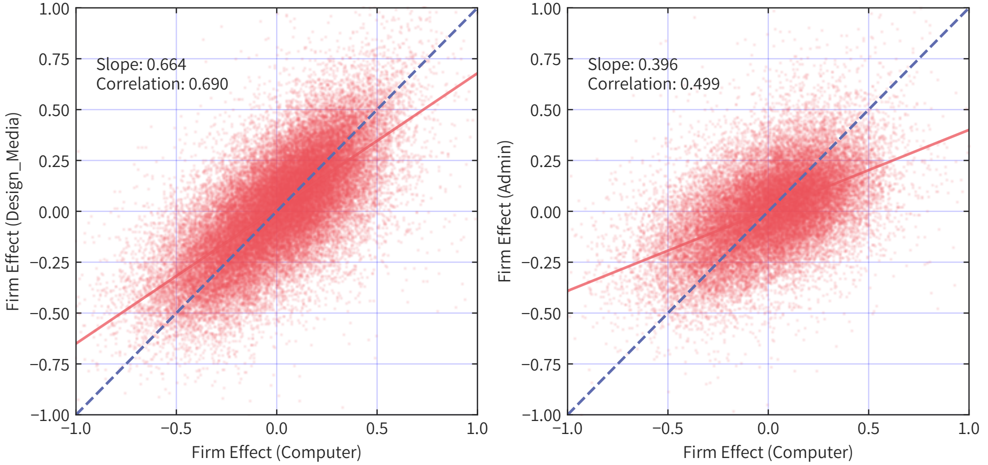
Back

$\ln w_i = X_i\beta + \psi_j + \delta_i + \iota_t + \epsilon_i$, where $\delta_i \equiv \Xi_{1,i}\beta^c$

	Pooled		Computer		Design_Media		Admin	
	Comp.	Share	Comp.	Share	Comp.	Share	Comp.	Share
$\text{Var}(\ln w)$	.362	-	.281	-	.254	-	.164	-
Panel A: $\delta_i \equiv \Xi_{1,i}\beta^c$								
$\text{Var}(\theta_i)$	.158	.437	.079	.282	.082	.324	.063	.385
$\text{Var}(\delta_i)$	.002	.004	.001	.003	.001	.002	.001	.006
$\text{Var}(\epsilon_i)$	.097	.269	.074	.262	.070	.277	.057	.349
$\text{Var}(\psi_j)$	.046	.128	.066	.234	.052	.207	.026	.161
$2\,\text{Cov}(\theta_j, \psi_j)$	.049	.137	.051	.181	.041	.160	.011	.066
$2\,\text{Cov}(\delta_i, \theta_i)$	.006	.017	.005	.018	.004	.015	.004	.027
$2\,\text{Cov}(\delta_i, \psi_j)$	.003	.008	.006	.021	.004	.014	.001	.006
Panel B: Decompose $2\,\text{Cov}(\delta_i, \theta_i)$								
$2\,\text{Cov}(\delta_i, X_e)$	.002	.006	.002	.007	.002	.007	.002	.011
$2\,\text{Cov}(\delta_i, \tilde{\Xi})$	.004	.011	.003	.011	.002	.009	.003	.016
$2\,\text{Cov}(\delta_i, \Xi_g)$	.000	.001	.000	.001	.000	.001	.000	.001
$2\,\text{Cov}(\delta_i, \Xi_m)$	.002	.004	.001	.003	.001	.004	.002	.012
$2\,\text{Cov}(\delta_i, \Xi_s)$	.002	.006	.002	.007	.001	.005	.001	.003
Obs	3998840		1325260		548808		260364	
Firm	86165		62628		55664		41448	

Firm Wage Premium: Difference Between Occupations

robustness Back

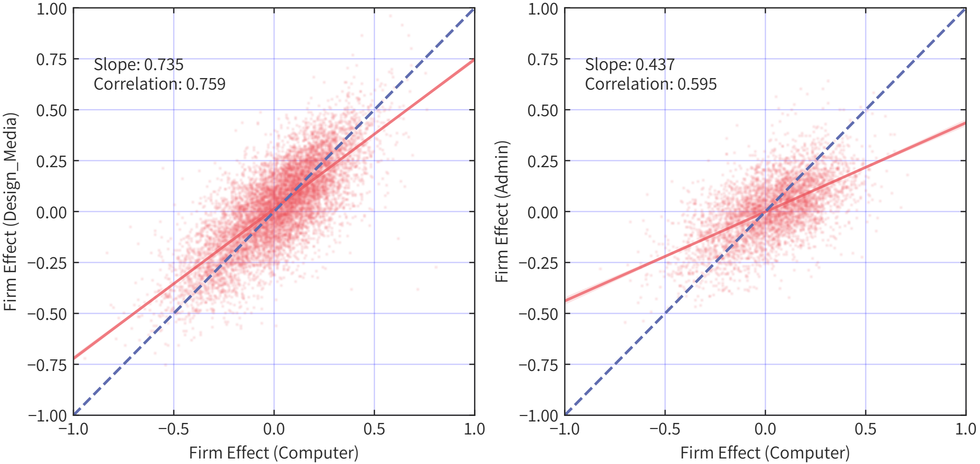


Firm Wage Premium: Firm Size and Firm Location

▸ robustness ◂ Back

	Pooled			Computer			Design_Media			Admin		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
fsize.15-50	.019**	.018**	.023**	.011+	.013*	.019**	.022**	.013**	.020**	.006	.005	.005
	(.004)	(.003)	(.003)	(.006)	(.005)	(.004)	(.005)	(.005)	(.004)	(.006)	(.006)	(.006)
fsize.50-150	.042**	.037**	.050**	.037**	.032**	.038**	.050**	.033**	.045**	.020**	.018**	.021**
	(.004)	(.003)	(.003)	(.006)	(.005)	(.004)	(.005)	(.005)	(.004)	(.006)	(.006)	(.005)
fsize.150-500	.067**	.057**	.067**	.072**	.054**	.051**	.086**	.058**	.063**	.035**	.031**	.030**
	(.004)	(.004)	(.003)	(.006)	(.005)	(.005)	(.005)	(.005)	(.004)	(.006)	(.006)	(.006)
fsize.500-2000	.095**	.078**	.085**	.108**	.074**	.066**	.127**	.087**	.086**	.050**	.043**	.040**
	(.005)	(.004)	(.004)	(.007)	(.006)	(.005)	(.006)	(.006)	(.005)	(.007)	(.007)	(.006)
fsize.2000+	.121**	.102**	.120**	.140**	.084**	.082**	.161**	.107**	.108**	.064**	.055**	.058**
	(.005)	(.005)	(.004)	(.008)	(.007)	(.006)	(.007)	(.007)	(.006)	(.008)	(.008)	(.007)
Job Effect ($\bar{\theta}$)		.287**	.201**		.643**	.498**		.391**	.292**		.118**	.063**
		(.004)	(.003)		(.007)	(.006)		(.006)	(.005)		(.008)	(.008)
const	.146**	-1.115**	-.633**	.222**	-2.684**	-1.905**	-.030**	-1.759**	-1.208**	.024**	-.478**	-.166**
	(.003)	(.016)	(.015)	(.005)	(.030)	(.027)	(.004)	(.028)	(.024)	(.006)	(.036)	(.033)
Location FE			✓			✓			✓			✓
Adj. R^2	.016	.096	.377	.016	.168	.436	.022	.100	.390	.006	.014	.229
No. Obs	86165	86165	86165	62628	62628	62628	55664	55664	55664	41448	41448	41448

Firm Wage Premium: Difference Between Occupations ◂ Back



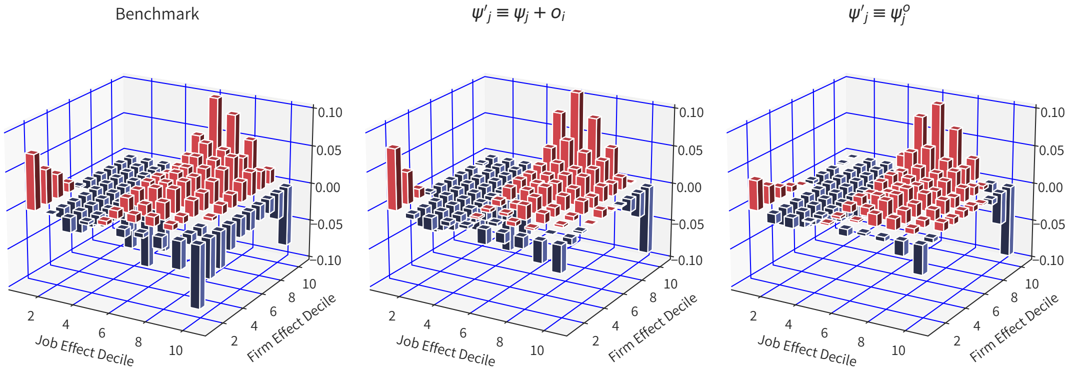
Firm Wage Premium: Firm Size and Firm Location

▸ Back

	Pooled			Computer			Design_Media			Admin		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
fsize.15-50	.019**	.018**	.023**	.012	.011	.014+	.049**	.035**	.045**	-.032	-.039	-.034
	(.004)	(.004)	(.003)	(.010)	(.009)	(.008)	(.011)	(.010)	(.008)	(.038)	(.034)	(.033)
fsize.50-150	.044**	.038**	.050**	.043**	.034**	.032**	.083**	.058**	.073**	-.023	-.038	-.035
	(.004)	(.004)	(.003)	(.010)	(.009)	(.007)	(.010)	(.010)	(.008)	(.038)	(.034)	(.033)
fsize.150-500	.069**	.059**	.068**	.079**	.053**	.043**	.127**	.087**	.094**	-.009	-.032	-.032
	(.004)	(.004)	(.003)	(.010)	(.009)	(.008)	(.011)	(.010)	(.009)	(.038)	(.034)	(.033)
fsize.500-2000	.099**	.081**	.086**	.119**	.070**	.053**	.176**	.121**	.120**	.015	-.014	-.019
	(.005)	(.004)	(.004)	(.011)	(.009)	(.008)	(.012)	(.011)	(.009)	(.038)	(.035)	(.033)
fsize.2000+	.125**	.105**	.121**	.154**	.077**	.065**	.213**	.140**	.134**	.028	-.005	-.006
	(.005)	(.005)	(.004)	(.011)	(.010)	(.008)	(.013)	(.012)	(.010)	(.038)	(.035)	(.034)
Job Effect ($\bar{\theta}$)		.284**	.200**		.793**	.622**		.479**	.395**		.262**	.171**
		(.004)	(.003)		(.009)	(.008)		(.010)	(.009)		(.020)	(.018)
const	.148**	-1.101**	-.630**	-.176**	-3.946**	-3.018**	.157**	-1.931**	-1.488**	.175**	-.919**	-.468**
	(.003)	(.016)	(.015)	(.010)	(.042)	(.037)	(.010)	(.046)	(.040)	(.038)	(.079)	(.073)
Location FE			✓			✓			✓			✓
Adj. R^2	.017	.096	.381	.025	.243	.515	.053	.190	.473	.014	.062	.292
No. Obs	84023	84023	84023	30658	30658	30658	13871	13871	13871	5592	5592	5592

Mean Residual for Work-Firm cells

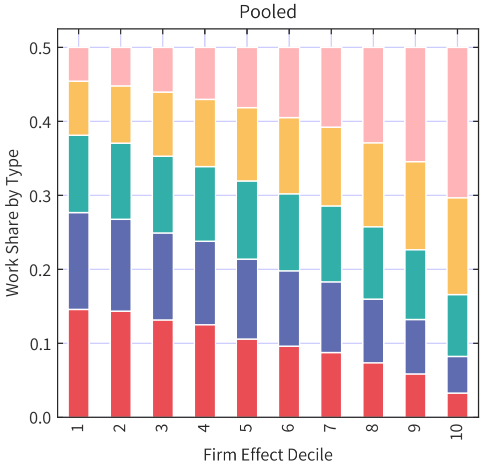
Back

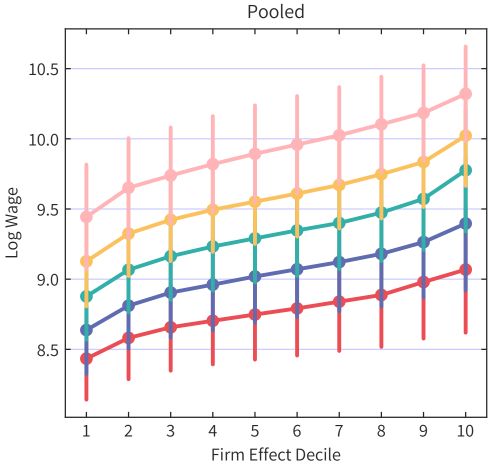


Occupational Specific Skill Prices

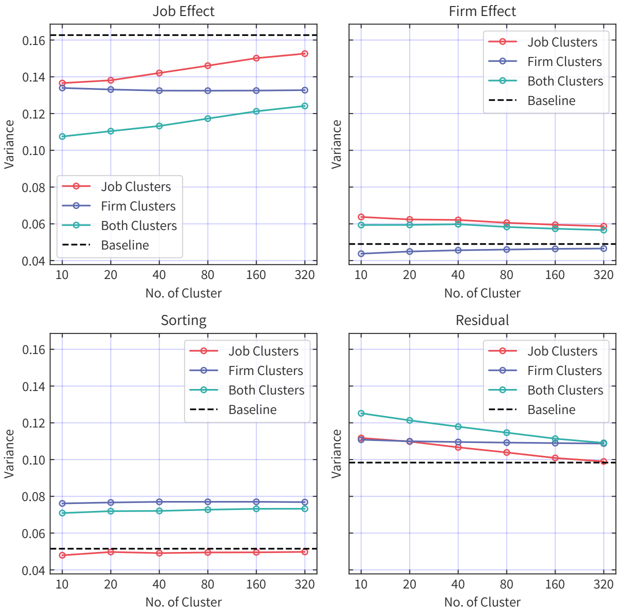
	Benchmark		$X_e\beta_o$		$\tilde{\Xi}\beta_o$		$X\beta_o$		$X\beta_o, \psi_j^o$	
	Comp.	Share	Comp.	Share	Comp.	Share	Comp.	Share	Comp.	Share
$\mathrm{Var}(\ln w)$	.362	-	.362	-	.361	-	.361	-	.359	-
Panel A: $X = \{$**EDU**, **EXP**, $\Xi_2, \ldots, \Xi_8\}$										
$\mathrm{Var}(\theta_i)$	.163	.450	.166	.459	.169	.469	.170	.470	.141	.393
$\mathrm{Var}(\epsilon_i)$	.098	.272	.095	.262	.092	.256	.092	.255	.085	.237
$\mathrm{Var}(\psi_j)$	.049	.136	.050	.137	.049	.136	.049	.136	.063	.175
$2\,\mathrm{Cov}(\theta_i, \psi_j)$	.051	.142	.051	.142	.050	.139	.050	.139	.072	.201
Panel B: Decompose θ **Terms**										
$\mathrm{Var}(X_{int})$	.042	.115	.053	.146	.040	.111	.048	.134	.039	.108
$\mathrm{Var}(X_{ext})$	.072	.199	.055	.152	.080	.221	.063	.175	.058	.162
$2\,\mathrm{Cov}(X_{int}, X_{ext})$	.049	.136	.058	.161	.049	.136	.058	.161	.044	.123
$2\,\mathrm{Cov}(X_{int}, \psi_j)$	.017	.048	.019	.053	.017	.048	.017	.048	.022	.061
$2\,\mathrm{Cov}(X_{ext}, \psi_j)$	.034	.094	.032	.089	.033	.092	.033	.091	.050	.141
Obs	3998840		3998840		3998840		3998840		3926231	
Firm	86165		86165		86165		86165		300079	

Work Types and Posted Wage by Firm Types



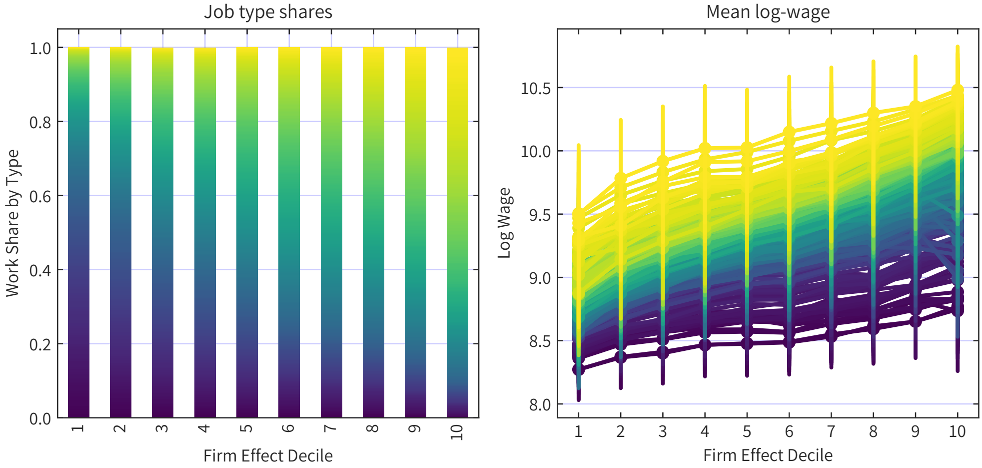


A Shortcut



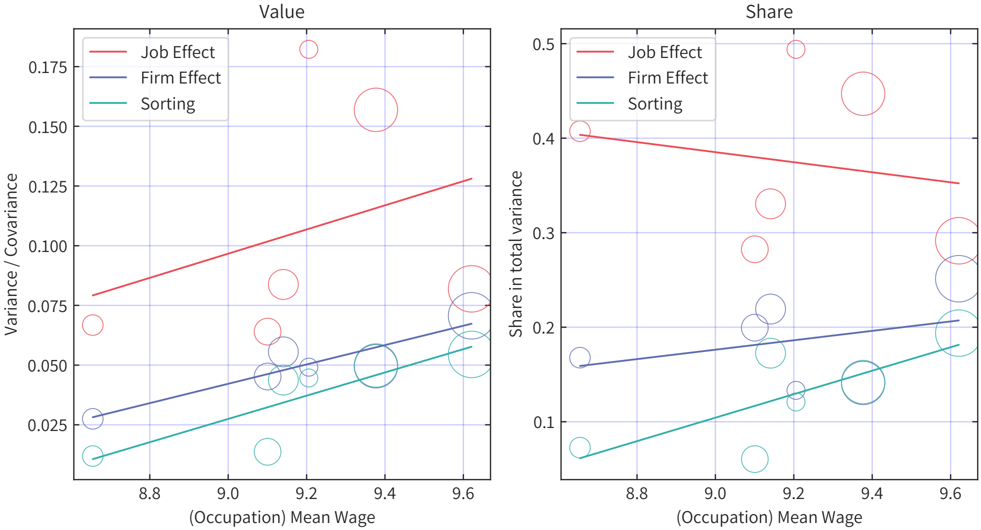
Job Effect
Variance
0.16
0.14
0.12
0.10
0.08
0.06
0.04
10
20
40
80
160
320
No. of Cluster
Job Clusters
Firm Clusters
Both Clusters
Baseline
Firm Effect
Variance
No. of Cluster
Sorting
Residual

Work Types and Posted Wage by Firm Types



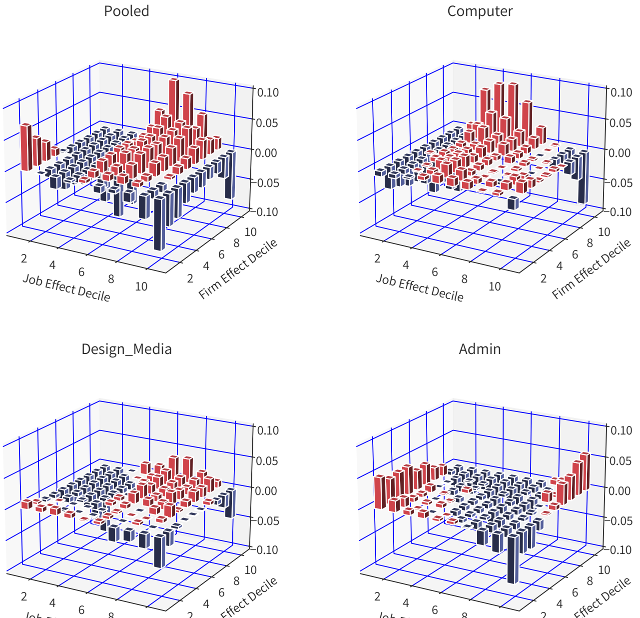
Shares Across Occupations

◂ Back



Mean Residual for Work-Firm cells

Back



Posted Wage Variance Trend Drivers (ψ_j^o) ◂ Back

	2014-2016		2017-2018		2019-2020	
	Comp.	Share	Comp.	Share	Comp.	Share
Var(ln w)	.322	-	.354	-	.373	-
Panel A: $X = \{$**EDU**, **EXP**, $\Xi_2, \ldots, \Xi_8\}$						
Var(θ_i)	.119	.370	.139	.392	.132	.354
Var(ϵ_i)	.086	.266	.082	.231	.083	.223
Var(ψ_j)	.064	.199	.066	.186	.076	.203
2 Cov(θ_i, ψ_j)	.053	.165	.068	.191	.082	.220
Panel B: Decompose θ Terms						
Var(X_{int})	.038	.117	.041	.115	.039	.104
Var(X_{ext})	.048	.148	.054	.153	.052	.138
2 Cov(X_{int}, X_{ext})	.034	.105	.044	.124	.041	.111
2 Cov(X_{int}, ψ_j)	.017	.053	.024	.067	.028	.075
2 Cov(X_{ext}, ψ_j)	.036	.112	.044	.124	.054	.144
Panel C: Further Decompose X_{ext} Terms						
Var(Ξ_g)	.001	.003	.001	.002	.001	.002
Var(Ξ_m)	.005	.014	.006	.016	.005	.013
Var(Ξ_s)	.025	.079	.028	.078	.026	.071
2 Cov(Ξ_g, Ξ_m)	.001	.004	.002	.005	.001	.004
2 Cov(Ξ_g, Ξ_s)	.005	.015	.005	.014	.005	.013
2 Cov(Ξ_m, Ξ_s)	.011	.034	.014	.039	.013	.036
2 Cov(Ξ_g, X_{int})	.003	.009	.003	.009	.003	.009
2 Cov(Ξ_m, X_{int})	.008	.024	.011	.030	.010	.026
2 Cov(Ξ_s, X_{int})	.023	.072	.030	.084	.029	.077
2 Cov(Ξ_g, ψ_j)	.003	.009	.003	.008	.004	.010
2 Cov(Ξ_m, ψ_j)	.009	.028	.012	.034	.013	.036
2 Cov(Ξ_s, ψ_j)	.024	.075	.029	.083	.037	.099
Obs	888345		1431781		1516033	
Firm	112096		167523		134233	

Posted Wage Variance Trend Drivers ($X\beta_o, \psi_j^o$) ◂ Back

	2014-2016		2017-2018		2019-2020	
	Comp.	Share	Comp.	Share	Comp.	Share
Var(ln w)	.322	-	.354	-	.373	-
Panel A: $X = \{$**EDU**, **EXP**, $\Xi_2, \ldots, \Xi_8\}$						
Var(θ_i)	.124	.384	.143	.405	.140	.376
Var(ϵ_i)	.083	.258	.079	.223	.081	.216
Var(ψ_j)	.062	.192	.063	.179	.073	.195
2 Cov(θ_i, ψ_j)	.059	.183	.068	.193	.077	.208
Panel B: Decompose θ Terms						
Var(X_{int})	.036	.113	.039	.111	.037	.100
Var(X_{ext})	.051	.158	.060	.168	.060	.160
2 Cov(X_{int}, X_{ext})	.036	.113	.044	.125	.043	.116
2 Cov(X_{int}, ψ_j)	.015	.046	.023	.065	.026	.070
2 Cov(X_{ext}, ψ_j)	.044	.137	.045	.127	.051	.137
Panel C: Further Decompose X_{ext} Terms						
Var(Ξ_g)	.001	.002	.001	.002	.001	.002
Var(Ξ_m)	.004	.013	.005	.015	.005	.013
Var(Ξ_s)	.031	.095	.033	.092	.033	.089
2 Cov(Ξ_g, Ξ_m)	.001	.003	.001	.003	.001	.004
2 Cov(Ξ_g, Ξ_s)	.002	.006	.005	.013	.007	.018
2 Cov(Ξ_m, Ξ_s)	.010	.033	.016	.044	.014	.037
2 Cov(Ξ_g, X_{int})	.002	.007	.003	.008	.003	.008
2 Cov(Ξ_m, X_{int})	.007	.023	.010	.028	.009	.023
2 Cov(Ξ_s, X_{int})	.026	.082	.032	.089	.032	.085
2 Cov(Ξ_g, ψ_j)	.005	.015	.003	.008	.001	.003
2 Cov(Ξ_m, ψ_j)	.010	.031	.011	.032	.013	.036
2 Cov(Ξ_s, ψ_j)	.029	.091	.031	.088	.037	.099
Obs	888345		1431781		1516033	
Firm	112096		167523		134233	

New Skills/Tasks

Back

	2014-2016		2017-2018		2019-2020	
	Comp.	Share	Comp.	Share	Comp.	Share
Var$(\ln w)$	.326	-	.357	-	.376	-
Panel A: $X = \{$**EDU**, **EXP**, $\Xi_2, \ldots, \Xi_8\}$						
Var(θ_i)	.148	.455	.163	.456	.156	.415
Var(ϵ_i)	.096	.294	.092	.257	.093	.248
Var(ψ_j)	.048	.148	.051	.142	.060	.159
2 Cov(θ_i, ψ_j)	.034	.103	.052	.145	.067	.178
Panel B: Decompose θ Terms						
Var(X_{int})	.040	.121	.043	.120	.041	.108
Var(X_{ext})	.069	.211	.071	.198	.068	.180
2 Cov(X_{int}, X_{ext})	.040	.122	.049	.138	.048	.127
2 Cov(X_{int}, ψ_j)	.012	.035	.018	.052	.023	.060
2 Cov(X_{ext}, ψ_j)	.022	.067	.033	.093	.044	.118
Panel C: Further Decompose X_{ext} Terms						
Var(Ξ_{new})	.000	.000	.001	.002	.001	.002
Var(Ξ_{gm})	.008	.024	.008	.023	.008	.021
Var(Ξ_s)	.038	.117	.035	.099	.033	.087
2 Cov(Ξ_{new}, Ξ_{gm})	.001	.002	.001	.004	.002	.004
2 Cov(Ξ_{new}, Ξ_s)	.001	.004	.003	.009	.003	.009
2 Cov(Ξ_{gm}, Ξ_s)	.021	.063	.022	.060	.021	.056
2 Cov(Ξ_{new}, X_{int})	.001	.002	.002	.005	.002	.005
2 Cov(Ξ_{gm}, X_{int})	.012	.038	.015	.042	.014	.038
2 Cov(Ξ_s, X_{int})	.027	.083	.033	.092	.032	.084
2 Cov(Ξ_{new}, ψ_j)	.001	.002	.002	.005	.002	.006
2 Cov(Ξ_{gm}, ψ_j)	.008	.026	.012	.034	.015	.039
2 Cov(Ξ_s, ψ_j)	.013	.040	.019	.054	.027	.073
Obs	930149		1494468		1565866	
Firm	41750		62907		53662	

Deming & Kahn (2018)

Back

Job Skills	Keywords and Phrases: Deming & Kahn (2018)	Keywords and Phrases: Chinese Correspondents
Cognitive	Problem solving, research, analytical, critical thinking, math, statistics	解决, 问题, 研究, 分析, 批判, 思考, 数学, 统计
Social	Communication, teamwork, collaboration, negotiation, presentation	交流, 沟通, 讨论, 演示, 展示, 合作, 团队, 协作
	Matched Keywords and Phrases in V': V_g, V_e	**Matched Keywords and Phrases in V': $V_{s1}, \ldots, V_{s5}$**
Cognitive	分析判断(analysis & judgment); 思考(reflections); 独立思考(independent thinking); 解决问题(problem solving); 数学(mathematics); 研究生(graduate students); 研究者(researchers); 统计学(statistics); 认真思考(think carefully)	统计(statistics); 统计分析(statistical analysis); 问题解答(question answers); 商业分析(business analysis); 行业研究(industry research); 业务分析(business analysis); 关键问题(key issues); 分析(analysis); 分析报告(analysis report); 功能分析(functional analysis); 可行性研究(feasibility study); 解决(solutions); 解决方案(solutions); 问题(question); 市场分析(market analysis); 数据分析(data analysis); 深入分析(in-depth analysis); 深入研究(in-depth research); 研究(research); 兼容性问题(compatibility issues); 定位问题(positioning issues); 疑难问题(difficult questions); 系统分析(system analysis); 面向对象分析(object-oriented analysis)
Social	交流(communication); 人际沟通(interpersonal communication); 协作(collaboration); 合作(cooperation); 团队(team); 团队精神(team spirit); 沟通(communication); 沟通交流(communication);学术交流(academic exchange)	合作项目(cooperation projects); 沟通了解(communication & understanding); 合作方(partners)

Deming & Kahn (2018) ◂ Back

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Cognitive	.045	.054	.027	.047	.013	.032	.011	.033
	(.000)	(.001)	(.000)	(.001)	(.000)	(.001)	(.000)	(.001)
Social	.035	.041	.030	.045	.020	.033	.025	.041
	(.001)	(.001)	(.001)	(.001)	(.000)	(.001)	(.001)	(.001)
Both required		-.012		-.026		-.024		-.029
		(.001)		(.001)		(.001)		(.001)
Ξ_g, Ξ_m			✓	✓			✓	✓
Ξ_s					✓	✓	✓	✓
Education FE	✓	✓	✓	✓	✓	✓	✓	✓
Experience FE	✓	✓	✓	✓	✓	✓	✓	✓
Occupation FE	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Adj. R^2	.582	.582	.604	.604	.636	.636	.641	.641