Graduate Labor Economics

Lecture 6: Amenities, Sorting, and Compensating Differentials

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Amenities

• Wages matter—but so do non-wage job attributes

- Health insurance, 401(k) plan
- Risk of injury, illness, or death
- Nice coworkers, good boss
- Discomfort, boredom, stress
- Inequality in amenities tends to amplify wage inequality
 - Both in levels and in growth
 - Hamermesh (1999), Pierce (2001, 2010)
 - · Powerful driver: income effects
- Key to assessing labor market regulations
 - What are the benefits to workers?
 - What are the costs to employers?

The basic framework (Rosen 1986)

• Two-sided matching market:

• Worker: $u(w, D; \theta)$ increasing in w, decreasing in D

• Firm: $\pi(w, D; \phi) = y(D; \phi) - w$ decreasing in w, increasing in D where D is a job disamenity

• Equilibrium given by:

- Hedonic wage function w(D)
- Workers sort to $D^*(\theta) = \operatorname{argmax}_D u(w(D), D; \theta)$
- Firms offer $D^*(\phi) = \operatorname{argmax}_D \pi(w(D), D; \phi)$
- Slope of hedonic function gives local valuations
 - Worker's WTP: $-\frac{u_w}{\mu_D} = w'(D)$
 - Firm's WTA: $y_D = w'(D)$

Key equilibrium construct: the hedonic wage function



The old-school approach: hedonic wage regressions

- How can we estimate worker and firm valuations?
- Traditional specification:

$$\log w_{ij} = \mathbf{x}'_i \beta + \mathbf{z}'_j \gamma + \varepsilon_{ij}$$

where \mathbf{x}_i are worker characteristics, \mathbf{z}_i are job characteristics

- Problem #1: omitted-variable bias
 - Unobserved worker ability
 - Unmeasured job characteristics
 - Slope coefficients often "wrong-signed"
- Problem #2: w'(D) only tells us marginal valuations

Mas and Pallais (2017): motivation

- Active debate about worker scheduling
 - Night shifts, weekend shifts
 - Erratic schedules, short notice
 - Scheduling software (e.g., Kronos)
- Growth in the "gig economy"
 - Katz and Krueger (2019)
 - Farrell and Greig (2016)
- Policy relevant
 - Overtime pay (Fair Labor Standards Act)
 - o 2017 Oregon law: seven days' notice of schedule
 - Family-friendly policies
 - Political pressure on big companies

Research question

• How much do workers value desirable working hours?

- Avoiding nights/weekends
- Predictable schedules
- Ability to telecommute
- Why do we need to know this?
 - Gauging how work schedules impact inequality
 - Cost-benefit analysis of proposed policies

OLS estimates are "wrong-signed"

	All		Phone occ	upations	All hourly workers		
	No industry	Industry	No industry	Industry	No industry	Industry	
	fixed	fixed	fixed	fixed	fixed	fixed	
	effects	effects	effects	effects	effects	effects	
Schedule flexibility							
Can vary the times at which	0.063	0.064	0.051	$\begin{array}{c} -0.109 \\ (0.078) \end{array}$	0.046	0.054	
workday starts or ends	(0.010)	(0.010)	(0.058)		(0.012)	(0.012)	
Work from home							
Does any work from home	0.080	0.101	0.322	0.234	0.107	0.098	
	(0.014)	(0.013)	(0.137)	(0.145)	(0.023)	(0.023)	
Formal work from home	0.100	0.071	0.030	0.316	0.145	0.124	
arrangement	(0.026)	(0.025)	(0.199)	(0.170)	(0.037)	(0.036)	
Irregular schedule							
Works an irregular schedule	-0.070	-0.029	-0.111	-0.131	-0.020	0.019	
	(0.011)	(0.012)	(0.074)	(0.081)	(0.012)	(0.012)	
Works an irregular but consistent schedule	t -0.053	-0.019	-0.100	-0.212	-0.010	0.021	
	(0.012)	(0.012)	(0.095)	(0.110)	(0.013)	(0.013)	
Works an irregular, inconsistent schedule	-0.079	-0.034	-0.090	0.024	-0.030	0.005	
	(0.019)	(0.019)	(0.100)	(0.121)	(0.020)	(0.019)	
Observations	27.030	27.030	306	306	16,446	16,446	

TABLE 1—ESTIMATING COMPENSATING DIFFERENTIALS FROM OBSERVATIONAL DATA USING WEEKLY EARNINGS: CPS Work Schedules Supplement

(Mas and Pallais, 2017, Table 1)

Two experiments

- Call-center sample
 - Pro: real stakes ("skin in the game")
 - Con: narrow sample, may not generalize
- Understanding America Study
 - Pros: broader population, richer covariates
 - Con: hypothetical stakes
- Combination: best of both worlds

Call-center experiment: avoiding "deception"

- Post ads for interviewer positions in 68 cities
 - Natural field experiment (Harrison and List, 2004)
 - Modeled after "real" ads: skills, tasks, wage range
 - No mention of job location or scheduling
- Challenge: economic experiments can't engage in "deception"
 - Ethical considerations
 - Tainting the subject pool
 - Be careful not to do this!
- Solution: Mas and Pallais set up their own call center
 - $\circ~$ Actual hiring process $\implies~$ no "deception"
 - Data collection for a separate project
- Applicants visit website, provide sex and race

Experimental protocol

Applicants choose between two jobs. Why only two?

- Avoid cognitive overload
- Avoid disclosing research intent
- Avoid "carry-over effects"
- Baseline: 40 hour week, M-F 9-5, located downtown
- Five alternatives (treatments):
 - 1. Flexible schedule (choose when to work)
 - 2. Flexible # hours (subset of standard workweek)
 - 3. Work from home (standard workweek)
 - 4. Full flexibility (package of 1, 2, 3)
 - 5. Employer discretion (40 hours, 7 days' notice)

The wage premium for flexibility

- Randomize wages on baseline + alternative jobs
 - High wage: $\overline{w} \in \{\$16,\$19\}$
 - Low wage: $\underline{w} = \overline{w} \varepsilon$, $\varepsilon \in \{\$0, \$0.25, \dots, \$2.75, \$3, \$4, \$5\}$
- Randomize which job pays more
 - Avoid imposing desire for flexibility
 - But costly in terms of power
- Lots of design details:
 - Randomize which job is listed first
 - Describe jobs by number, not name
 - Force applicants to type in job number
- Promise answers won't affect hiring decisions (why?)

Measuring inattention

• Concern: applicants may be inattentive

- Amenity affects welfare but not choices
- Direction of bias?
- Three checks
 - "Position unavailable, pick the other one"
 - Quiz workers ex post about their choice
 - Share choosing (very) dominated jobs
- About 13–15% make wrong/dominated choices
- Implies ${\sim}25\%$ inattentive (of whom half "guess wrong")

Conceptual framework

• Job A = 1 has the amenity, A = 0 doesn't

- Wage difference $\Delta w \equiv w_1 w_0 \in [-5, 5]$
- WTP for A = 1 continuously distributed
- True preference:

$$P_{\Delta w} \equiv \Pr(WTP_i > -\Delta w)$$

• Suppose 2α inattentive, α choose A = 1 by chance

$$\Pr(A_i = 1 \mid \Delta w) = P_{\Delta w}(1 - \alpha) + (1 - P_{\Delta w})\alpha$$

(derivation?)

Estimation details

• Impose functional form assumption

- $\circ~$ WTP distributed logistically ($\mu,\sigma)$
- Nice feature: can assess this visually
- Estimate by maximum likelihood
 - $\circ\,$ First step: estimate $\hat{\alpha}$ using dominated responses
 - Second step: estimate $(\hat{\mu}, \, \hat{\sigma})$ and thus the CDF
- Bootstrap standard errors (why?)
- Breakpoint model to allow for point mass

Sample descriptives: is it representative?

	P	Panel A. Experiment				
	Experiment main treatments (1)	CPS phone occupations (2)	CPS phone occupations, in cities (3)	UAS (4)	CPS all (5)	
Female	75	66	65	47	52	
Currently employed Full-time Part-time Unemployed	39 16 23 61	100 81 19 0	100 82 18 0	92 76 16 8	95 77 18 5	
Age Average age (years) < 30 years old 30–40 years old > 40 years old	33.0 49 28 23	38.9 32 25 43	38.8 32 27 42	42.9 18 29 52	44.4 24 18 58	
Education Less than high school High School Some college College degree Advanced degree	2 28 46 22 2	6 31 28 31 4	6 29 28 32 4	7 29 19 33 12	15 28 18 28 11	
<i>Race</i> White Black Hispanic Other	43 34 14 9	58 17 18 7	53 18 21 8	64 11 17 8	64 12 16 8	
Observations	3,245	1,038	735	1,950	100,400	

TABLE 3-DESCRIPTIVE STATISTICS EXPERIMENT, UAS, AND COMPARISON SAMPLES (Percent)

(Mas and Pallais, 2017, Table 3)

Covariate balance: did the randomization work?

	Flexible schedule	Flexible number of hours	Work from home	Combined flexible	Employer discretion
Age	0.750	0.271	0.875	0.720	0.200
Female	0.677	0.573	0.065	0.630	0.734
White	0.327	0.829	0.313	0.583	0.811
Black	0.372	0.083	0.328	0.437	0.983
Hispanic	0.039	0.292	0.035	0.764	0.293
Other race	0.101	0.302	0.328	0.967	0.133

TABLE 4-RANDOMIZATION ASSESSMENT: p-VALUES FROM REGRESSIONS OF COVARIATES ON WAGE GAP DUMMIES

(Mas and Pallais, 2017, Table 4)

Treatment #1: WTP for flexible schedule



(Mas and Pallais, 2017, Figure 1)

Interpreting the results on flexible schedules

- 1. Raise wage on flexible job \implies more choose it
- 2. Baseline model: median valuation = 0.48/hour (small)
- 3. ~20% decline flexible job even when $\Delta w =$ \$5.00
- 4. Correcting for inattention compresses the WTP distribution
- 5. After this correction, ${\sim}60\%$ of workers have WTP ≈ 0
- 6. But a long tail really values flexibility

Treatment #2: WTP for flexible # hours



(Mas and Pallais, 2017, Figure 2)

Why do some applicants dislike flexibility?

- Neoclassical answer: impossible!
- Behavioral answer: commitment device
 - Hyperbolic discounting (Laibson 1997)
 - Supported by Mechanical Turk focus group
- Other explanations?
 - Household bargaining
 - Signaling dedication
 - Inferences about fringe benefits
 - Inferences about office culture

Other results

- Workers prefer 40 hours to 20 hours (and 40 to 60)
 - Supply-side reason for observed hours distribution
 - "Time-and-a-half" overtime premium is about right
- Median worker would pay 8% of wages to work from home

Strong aversion to employer discretion



(Mas and Pallais, 2017, Figure 5)

Why do workers hate employer discretion?

• Two stories:

- I'll get assigned bad hours (nights, weekends)
- I won't be able to plan my schedule
- Evidence points to aversion to non-standard hours
 - Cost of childcare
 - Social coordination (Young and Lim, Sociological Science, 2014)

Many early birds, few night owls

			Quantiles				
Alternative option	Base option	Mean	SD	25th	50th	75th	Observations
Irregular hours, consistent schedule	М–F 9 ам–5 рм	\$3.42 (0.50)	\$5.73 (1.05)	-\$0.05 (0.48)	\$3.42 (0.50)	\$6.89 (1.04)	626
Morning schedule (M–F 7 AM–3 PM)	М–F 9 ам–5 рм	-\$1.09 (0.44)	\$1.12 (1.52)	-\$1.77 (0.74)	-\$1.09 (0.44)	-\$0.41 (1.24)	202
Afternoon/evening schedule (M-F 12 PM-8 PM)	М–F9 ам–5 рм	\$2.39 (0.73)	\$4.34 (1.04)	-\$0.24 (0.46)	\$2.39 (0.73)	\$5.02 (1.28)	195
Weekend schedule (Th-M 9 AM-5 PM)	М–F9 ам–5 рм	\$3.27 (0.70)	\$4.13 (0.99)	\$0.76 (0.55)	\$3.27 (0.70)	\$5.77 (1.18)	209
2nd shift (M-F 3 рм-11 рм)	1st shift (M–F 7 ам–3 рм)	\$5.20 (1.72)	\$6.21 (2.13)	\$1.43 (0.76)	\$5.20 (1.72)	\$8.96 (2.94)	192

TABLE 7-UNPACKING AVERSION TO EMPLOYER DISCRETION

Notes: The table provides statistics on workers' willingness to pay for the base option relative to the alternative option. Estimates are based on an inattention-corrected maximum likelihood logit model using data from the experiment. Bootstrapped standard errors based on 500 samples are in parentheses. Online Appendix Table 13 contains the job description text for each treatment.

(Mas and Pallais, 2017, Table 7)

Reweighting for external validity

- Main concern: are results externally valid?
- First approach: "DFL reweighting"
 - Pioneered by DiNardo, Fortin, Lemieux (1996)
 - Widely used empirical tool
 - Autor notes: https://economics.mit.edu/files/15388
- Basic idea: put more weight on underrepresented groups
 - Divide workers into sex/age/race cells $k \in \{1, \dots, K\}$
 - Compute shares λ_k both in sample and in population
 - $\circ~$ Weight each sample participant by $\frac{\lambda_k^{\rm pop}}{\lambda_{\cdot}^{\rm sample}}$
 - DFL show how to do this with continuous covariates
- Similar results using reweighted sample
- Limitation: can only reweight by observables

The Understanding America Study

- Second sample: Understanding America Study
- Complements the call-center sample
 - Main reason: probe external validity
 - $\circ~$ No stakes \ldots but may promote honesty here
- In brief: results are very similar
- So: focus instead on sorting patterns
 - Elicit workers' WTP for job amenities
 - Are WTPs correlated with *current* job characteristics?

Sorting in action!



Gender gaps in WTP for telecommuting, control

	Flexible schedule			Work from home			Employer discretion		
	% in flexible schedule jobs	WTP for flexible schedule	Obs.	% with formal work from home arrangement	WTP to work from home	Obs.	% in irregular, inconsistent schedule jobs	WTP to avoid employer discretion	Obs.
Panel A. Women									
Women with children under 4	27.6%	1.6% (0.8%)	138	18.6%	15.4% (5.4%)	120	13.6%	37.9% (7.4%)	141
Women without children under 4	28.9%	1.7% (0.5%)	724	10.8%	8.4% (2.6%)	638	12.4%	29.8% (2.5%)	742
p-value of difference	0.79	0.88		0.09	0.24		0.76	0.30	
Panel B. Men Men with children under 4	19.3%	1.8% (0.6%)	118	9.2%	8.0% (5.6%)	87	13.6%	24.4% (3.9%)	110
Men without children under 4	26.7%	3.6% (0.6%)	617	9.6%	10.3% (1.8%)	524	18.9%	29.0% (2.9%)	620
p-value of difference	0.14	0.05		0.91	0.70		0.25	0.34	
<i>p</i> -value: difference between women with children under 4 and all other groups	0.85	0.25		0.05	0.29		0.59	0.22	

TABLE 11-WTP BY GENDER AND PARENTAL STATUS (Data from Understanding America Study)

Notes: Estimates are generated using an inattention-corrected maximum likelihood logit model using data from the UAS. Standard errors calculated using the delta method are in parentheses. Respondents are considered to have a flexible schedule job if they are able to set their won schedule and are considered to have an irregular, inconsistent schedule job if their employer sets their schedule and their schedule varies from week to week. The fraction of each group in each type of job is conditional on employment.

(Mas and Pallais, 2017, Table 11)

Epilogue: endogenous occupations

- Occupation: equilibrium bundle of tasks, amenities
- Shaped by both demand-, supply-side forces
 - Example: university professors
 - Demand: research/teaching/service
 - Supply (maybe): flexibility, sabbaticals
- Recent work on gender mix and occupations
 - Goldin and Katz 2011: pharmacists, part-time penalty
 - Goldin 2014: "pollution" model of occupational status
 - Pan 2015: "tipping-points" in occupational gender mix
 - Wasserman 2018: long hours and physician specialties
- Multiple equilibria, coordination, path dependence