### CONSIDERATION SCOPES IN JOB SEARCH

Jeremias Klaeui | University of Lausanne

SKILS

January 2024

### JOB OPENINGS AND CONSIDERATION SCOPES IN JOB SEARCH

- Labour demand does not always align with labour supply
- New job openings might need occupations not held by jobseekers
- New jobs openings might not match the locations of jobseekers

- Jobseekers differ in their flexibility and constraints
- Who is able to benefit from new job openings?

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- Who is able to benefit from new job openings?

- 1) Estimate how workers distribute their consideration across various job dimensions
  - I use click behaviour on a job portal to estimate which jobs workers are likely to consider
  - Map local job openings to search scopes on a granular "submarket" level
- 2) Identify relevant granular submarkets for individual jobseekers
  - Use unprecedentedly large hiring events by single firms as shocks
  - Only high-consideration submarkets matter for job finding
- 3) Show that those who distribute consideration accross more submarkets find a job faster
  - Sizeable differences between jobseekers within conventional labour markets

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## USING CLICKS TO MEASURE JOB CONSIDERATION

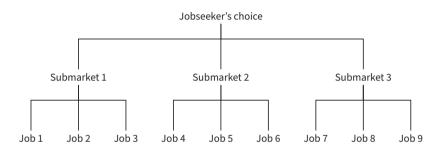
### CLICK DATA FROM JOB-ROOM.CH

- Job portal of the Swiss employment services
- Measurement period: Jun 2020 Jun 2021

- Around a third of registered unemployed uses the platform
- Jobroom-users are slightly older, more educated and more qualified
- I use clicks from the first 3 months of unemployment
- ho pprox 2m clicks, made in 55k unemployment spells

### ESTIMATE WHICH JOB WORKERS CHOOSE TO CLICK ON

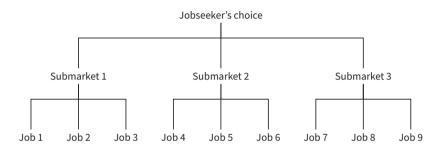
Nested logit model, similar to Azar, Berry, Marinescu (2022)



- Occupation (ISCO 3-dig) × location (100 small labour market zones) × part-time vs full-time
- $\sim$  7000 submarkets (nests); 3 105 jobs per submarket
- $u_{ij} = JobFE + \beta^g \log(\text{distance}) + \beta^o \{\text{occ.} = \text{past experience}\} + \beta^h \{\text{hours} = \text{stated preference}\} + \varepsilon_{ij}$

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### COMMUTING DISTANCE AND OCCUPATION DRIVE JOB CONSIDERATION

	(1)
Dependent Var.:	N clicks
log(Commuting time)	-2.506*** (0.0095)
Match in 2-digit occupation	0.7843*** (0.0204)
Match in 3-digit occupation	1.692*** (0.0231)
Match in hours	0.5982*** (0.0118)
Inclusive value	0.0125*** (0.0013)
Spell x month	Yes
Submarket	Yes
S.E.: Clustered	by: Jobseeker sp
Observations	367,496,293
Within Pseudo R2	0.33087

- Occupation match: same utility increase as a 63% decrease in commute (e.g. 26 to 10min)
- Workload match:
   Same as -28%. (26 to 20min)

Difference between a very popular job an a less popular job within a submarket:
Only comparable to 1% decrease in commuting time

N spells=55 615; Spell-months=173 202; Clicks = 2 044 882

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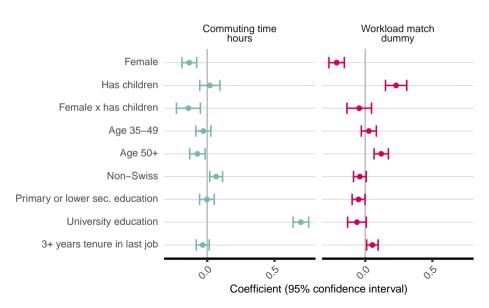
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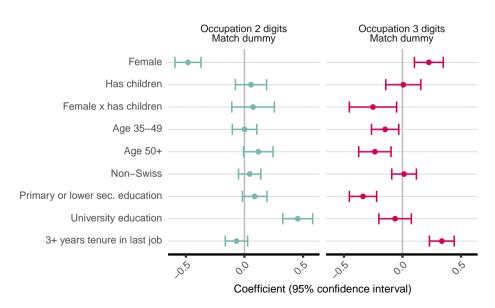
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### CONSIDERATION DIFFERS FOR WORKERS WITH SAME OCCUPATION AND LOCATION



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### MAP CONSIDERATION PROBABILITY TO LABOUR DEMAND

### PANEL OF UNEMPLOYED, SEARCH SCOPES AND JOB OPENINGS

- Estimation sample: 60% "training" sample of all job-room users
- Prediction sample: 40% of job-room users and all other registered jobseekers
- $\bullet \ \ \, \textbf{Predict consideration probability on submarket level} \ \, \textbf{Occupation} \times \textbf{location} \times \textbf{part-time vs full-time} \\$
- Compute monthly number of online job-openings per submarket
   Source: near-universe of online vacancies, webscraped by X28
- Submarkets are granular: 7 vacancies on avg, 18 in high-consideration submarkets
- $\Rightarrow$  Large spell-month panel of all unemployed between 2019 and mid-2021

### PREDICTED CONSIDERATION BY SUBMARKET: EXAMPLE

### Jobseeker with *broad* consideration: top 5 submarkets

Rank	Consideration	Location	Commuting time	Occupation	Hours
1	79.0	Montreux-Vevey	18 min	Shop salespersons	Part-time
2	43.8	Montreux-Vevey	18 min	Shop salespersons	Full-time
3	37.4	Montreux-Vevey	18 min	General office clerks	Part-time
4	34.0	Montreux-Vevey	18 min	Other clerical support workers	Part-time
5	32.1	Montreux-Vevey	18 min	Client information workers	Part-time

### Jobseeker with narrow consideration: top 5 submarkets

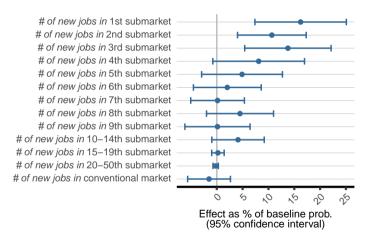
Rank	Consideration	Location	Commuting time	Occupation	Hours
1	153.2	Montreux-Vevey	18 min	Shop salespersons	Part-time
2	75.7	Montreux-Vevey	18 min	Shop salespersons	Full-time
3	44.5	Aigle	34 min	Shop salespersons	Part-time
4	41.1	Lausanne	32 min	Shop salespersons	Part-time
5	39.5	Montreux-Vevey	18 min	General office clerks	Part-time

### EXTRAORDINARY HIRING EVENTS BY FIRMS

- Endogeneity conerns
  - Measurement error: Number of vacancies is measured with error
  - Reverse causality: Firms might target vacancies towards jobseeker skills

- Use large spikes in hiring by single firms as a measure of change in labour demand
  - 1. More than 20 new vacancies in a month
  - 2. More new vacancies than in the whole past year
- For each event and jobseeker compute the number of created jobs per submarket
- Order the submarket by predicted consideration probability (1st = most attention)

### "VERY REDUCED" FORM: FIND JOB AT THE HIRING COMPANY



Hiring shocks by company: Explaining whether a jobseeker finds a job at the company with the probability that the jobseeker considers the newly created vacancies given their occupation, location and hours worked. N= 956 942 hiring shock  $\times$  jobseeker combinations.

		Logit		OLS	IV
	(1)	(2)	(3)	(4)	(5)
Dependent Var.:					
log(V in 1-4th submarket)					
log(V in 5-9th submarket)					
log(V in 10th-14th submarket)					
log(V in 15-19th submarket)					
log(U in 1-4th submarket)					
og(U in 5-9th submarket)					
log(U in 10th-14th submarket)					
log(U in 15-19th submarket)					
Controls					
Last occ x residence location					
Elapsed spell duration					
Calendar month					
Part time x last occ (2-dig)					
Observations	3,358,836				
Pseudo R2					
Number of unemp. spells					

Baseline probability: 0.105; SE clustered by spell

		Logit		OLS	IV
	(1)	(2)	(3)	(4)	(5)
Dependent Var.:	Exit unemployment				
og(V in 1-4th submarket)	0.0046*** (0.0001)				
log(V in 5-9th submarket)	-0.0003** (0.0001)				
log(V in 10th-14th submarket)	0.0001 (0.0002)				
log(V in 15-19th submarket)	-0.0011*** (0.0001)				
log(U in 1-4th submarket)	-0.0141*** (0.0005)				
og(U in 5-9th submarket)	-0.0037*** (0.0006)				
log(U in 10th-14th submarket)	0.0004 (0.0007)				
log(U in 15-19th submarket)	-0.0015*** (0.0006)				
Controls	No				
Last occ x residence location	No				
Elapsed spell duration	Yes				
Calendar month	Yes				
Part time x last occ (2-dig)	No				
Observations	3,358,836	3,358,836			
Pseudo R2	0.02747				
Number of unemp. spells	491,677				

Baseline probability: 0.105; SE clustered by spell

		Logit		OLS	IV
	(1)	(2)	(3)	(4)	(5)
Dependent Var.:	Exit unemployment	Exit unemployment			
og(V in 1-4th submarket)	0.0046*** (0.0001)	0.0031*** (0.0001)			
og(V in 5-9th submarket)	-0.0003** (0.0001)	0.0005*** (0.0001)			
og(V in 10th-14th submarket)	0.0001 (0.0002)	0.0006*** (0.0002)			
og(V in 15-19th submarket)	-0.0011*** (0.0001)	-0.0007*** (0.0001)			
og(U in 1-4th submarket)	-0.0141*** (0.0005)	-0.0115*** (0.0005)			
og(U in 5-9th submarket)	-0.0037*** (0.0006)	-0.0043*** (0.0006)			
og(U in 10th-14th submarket)	0.0004 (0.0007)	-0.0007 (0.0007)			
log(U in 15-19th submarket)	-0.0015*** (0.0006)	-0.0059*** (0.0006)			
Controls	No	Yes			
Last occ x residence location	No	No			
Elapsed spell duration	Yes	Yes			
Calendar month	Yes	Yes			
Part time x last occ (2-dig)	No	No			
Observations	3,358,836	3,358,836	3,358,812		
Pseudo R2	0.02747	0.04412			
Number of unemp. spells	491,677	491,677			

Baseline probability: 0.105; SE clustered by spell

		Logit		OLS	IV
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Dependent Var.:	Exit unemployment	Exit unemployment	Exit unemployment		
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log(V in 5-9th submarket)	-0.0003** (0.0001)	0.0005*** (0.0001)	0.0007*** (0.0002)		
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log(V in 15-19th submarket)	-0.0011*** (0.0001)	-0.0007*** (0.0001)	7.77e-5 (0.0002)		
log(U in 1-4th submarket)	-0.0141*** (0.0005)	-0.0115*** (0.0005)	-0.0063*** (0.0008)		
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Controls	No	Yes	Yes		
Last occ x residence location	No	No	Yes		
Elapsed spell duration	Yes	Yes	Yes		
Calendar month	Yes	Yes	Yes		
Part time x last occ (2-dig)	No	No	Yes		
Observations	3,358,836	3,358,836	3,358,812	3,358,838	
Pseudo R2	0.02747	0.04412	0.05436		
Number of unemp. spells	491,677	491.677	491.674		

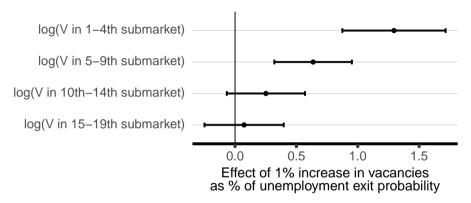
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og(V in 10th-14th submarket)	0.0001 (0.0002)	0.0006*** (0.0002)	0.0003 (0.0002)	0.0004** (0.0002)	
log(V in 15-19th submarket)	-0.0011*** (0.0001)	-0.0007*** (0.0001)	7.77e-5 (0.0002)	0.0002 (0.0002)	
og(U in 1-4th submarket)	-0.0141*** (0.0005)	-0.0115*** (0.0005)	-0.0063*** (0.0008)	-0.0068*** (0.0008)	
og(U in 5-9th submarket)	-0.0037*** (0.0006)	-0.0043*** (0.0006)	-0.0004 (0.0007)	-0.0003 (0.0007)	
og(U in 10th-14th submarket)	0.0004 (0.0007)	-0.0007 (0.0007)	0.0006 (0.0007)	0.0006 (0.0008)	
log(U in 15-19th submarket)	-0.0015*** (0.0006)	-0.0059*** (0.0006)	-0.0009 (0.0007)	-0.0009 (0.0007)	
Controls	No	Yes	Yes	Yes	
Last occ x residence location	No	No	Yes	Yes	
Elapsed spell duration	Yes	Yes	Yes	Yes	
Calendar month	Yes	Yes	Yes	Yes	
Part time x last occ (2-dig)	No	No	Yes	Yes	
Observations	3,358,836	3,358,836	3,358,812	3,358,838	3,358,838
Pseudo R2	0.02747	0.04412	0.05436	0.07563	
Number of unemp. spells	491,677	491.677	491.674	491.677	

Baseline probability: 0.105; SE clustered by spell

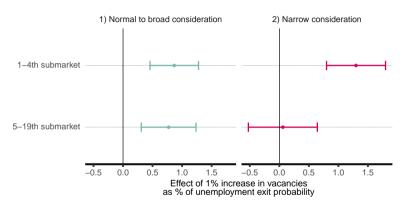
		Logit		OLS	IV
	(1)	(2)	(3)	(4)	(5)
Dependent Var.:	Exit unemployment	Exit unemployment	Exit unemployment	Exit unemployment	Exit unemploymen
og(V in 1-4th submarket)	0.0046*** (0.0001)	0.0031*** (0.0001)	0.0014*** (0.0002)	0.0015*** (0.0002)	0.0159*** (0.0046)
og(V in 5-9th submarket)	-0.0003** (0.0001)	0.0005*** (0.0001)	0.0007*** (0.0002)	0.0007*** (0.0002)	0.0036* (0.0020)
og(V in 10th-14th submarket)	0.0001 (0.0002)	0.0006*** (0.0002)	0.0003 (0.0002)	0.0004** (0.0002)	0.0021 (0.0017)
og(V in 15-19th submarket)	-0.0011*** (0.0001)	-0.0007*** (0.0001)	7.77e-5 (0.0002)	0.0002 (0.0002)	-0.0003 (0.0021)
og(U in 1-4th submarket)	-0.0141*** (0.0005)	-0.0115*** (0.0005)	-0.0063*** (0.0008)	-0.0068*** (0.0008)	-0.0133*** (0.0024)
og(U in 5-9th submarket)	-0.0037*** (0.0006)	-0.0043*** (0.0006)	-0.0004 (0.0007)	-0.0003 (0.0007)	-0.0008 (0.0011)
og(U in 10th-14th submarket)	0.0004 (0.0007)	-0.0007 (0.0007)	0.0006 (0.0007)	0.0006 (0.0008)	-0.0012 (0.0012)
og(U in 15-19th submarket)	-0.0015*** (0.0006)	-0.0059*** (0.0006)	-0.0009 (0.0007)	-0.0009 (0.0007)	-0.0028 (0.0020)
Controls	No	Yes	Yes	Yes	Yes
Last occ x residence location	No	No	Yes	Yes	Yes
Elapsed spell duration	Yes	Yes	Yes	Yes	Yes
Calendar month	Yes	Yes	Yes	Yes	Yes
Part time x last occ (2-dig)	No	No	Yes	Yes	Yes
Observations	3,358,836	3,358,836	3,358,812	3,358,838	3,358,838
Pseudo R2	0.02747	0.04412	0.05436	0.07563	0.07276
Number of unemp. spells	491,677	491,677	491,674	491,677	491,677

Baseline probability: 0.105; SE clustered by spell



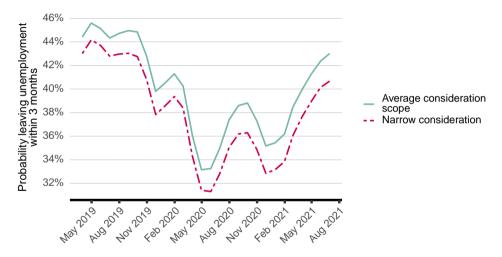
Effect of the number of vacancies per individual submarkets. V is the three months rolling average. Job finding is defined as deregistering from unemployment in the next month. The estimation controls for individual characteristics, location of residence, occupation of the last job, elapsed unemp. duration and the calendar month.  $N = 3\,358\,812$  spell-months, 491 674 spells.

### RESULTS DRIVEN BY JOBSEEKERS WITH NARROW CONSIDERATION



Effects from interaction of search scope and vacancies per individual top submarkets. Average marginal effects from a logit model. Controls: Characteristics, time, location and occupation-cell FE.

### BACK-OF-THE-ENVELOPE: JOB FINDING PROBABILITY BY SEARCH SCOPE



Comparison within occupation  $\times$  location cells: Simulated probability of leaving unemployment the next month. Conditional on being unemployed for 5 months. Narrow: p90 of narrowness measure per cell. Broad: p10. Covariates fixed at cell averages.

Combination of online search data and admin data allows to uncover "real-world" facts

- Job search scopes vary between jobseekers with the same conventional labour market
- Only job openings in submarkets with high attention substantially alter job finding chance
- Broader focus leads to better job prospects
- Concentrated focus narrows job finding opportunities

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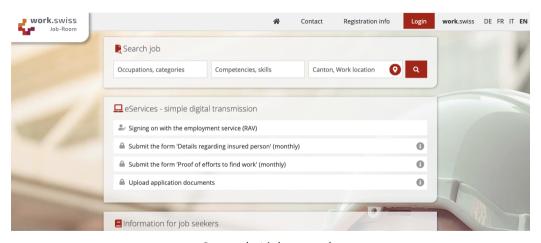
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# Thank you

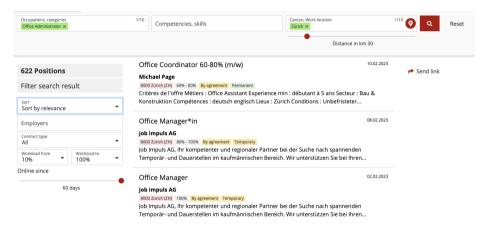
Looking forward to your feedback jeremias.klaeui@unil.ch Twitter: jklaeui

### JOB-ROOM.CH: HOME SCREEN



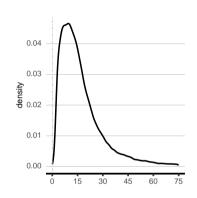
Screenshot job-room.ch.

#### AFTER FILTERING: PREVIEW VISIBLE

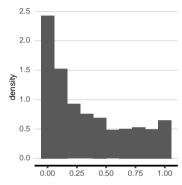


Screenshot job-room.ch. Jobseekers see previews

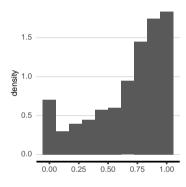
### SIZEABLE HETEROGENEITY IN CONSIDERATION SCOPES OVER JOBSEEKERS



Average distance between clicked jobs and home



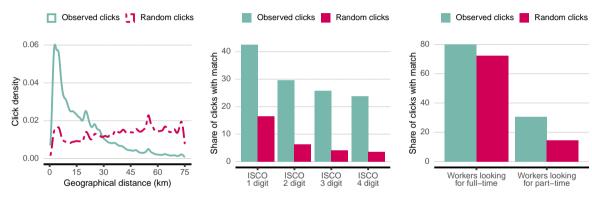
Share of clicked job where the occupation matches past employment



Share of clicked job where the hours worked match preference

Distribution over spells

### JOB CONSIDERATION IS TARGETED

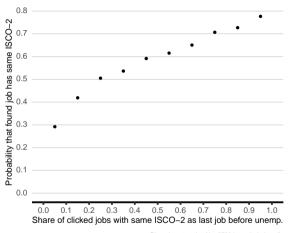


Distance between job and home

Occ. matches past employment

Hours worked match preference

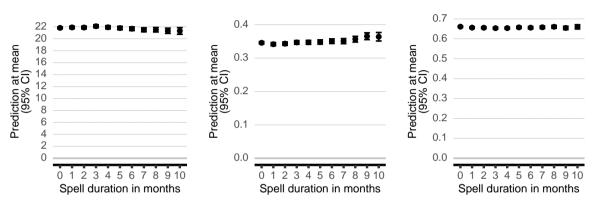
#### CLICKS RELATE TO SEARCH OUTCOMES



Binned scatter plot. N = 27884 concluded spells

Binned scatter plot on jobseeker level. Occupational match of clicks vs the job found after the spell

### SPAN OF SEARCH REMAINS CONSTANT OVER THE FIRST 9 MONTHS OF SPELL



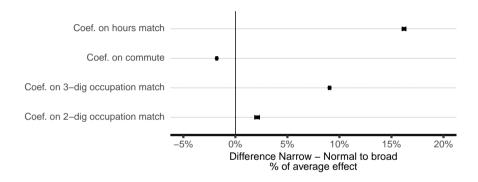
Occ. matches past employment

Properties of clicked jobs over the spell. Within spell-estimates.

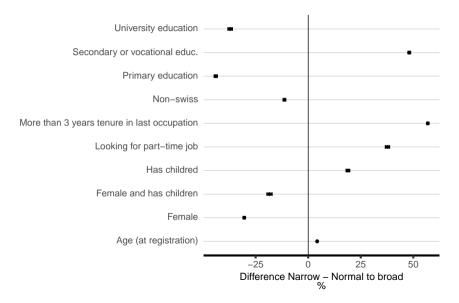
Distance between job and home

Hours worked match preference

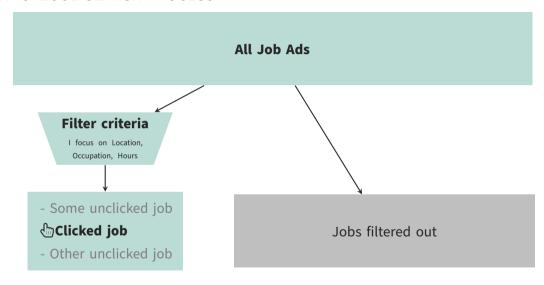
# WHO SEARCHES NARROWLY? BETAS



## WHO SEARCHES NARROWLY? BETAS



#### TYPICAL JOB SEARCH PROCESS



# WHAT CAN WE LEARN FROM BEHAVIOUR ON A JOB PLATFORM?

- Jobseekers typically engage with multiple search channels simultaneously, the mode is 9 (Liechti et al., 2020)
- Number of clicks observed might not reflect the total search effort
- Condition the analysis on clicks. I.e given a jobseeker clicks on a job: which one is it?

# Search is costly

 $\Rightarrow$  How do jobseekers allocate their interest over occupations, locations, and vacancies?

#### WHY THE NESTED LOGIT

- A simple logit has dimensionality problem: Many jobseeker-job combinations.
- We know which jobs people clicked on, but which jobs did they NOT click on?
- Problem: potential inclusion of jobs unknown to jobseekers
- Literature restricts choice sets, e.g to jobs similar to the ones clicked
  - Works well for examining specific job attributes (amenities, wage)
  - Less well for high-level questions: How broad are jobseekers in their consideration?
- Solution: Nested logit model:

# WHICH JOBS DO JOBSEEKERS CLICK ON?

- Search is costly ⇒ have to focus their interest, i.e form a consideration set
- Click = "I want to know more about this job"
- Which jobs, j, does jobseeker i consider? (Given a jobseeker clicks on a job: which one is it?)

$$u_{ij} = \delta_j + Z'_{ij}\beta_i + \varepsilon_{ij}$$

- Job FE  $\delta_i$ : Captures wage believes, firm characteristics, amenities, etc
- $Z_{ij}$ : Job features & amenities that vary over jobseeker *times* job
  - commuting distance, occupational fit to the worker's profile, hours worked
- $\beta_i$ : The weight put on different job features, can vary over workers

### NESTED: CHOOSE WHICH MARKETS TO CONSIDER AND THEN WITHIN MARKET

$$u_{ij} = \delta_j + Z'_{ij}\beta_i + \varepsilon_{ij}$$

- Within-market model (bottom nest) tells us:
  - Within a market, which jobs are clicked on? commuting zone × full-time (Y/N) × occupation
  - P(i considers job j | considers market m) =  $\frac{e^{\delta j}}{\sum_{k \in \mathcal{A}} e^{\delta k}}$
- Between-markets model (top nest) tells us:
  - How do jobseeker distribute their clicks over these markets?
  - $P(\text{i considers market m}) = \frac{e^{Z'_{im}\beta_i + \lambda I_m}}{\sum_{n=1}^{M} e^{Z'_{im}\beta_i + \lambda I_m}}$   $I_m = \log \sum_{k \in \mathcal{J}_m} \exp(\delta_k)$

### ESTIMATE LOGIT MODEL SEQUENTIALLY AND VIA POISSON

- The data is still big. 12 months of data, 60K spells, 261 nests
  - 35 (ISCO 2-digit level)  $\times$  16 (OFS definition)  $\times$  2 (part-time and full-time)
- Estimate nests sequentially.
  - First estimate bottom nest = One job FE for every job
     sample restricted to people with at least one click in market
  - Inclusive value: Specific functional form that links the bottom and top level  $I_m = \log \sum_{k \in \mathcal{I}_m} \exp(\delta_k)$
  - Bottom models estimated separately for each market-month
- Futher trick to ease computation: Aggregate over jobseeker's choices for each month and use
   Poisson model with high dimensional FE (Baker, 1994; Guimaraes, 2004; Taddy, 2015; Hirsch et al., 2021)
- ullet One row per choice situation (Person imes month). FE ensures equivalence to logit
- Bottom models: Person  $\times$  month  $\times$  job | conditional on in market m

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### FRAMEWORK: SEARCH IS COSTLY $\Rightarrow$ HAVE TO FORM A CONSIDERATION SET

Following Weitzman (1979); Ursu et al. (2022)

• A decision maker i faces a set of boxes. There is a cost to open box j and reveal its reward

$$u_{ij} = \underbrace{\delta_j - x'_{ij}\beta_i + \mu_{ij}}_{\text{Known pre-search}} + \underbrace{\varepsilon_{ij}}_{\text{Revealed if opened}}$$
 (Here: open box = click on job)

- Each job has a reservation utility z<sub>ii</sub>.
- $z_{ij}$  dictates opening order and stoppage rule  $\Rightarrow$  shape and size of consideration set

$$\int_{z_{ij}-(\delta_j-x'_{ij}\beta_i+\mu_{ij})}^{\infty} (\delta_j-x'_{ij}\beta_i+\mu_{ij}+\varepsilon_{ij}-z_{ij}) dF_{ij}(\varepsilon_{ij}) = c_{ij}$$

- Depends on job value, distances, search costs and distribution of  $\varepsilon_{ij}$ .
- I will use  $c_{ij} = c_i$  and a discrete choice model to get an idea of  $\delta_j x'_{ij}\beta_i$

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