

# Posted Compensation Inequality

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# Roadmap

Introduction

Data

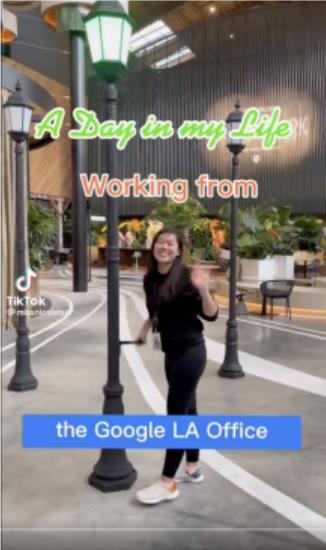
Empirical Facts

Discussion

A Simple Theory

Conclusion

# A Vignette



# A Vignette



→ Compensating Differential?

# Research Questions

## Empirical:

1. What consists **non-wage compensations** in today's labor market?
2. Do firms distinguish in their **provision of amenities/disamenities**? How?
3. What are their **impact on wage disparity**?

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## Empirical:

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3. What are their **impact on wage disparity**?

## Theoretical:

1. Do observed **firms' provision patterns** consisting with existing theories?
2. Why empirical tests of **compensating differential** often fail?
3. What are **general implications** of non-wage compensations on labor market?

# What This Paper Does

1. Investigate the **provision patterns & wage effects of non-wage compensation** (both pecuniary & nonpecuniary) by using **job ads/vacancy data**
  - Difficult to observe in census/survey data
  - Extract info from job texts using (basic) ML methods
  - Find stylized patterns in the data
  - Discuss the inconsistency between findings and existing theories

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  - Extract info from job texts using (basic) ML methods
  - Find stylized patterns in the data
  - Discuss the inconsistency between findings and existing theories
2. Construct **a new & simple theory** to rationalize our empirical findings
  - Extend the idea of compensating differential with a new force
  - Reconcile our empirical findings and offer important implications

# Preview of Empirical Findings

1. Firms use **common non-wage compensations** to **attract job seekers**:
  - insurance; work-time; additional pay; environment; other fringe benefits
2. Non-wage compensations **can predict posted wages**, but mainly through their **correlations with job/firm qualities**
3. **Diff firms in diff jobs** have **distinct compensation-provision patterns**
  - High-wage firms w/ high-skill jobs: general better except leisure
  - Low-wage firms w/ low-skill jobs: general worse except leisure
4. **Hedonic regression** shows **mixed results of compensating differential**
  - Yes in low-wage firms; No in high-wage firms

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  4. **Hedonic regression** shows **mixed results of compensating differential**
    - Yes in low-wage firms; No in high-wage firms
- These findings are **inconsistent** with the views of existing theories

# Preview of Theoretical Model

- We suggest a new theory that extends **Compensating Differential** with "Efficiency Compensation" and **productivity-based firm-worker Sorting**
- **Key idea:**
  1. Many compensations observed in data are (in)efficiency compensation
  2. The level of efficiency depends on firm & worker productivity
- **Mechanism:** **A new channel** works in addition to compensating differential
  1. When a compensation is **efficient**, it **counteracts** compensating differential effect
  2. When a compensation is **inefficient**, it **magnifies** compensating differential effect
  3. Extent of this (in)efficiency channel depends on firm-worker productivity sorting

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- This simple modification **reconciles all findings** and generates many important **general implications**

# Related Literature

## 1. Literature on Compensating Differential:

- Classic: Rosen (1974); Brown (1980); Rosen (1986); Hwang et al. (1992)
  - Recent: Mas and Pallais (2017); Maestas et al. (2018); Wissmann (2022) / Sorkin (2018); Taber and Vejlin (2020); Lamadon et al. (2022)
- New insights & New theory that reconciles existed empirical failures

## 2. Literature on Compensation Provision:

- Theory: Rosen (1974, 1986); Hwang et al. (1998); Hamermesh (1999); Mortensen (2005); Dey and Flinn (2005); Bonhomme and Jolivet (2009)
  - Empirical: Sockin (2022); Lachowska et al. (2022); Bana et al. (2022); Lamadon et al. (2022)
- New evidences & New theory that explains those new evidences

## 3. Literature on Efficiency Wage:

- Salop and Salop (1976); Shapiro and Stiglitz (1984); Katz (1986); Krueger and Summers (1988); Bloesch et al. (2021)
- Apply the insights to a more suitable place: "Efficiency Compensation"

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# Data Source

Lagou.com: the largest IT-centered online job board in **China**

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

# Posted Compensation/Amenity Information

- Pros:

1. Hard to observe in census or survey data
2. Compensations or amenities that firms regard as important to attract workers
3. Also observe detailed job information

- Cons:

1. Not a full list of the compensations that a firm offer
2. Mainly amenities, rare disamenities (strategic hiding?)
3. Maybe cheap talk?

- Our empirical results will be mainly **descriptive & exploratory**

- No priori, let the data speak
- Find stylized facts of patterns & correlations in the data
- Shed new insights in thinking theories

# Unstructured Text Data

- $V$ : full vocabulary set with 110,000+ tokens/features (i.e. words or terms)
- $V_{\text{comp}} \subset V$ : compensation vocabulary set with 13,000+ features
  - Not all uniques: synonyms, different versions, typos
  - Common words or stop words
  - Irrelevant texts
- $\mathbf{C}_{\text{comp}} \in \mathbb{R}^{N \times |V_{\text{comp}}|}$ : an indicator matrix to run regression
- So, high-dimensional data  $\rightarrow$  (basic) Machine Learning methods

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Q1: What are the non-wage compensations that firms use to attract workers?



Q2: How do non-wage compensations affect wage?

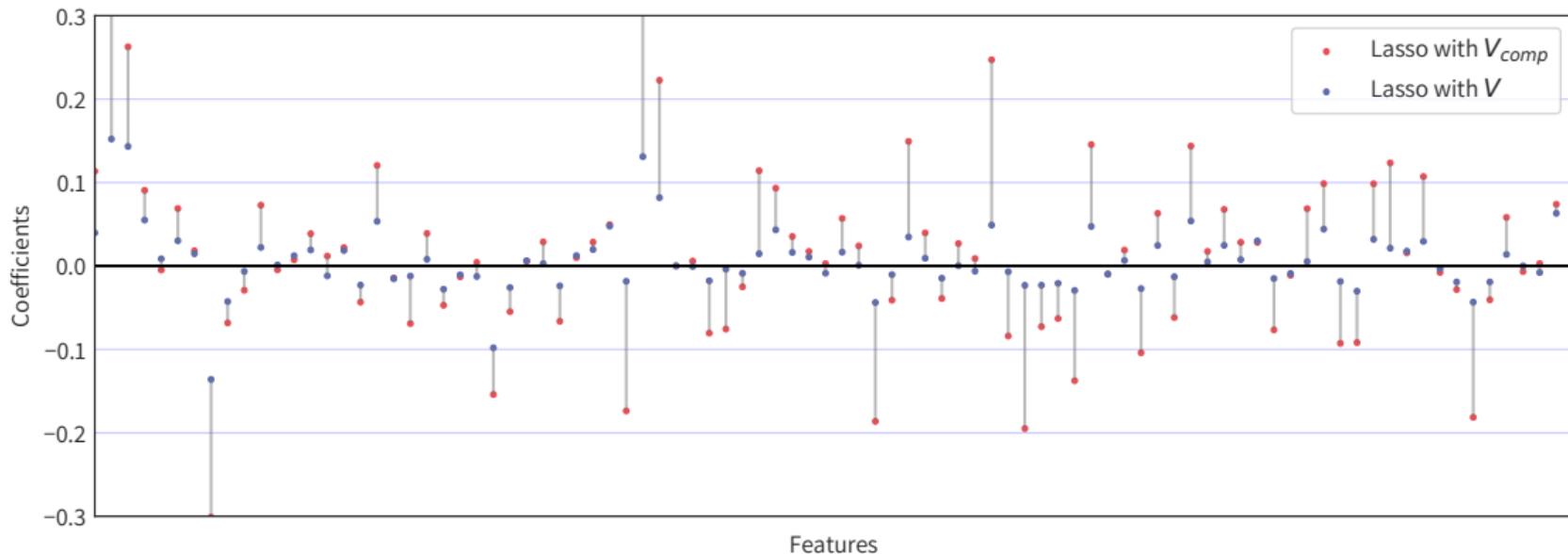
# Lasso Regression using $V_{\text{comp}}$ : Top Features (Frequency > 1%)

[lasso details](#)

	Top Positive			Top Negative		
	token	coef	freq	token	coeff	freq
1	14th month pay	.331	.013	five insurance	-.301	.020
2	large platform	.310	.016	commission	-.195	.022
3	three meals	.263	.013	young	-.186	.012
4	technology	.247	.025	easy	-.181	.014
5	guru	.223	.024	training	-.174	.018
6	flexibility	.149	.091	two-day weekend	-.154	.140
7	options	.146	.043	promotion	-.138	.068
8	shuttle	.144	.015	events	-.104	.010
9	remuneration	.124	.015	holiday	-.093	.017
10	six insurance & one fund	.121	.050	holidays	-.092	.046
11	platform	.114	.046	provide	-.084	.012
12	13th month pay	.114	.021	jobs	-.080	.097
13	supplementary	.107	.011	achievements	-.077	.010
14	stock	.099	.017	work system	-.076	.012
15	salary	.099	.025	travel	-.073	.058
16	good platform	.093	.010	entrepreneurship	-.069	.013
17	listed company	.091	.023	five insurance & one fund	-.068	.261
18	high salary	.074	.018	employees	-.066	.029
19	products	.073	.012	time	-.063	.012
20	lucrative	.069	.018	environment	-.062	.038
21	shareholding	.069	.012	double pay	-.055	.032
22	benefits	.068	.035	office	-.047	.018
23	motivation	.063	.016	company	-.043	.050
24	projects	.058	.030	wide	-.041	.012
25	year-end bonus	.057	.042	snacks	-.041	.013
26	team	.050	.108	growing	-.039	.025

# Fact 2a: Firm Non-wage Compensations Correlated With Job Attributes

◀ Lasso top features using  $V$



◀ All  $V'_{comp}$

## Fact 2b: Compensations Explain Wage Differentials Through Linkage with (Both Job and) Firm Heterogeneity

◀ posted wage regression details

$$\ln w_{i,j,t} = \theta_i + \psi_j + \delta_i + \iota_t + \epsilon_i$$

	With $\delta$		Without $\delta$	
	Comp.	Share	Comp.	Share
Var( $\ln w$ )	.362	-	.362	-
Var( $\theta_i$ )	.158	.437	.163	.450
Var( $\psi_j$ )	.046	.128	.049	.136
Var( $\delta_i$ )	.002	.004		
Var( $\epsilon_i$ )	.097	.269	.098	.272
2 Cov( $\theta_i, \psi_j$ )	.049	.137	.052	.142
2 Cov( $\delta_i, \theta_i$ )	.006	.017		
2 Cov( $\delta_i, \psi_j$ )	.003	.008		
Corr( $\theta_i, \psi_j$ )	.289		.288	
Corr( $\delta_i, \theta_i$ )	.193			
Corr( $\delta_i, \psi_j$ )	.174			
<b>Obs</b>	3998840		3998840	
<b>Firm</b>	86165		86165	

## Fact 2b: Compensations Explain Wage Differentials Through Linkage with (Both Job and) Firm Heterogeneity

◀ posted wage regression details

**Interpretation** of the  $\delta$  terms depends on how the amenity-wage relationship is modeled

	With $\delta$		Without $\delta$	
	Comp.	Share	Comp.	Share
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Q3: How exactly firms & jobs vary in their compensation provision?

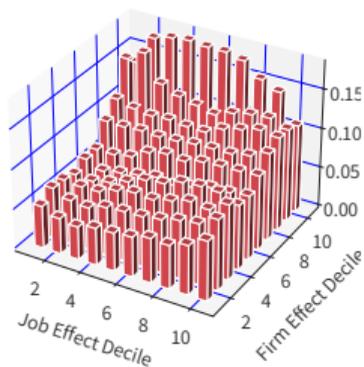
## Gather Important Types and Check Occurrence

- We can take a direct look on if high/low wage firms or jobs are accompanied with low/high valued amenities
- We do this by selecting a set of major, well-defined, and economic important compensations from  $V_{\text{comp}}$  based on the frequency & Lasso coefficient
- We gather all relevant terms by checking proximate terms in the embedding space of a work-embedding model trained on the whole job texts
- We then examine how the occurrence ratio for each type differ across different firms & jobs

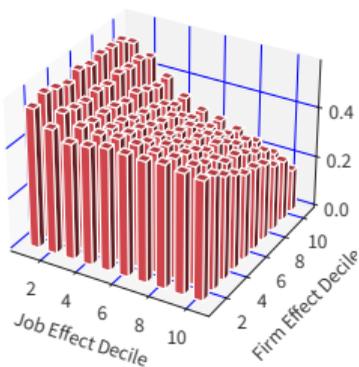
# Fact 3: Systematic Differences in Compensation Provision Across Firms and Jobs

◀ more types

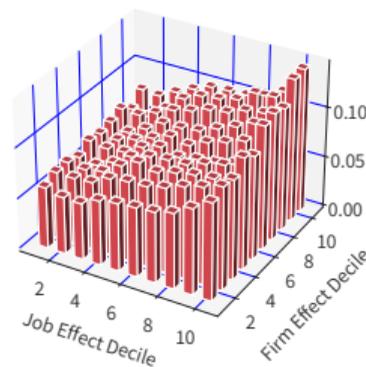
(a) Advanced Insurance



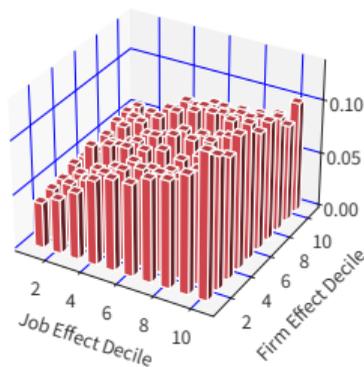
(b) Basic Insurance



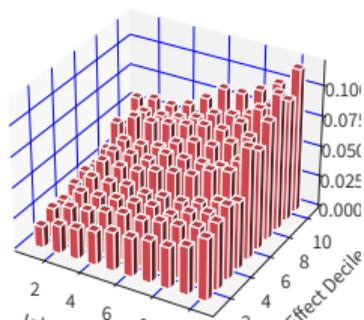
(c) Backloading Wage



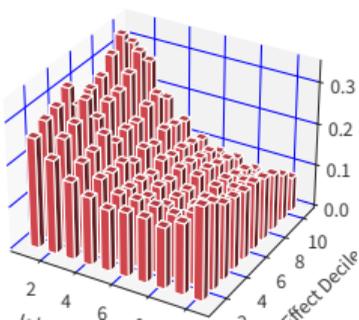
(d) Stock Option



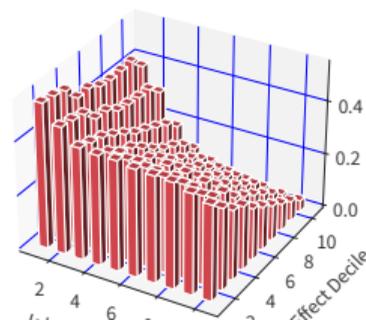
(e) Coworker Quality



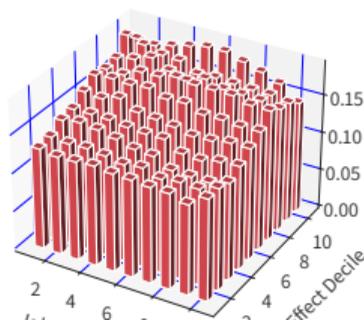
(f) Training



(g) Weekend, Holiday, Fixed Work-Time



(h) Work(-Time) Flexibility



Q4: What if we test for compensating differential using hedonic regression?

## Fact 4: Hedonic Regression Results are Mixed but in A Systematic Way

	(1)	(2)	(3)
Advanced Insurance	.117** (.001)	.087** (.001)	.014** (.001)
Backloading Wage	.054** (.001)	.030** (.001)	.010** (.001)
Stock Option	.114** (.001)	.058** (.001)	.087** (.001)
Coworker Quality	.140** (.001)	.059** (.001)	.024** (.001)
Work-Flexibility	.046** (.001)	.032** (.001)	.010** (.001)
Basic Insurance	-.062** (.000)	-.046** (.000)	-.025** (.000)
Training	-.057** (.001)	-.012** (.001)	-.003** (.001)
Work-Time	-.113** (.001)	-.081** (.000)	-.021** (.000)
Education FE	✓	✓	✓
Experience FE	✓	✓	✓
Year FE	✓	✓	✓
$C_{comp}$ Firm FE		✓	✓
Adj. R <sup>2</sup>	.506	.633	.738
No. Obs	3998840	3998840	3998840

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# Summary of Empirical Findings & Implications on Theory

1. Most non-wage compensations in the labor market are **common stuffs**: insurance, work-time, extra pay, workplace, ...  
→ **endogenous rather than exogenous variations** in firm cost functions (& variations in worker preference?)

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3. Firms in different jobs **vary significantly in their compensation-provision patterns**  
→ important mechanism of **compensation provision linked with firm/worker quality**
4. Hedonic regression shows **systemically mixed results of compensating differential** for compensations provided by diff firms in diff jobs  
→ reason of the **empirical failures linked with the provision patterns**

# The Phantom of Unobserved Worker Ability

- Yes, there still could be **unobserved worker ability** not-captured which cause bias in the estimation above (Rosen, 1986; Hwang et al., 1992)

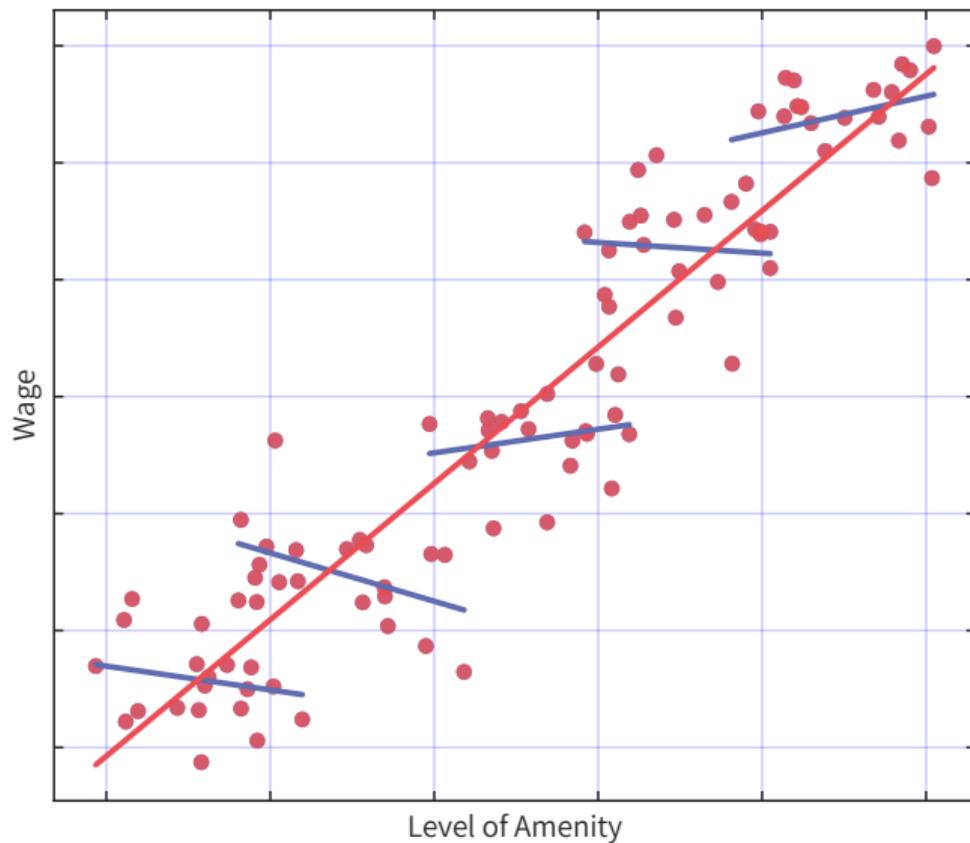
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- But would unobserved skill heterogeneity **matter so much?**
  - In our job vacancy data, the **usually-unobserved job heterogeneity** accounts for **additional 5 percent** of the posted wage variances
  - Unobserved job heterogeneity is typically **positively correlated with observed job heterogeneity**

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  - Unobserved job heterogeneity is typically **positively correlated with observed job heterogeneity**
- Perhaps compensation differential is not **the sole or the major force**?
  - The **toughness of the omitted-variable problem** indicates **other dominant mechanism of compensating dispersion**

# Unobserved Worker Ability $\rightarrow$ Compensation Inequality?



## Can Existing Theories Explain Positive Wage-Amenity Relationship?

- Hwang et al. (1992); Mortensen (2005): income effect
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- Problem 2: amenity-producing cost cannot explain why it is high-pay firms provide many superior amenities like insurance or backloading wages
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- Our new model reconciles all these from a simple yet new angle

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# Model Overview

- **Workers**: heterogeneous in productivity; homogenous in preference
- **Firms**: heterogeneous in productivity; homogenous in (dis)amenity prod func
- **Firm-worker sorting** is thus solely based on productivity
  - In the classic Rosen model, sorting purely on worker preference & firm cost
  - Reality is likely a mix and depends on demographics ([Lentz et al., 2021](#))
  - We use O-Ring structure, so workers-sorting & only ex-post firm heterogeneity
- Key element: **Non-wage compensations can be "(in)efficient"**
  - Motivation: our observation; efficiency wage & its critiques; [Dey and Flinn \(2005\)](#)
  - Various micro-foundations: here the simplest way—"inducing effort"
  - Extra feature: the level of (in)efficiency depends on productivity sorting
  - We set one efficient amenity and one inefficient amenity for illustration

## Model Setting: Worker

- A continuum of worker with **heterogenous productivity**  $q \in [0, 1]$  and additively separable (quasi-linear) **utility function**  $U(C, a, h) = C + \phi_a a - \frac{h^{1+\phi_h}}{1+\phi_h}$ 
  - $C$  is monetary consumption
  - $a \in \{0, 1\}$  is the indicator of **a discrete amenity**, e.g. insurance
  - $h$  is **a continuous disamenity**, e.g. additional working hour

# Model Setting: Firm

- Firms are ex-ante homogenous with O-Ring production function:

$$Y_j = AN_j^{1+\alpha} \prod_{i=1}^{N_j} q_i e(a, h)$$

- $N$  is assumed to be fixed exogenously ◀ can relax
- **Compensations are (in)efficient:**  $e(a, h) = 1 + \gamma_a a + \frac{h^{\gamma_h}}{\gamma_h}$   
(microfoundations: e.g. less exogenous or endogenous exit (Hwang et al., 1998; Dey and Flinn, 2005); convexity in hour productivity (Goldin, 2014))
- Firm pay direct cost  $\kappa$  for  $a$  and compensate wage  $w$  for  $h$

# Competitive Equilibrium & Matching

- **Competitive equilibrium** in this economy is defined as an **assignment** of worker types to firms and a **utility schedule**,  $u(q)$  such that
  - Firms maximize their profits
  - Labor market clears
- Complementary production function & additively separable utility function ensure **positive assortative matching (PAM)** even under imperfect transferable utility
  - each firm will employ workers with same  $q$

# Firms' Optimal Choices

- A firm chooses  $\{q, a, h, w\}$  to maximize profit s.t. market utility schedule ◀ firm problem

$$- a^* = \begin{cases} 1, & \text{if } q \geq q_a \\ 0, & \text{if } q < q_a \end{cases}, \text{ and } \underbrace{AN^\alpha q_a^N \gamma_a + \phi_a}_{\text{mb}} = \underbrace{\kappa}_{\text{mc}}$$

- If  $a$  is not efficient, i.e.  $\gamma_a = 0$ , return back to the canonical compensating differential
- If unit cost is  $q\kappa$ , higher  $q$  firms are still more likely to provide  $a$
- $h^* = (AN^\alpha q^N)^{\frac{1}{1+\phi_h-\gamma_h}}$  increases in  $q$ 
  - $h^*(q)$  will be fully compensated by  $w(q)$ , thus provision cost ex-post depends on  $q$

$$- w(q) = \begin{cases} \bar{A}q^N + \underbrace{\gamma_a \bar{A}q^N - \kappa}_{\text{wage effect of } a} + \underbrace{\frac{(\bar{A}q^N)^{1+\omega}}{(1+\omega)(1+\gamma_h)} + \frac{(\bar{A}q^N)^\omega}{1+\gamma_h}}_{\text{wage effect of } h}, & \text{if } q \geq q_a \\ \bar{A}q^N + \underbrace{\frac{(\bar{A}q^N)^{1+\omega}}{(1+\omega)(1+\gamma_h)} + \frac{(\bar{A}q^N)^\omega}{1+\gamma_h}}_{\text{wage effect of } h}, & \text{if } q < q_a \end{cases}$$

- Recall  $\gamma_a \bar{A}q^N - \kappa = -\phi_a$  when  $q = q_a$  and can be positive when  $q \uparrow$   
 → offsetting compensating differential
- $\frac{(\bar{A}q^N)^{1+\omega}}{(1+\omega)(1+\gamma_h)}$  is the efficiency gain from  $h$ ;  $\frac{(\bar{A}q^N)^\omega}{1+\gamma_h}$  is the compensation for  $h$   
 → magnifying compensating differential

# Model Implications 1. Compensating Differential

## 1.1 Compensating effects can be **confounded with productivity effects**

- Esp. for the up-end labor market where (in)efficiency forces are strong

## 1.2 The result of an **empirical test on compensating differential** will depend on the **targeted labor market**

- If focusing on low-end labor market (close to  $q_a$  or  $q < q_a$  with imperfectly mandated policies) → easy to find clear evidence
- If focusing on board or high-end labor market (& with heterogeneous usage in efficiency compensation or imperfect matching) → tests likely to fail

## 1.3 **Available variations for wage-amenity packages can be limited** conditional on worker

- Depends on exogenous heterogeneity v.s. endogenous heterogeneity
- Constrains on both low-end and high-end markets

→ Field/choice experiments (WtP) or RCT-like experiments (exogenous variations) not necessarily capture the whole picture of how labor market works

## Model Implications 2. Labor Market Inequality

- 2 Efficiency compensations can **enlarge both utility dispersion & wage dispersion**
    - Ignoring non-wage compensations can underestimate labor market inequality
    - Moreover those compensations per se can actually be the drivers of wage inequality
- Increased sorting or better use of efficiency compensations increases wage inequality

## Model Implications 3. Job Mobility & Choice

3.1 The set of non-wage compensations that can justify job moves to low wage-premium firms is likely **limited to inefficient amenities**

- Work-time/effort is the most likely culprit for moving downgrade

3.2 **Greater compensating** than just "compensating differential"

- A worker with a  $\phi_h$  shock would suffer not only traditional compensation differential but also a worse matching & an inferior package of other compensations
- Again, available choices for wage-amenities packages are limited

→ Potential implications for gender wage gap and etc.

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**Conclusion**

# Take-Away Message

1. **Think explicitly** about non-wage compensations: insurance/fund, work-time, pay schemes, work environment, fringe benefits, ...  
→ empirical focus & policy targets & intuition when back-out revealed preference
2. Different Firms in different jobs have **distinct provision patterns**  
→ compensating differential  $\neq$  provision inequality
3. **(In)Efficiency compensations & productivity sorting** reconciles empirical findings and generates important implications  
→ high-wage firms can also offer better compensations without wage discounts

# Appendix

## Future Plan/Possibility

- Model the posted compensation as a discrete choice of firms?
- Interact/Distinguish with the income effect?
- Allow for heterogeneous preference and multi-dimensional sorting?
- Allow for search frictions and mismatch?
- Bring the model implications to the data?
- Combine with worker self-reporting data?
- Test if the similar empirical facts in the Japanese Data?

# Shortcomings & Some Reliefs

◀ Back Intro

◀ Back Data

- Vacancy data may be **selective or less representative**
  - Vacancy data is inclined to **young and more educated** workers, esp. here
  - **Not all jobs on the internet** or different post frequency than job composition

*(Valid issue for all vacancy data; Extent is an **empirical question**; With dev and structural transform, more and more likely to **become the dominant cases**; help to consider the aging worker cases)*

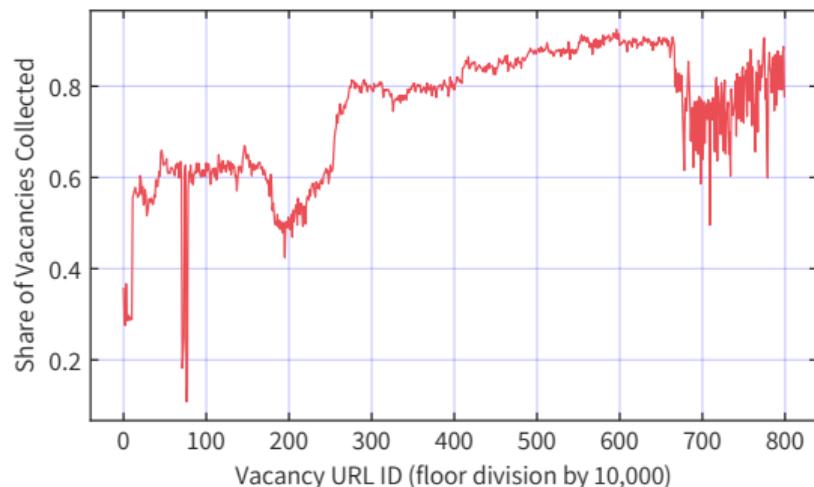
- Our wage measure incorporates **variation in hours**
  - One might worry that those efficient compensations are **solely compensating more working hours**

*(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 / 本科及以上学历 / 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**

△ ② ③

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 Requirement**

岗位职责:

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

职位要求:

- 本科及以上学历, 计算机相关专业;
- 热爱计算机科学和互联网技术, 对移动产品有浓厚兴趣;
- 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;
- 熟悉 iOS平台原理, 具备将产品逻辑抽象为技术方案的能力;
- 关注用户体验, 能够积极把技术转化到用户体验改进上;
- 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**

 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>

- 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](#)

- 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](#)

# Data: Summary Statistics [◀ Back](#)

	Pooled	Computer	Design_	Major Occupation			Sales	Admin
	-		Media	Business_	Financial_			
				Operations	Legal			
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	



# Lasso Regression

[◀ Back](#)

- Two purposes: (i) a first look of the wage-amenity relationship (ii) shrink features
- Run a **Lasso regression** of log posted wage  $\ln w$  on an **indicator matrix**  $\mathbf{C}_{\text{comp}} \in \mathbb{R}^{N \times |V_{\text{comp}}|}$ 
  - Use **BIC** to tune the Lasso penalization hyper-parameter [▶ lasso details](#)
- It shrinks  $V_{\text{comp}}$  to a **vocabulary subset**  $V'_{\text{comp}}$  with only 800 features (and  $\mathbf{C}_{\text{comp}}$  to  $\mathbf{C}'_{\text{comp}}$ )
- Inference & Robustness:
  - Coefficients are in general **not interpretable** due to multicollinearity & flexibility
  - Use **subsampling** to do inference, results are robust [▶ subsampling](#)
- Conduct **same Lasso regression** for  $\mathbf{C} \in \mathbb{R}^{N \times |V|}$ , and **inspect** top features & changes

- Lasso regression (L1 penalization):

$$\hat{\zeta} = \arg \min_{\zeta} \sum_{i=1}^N \left( \ln w_i - \sum_{k=1}^K c_{ik} \zeta_k \right)^2 + \lambda \sum_{k=1}^K |\zeta_k|$$

- BIC as the criterion to gauge the hyperparameter  $\lambda$ :

$$\min \text{BIC}(\lambda) = \frac{\| \ln \mathbf{w} - \mathbf{C} \hat{\zeta}_{\lambda} \|^2}{\sigma^2} + \hat{df}_{\lambda} \log N$$

- Inference via [subsampling](#) (10x10)

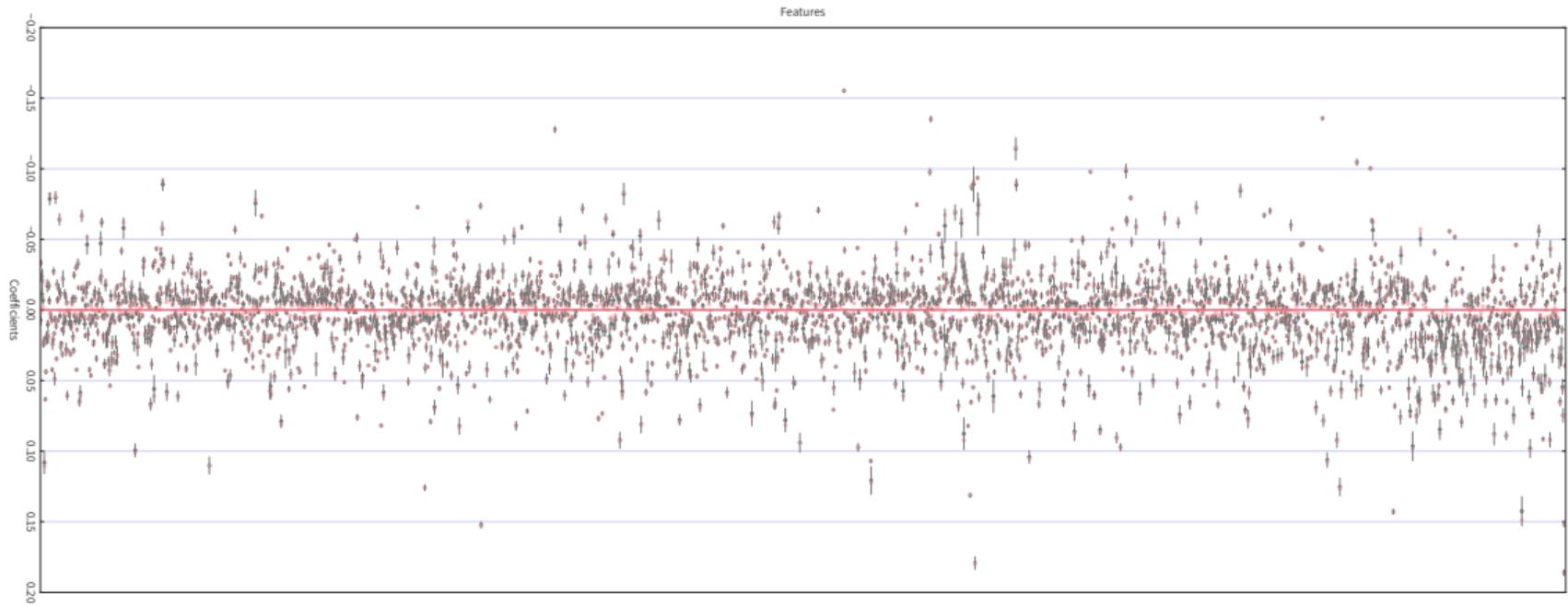
# Lasso Regression using $V$ : Top Features (Frequency $> 1\%$ )

[▶ back](#)

	Top Positive			Top Negative		
	token	coef	freq	token	coeff	freq
1	<u>14th month pay</u>	.152	.014	freshmen	-.155	.018
2	<u>three meals</u>	.143	.014	<u>five insurance</u>	-.136	.030
3	<u>large platform</u>	.131	.019	graduates	-.128	.033
4	master degree	.126	.015	vocational major	-.100	.036
5	lead	.107	.041	<u>two-day weekend</u>	-.098	.166
6	c++	.092	.051	vocational college	-.094	.148
7	algorithm	.082	.061	assistant	-.079	.011
8	<u>guru</u>	.082	.028	customer service	-.075	.030
9	famous	.079	.019	<u>social insurance</u>	-.073	.028
10	machine learning	.077	.016	accounting	-.071	.019
11	formation	.076	.013	<u>accommodation</u>	-.067	.016
12	undergraduate	.074	.319	administration	-.067	.027
13	overseas	.072	.026	commissioner	-.063	.011
14	react	.072	.020	taobao	-.059	.015
15	<u>development</u>	.071	.374	assistance	-.058	.164
16	undergraduate	.066	.029	ps	-.056	.029
17	<u>high salary</u>	.063	.028	ltd.	-.056	.012
18	landing	.060	.067	installation	-.055	.020
19	strategy	.057	.047	photoshop	-.052	.039
20	live streaming	.056	.014	careful	-.050	.032
21	<u>listed company</u>	.055	.027	hardworking	-.050	.032
22	large scale	.055	.072	verification	-.048	.011
23	responsibilities	.055	.048	human resources	-.047	.032
24	<u>shuttle</u>	.054	.018	website	-.047	.090
25	<u>finance</u>	.054	.070	any major	-.047	.020
26	<u>six insurance &amp; one fund</u>	.053	.055	humanization	-.046	.012

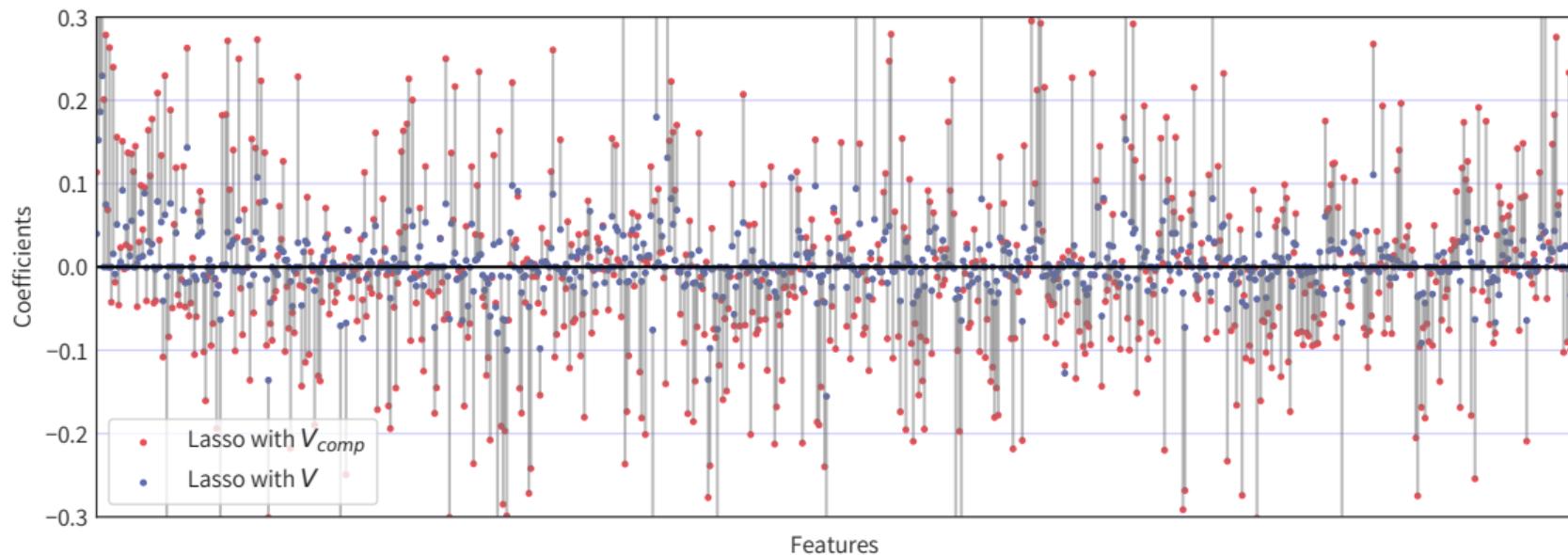
# Confidence Intervals on Lasso Coefficients via Subsampling

[◀ Back](#)



# Compare Lasso Coefficients

[← Back](#)

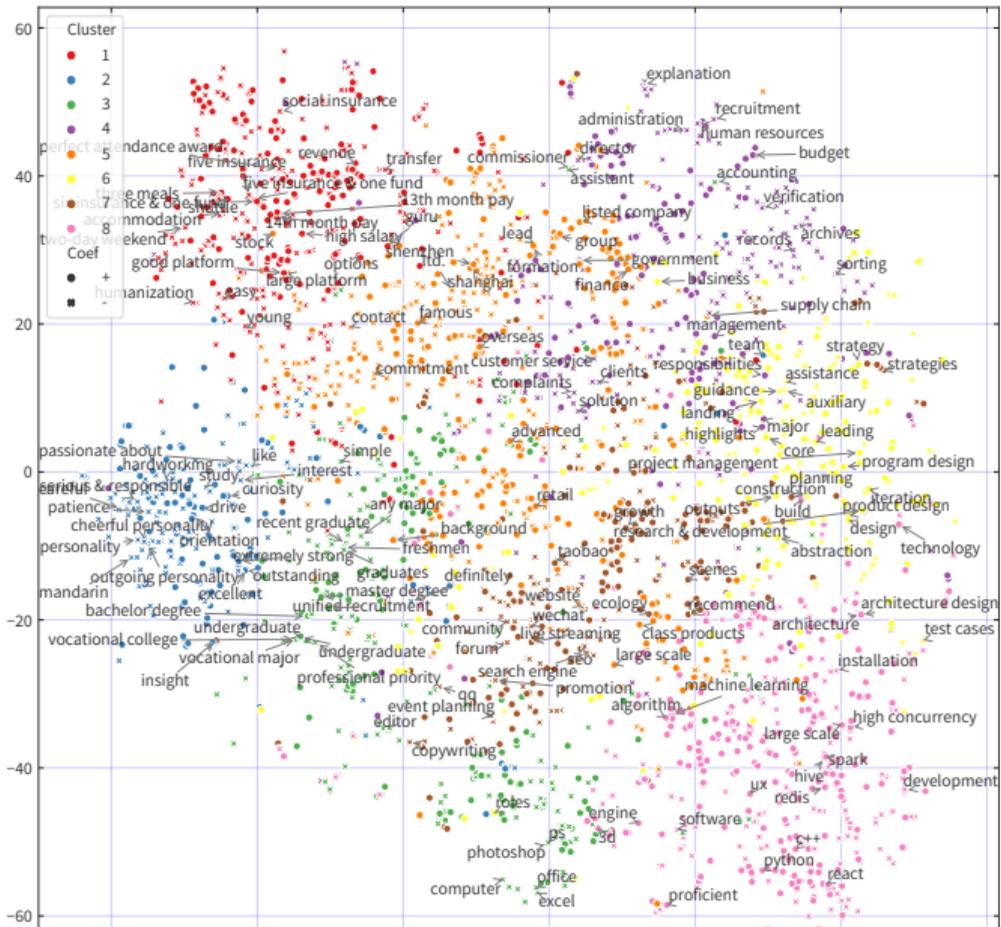


# Posted-Wage Regression ◀ Back

- So the predictive power of non-wage compensations in part comes from their correlation with **job skills/tasks**; What about **firms**?
- **Posted wage regression**:  $\ln w_{i,j,t} = \theta_i + \psi_j + \delta_i + \iota_t + \epsilon_i$ 
  - $\theta_i \equiv X_i \beta$  (job/worker effect),  $X_i = \{\text{EDU}_i, \text{EXP}_i, \mathbf{c}'_{i,\backslash\text{comp}}\}$
  - $\psi_j$  (firm fixed effect)
  - $\delta_i \equiv \mathbf{c}'_{i,\text{comp}} \gamma$  (compensation effect)
  - $\iota_t$  (year fixed effect)
  - In practice, further dimensional reduction on  $\mathbf{c}'_{i,\backslash\text{comp}}$  &  $\mathbf{c}'_{i,\text{comp}}$  using PLS
  - This posted wage regression does a similar job to the AKM framework (Zhu, 2022)
- **Variance decomposition**:  $\text{var}(\ln w_i) = \text{var}(\theta_i) + \text{var}(\psi_j) + \text{var}(\delta_i) + 2 \text{cov}(\theta_i, \psi_j) + 2 \text{cov}(\theta_i, \delta_i) + 2 \text{cov}(\psi_j, \delta_i) + \text{var}(\epsilon_i)$

# Feature Clustering: Visualization

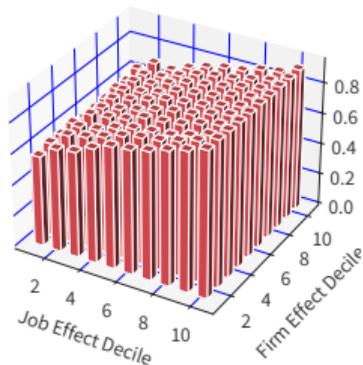
[◀ Back](#)



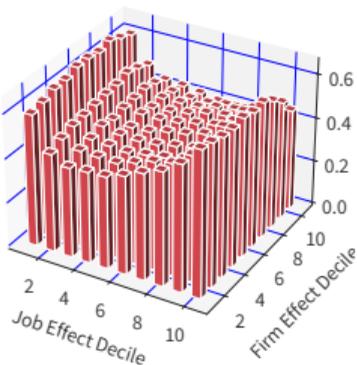
# Compensation Occurrence (More)

[◀ Back](#)

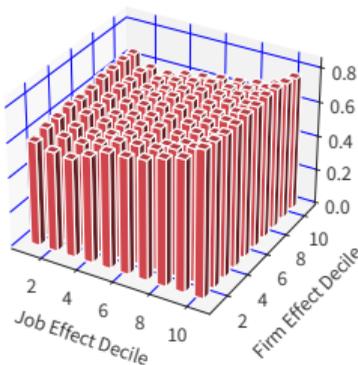
(a) Development



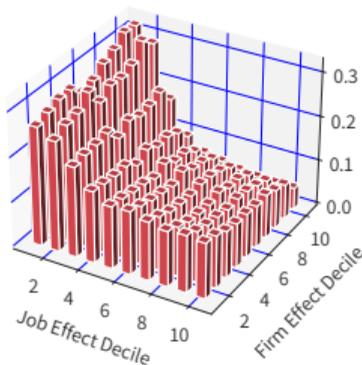
(b) Management



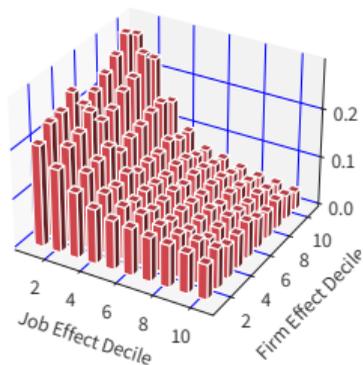
(c) Environment



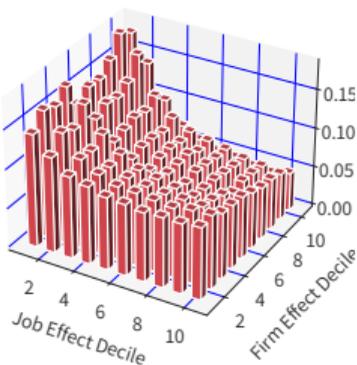
(d) Commission



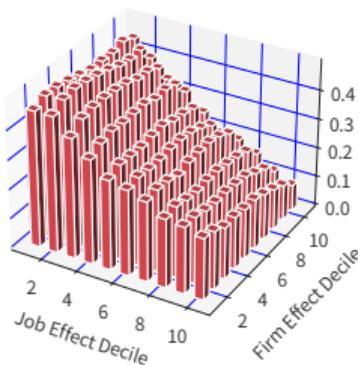
(e) Promotion



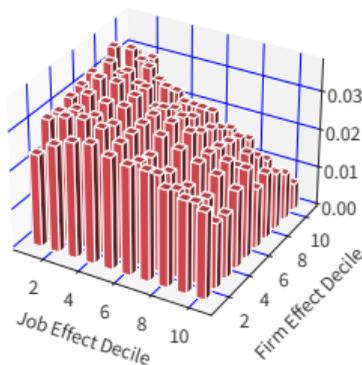
(f) Location



(g) Team Building



(h) Coworker Looking



# Hedonic Regression

	Pooled	Computer	Design_ Media	Admin
	(1)	(2)	(3)	(4)
Advanced Insurance	.014** (.001)	.016** (.001)	.009** (.002)	.002 (.003)
Backloading Wage	.010** (.001)	.013** (.001)	.022** (.002)	.011** (.002)
Stock Option	.087** (.001)	.068** (.001)	.060** (.002)	.040** (.003)
Coworker Quality	.024** (.001)	.016** (.001)	.005* (.002)	.008+ (.004)
Work-Flexibility	.010** (.001)	.007** (.001)	.009** (.001)	.005** (.002)
Basic Insurance	-.025** (.000)	-.024** (.001)	-.017** (.001)	-.013** (.001)
Training	-.003** (.001)	-.019** (.001)	-.003 (.002)	.013** (.002)
Work-Time	-.021** (.000)	-.018** (.001)	-.020** (.001)	-.022** (.001)
Education FE	✓	✓	✓	✓
Experience FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
$\Xi_2, \dots, \Xi_8$	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓
Adj. R <sup>2</sup>	.738	.748	.730	.657
No. Obs	3998840	1325260	548808	260364

# Firms' Problem ◀ Back

- Firm problem: 
$$\max_{\{q_i\}_{i=1}^N, a, h, w(q)} AN^{1+\alpha} \prod_{i=1}^N q_i e(a, h) - \sum_{i=1}^N w(q_i) - a\kappa N$$

s.t. 
$$w(q) + \phi_a a - \frac{h^{1+\phi_h}}{1+\phi_h} \geq u(q) \quad \forall q \in \{q_i\}_{i=1}^N$$

- Complementary production function & additively separable utility function ensure **positive assortative matching (PAM)** even under imperfect transferable utility  
→ a firm will employ workers with same  $q$

- Rewrite the firm problem given equilibrium allocation:

$$\max_{q, a, h} AN^{1+\alpha} q^N \left(1 + \gamma_a a + \frac{h^{\gamma_h}}{\gamma_h}\right) - N \left(u(q) - \phi_a a + \frac{h^{1+\phi_h}}{1+\phi_h}\right) - a\kappa N$$

- FOCs: 
$$AN^{1+\alpha} q^{N-1} e(a, h) = u'(q)$$

$$AN^\alpha q^N h^{\gamma_h-1} = h^{\phi_h}$$

$$- u(q) = \begin{cases} \frac{(\bar{A}q^N)^{1+\omega}}{(1+\omega)(1+\gamma_h)} + (1 + \gamma_a)\bar{A}q^N + u_a, & \text{if } q \geq q_a \\ \frac{(\bar{A}q^N)^{1+\omega}}{(1+\omega)(1+\gamma_h)} + \bar{A}q^N + u_0, & \text{if } q < q_a \end{cases}$$

- where  $\bar{A} \equiv AN^\alpha$ ,  $\omega = \frac{1+\gamma_h}{1+\phi_h-\gamma_h}$ ,  $u_0 = 0$ , and  $u_a = \phi_a - \kappa$ .

## If Firm Size Is Endogenous (Typical O-Ring Results) [◀ Back](#)

- $N$  is also a choice of the firm
- Additional FOC:  $AN^\alpha q^N e(a, h) (1 + \alpha + N \ln(q)) = w + ac$
- Optimal choice on firm size:  $N(q) = \frac{1+\alpha}{-\ln(q)}$
- Firm size increases in productivity  $q$  and is irrelevant to the choices of amenities
- All the relationships between productivity and amenity provision can be now directly translate to the firm size