

Firm Concentration & Endogenous Amenity Provision: The Case of Schedule Flexible Work Arrangements

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- Iong history & renewed interest in monopsonistic labour markets
 - measuring employer power in the labour market: Yeh, Macaluso & Hershbein (2022); Azar et al. (2020); Azar, Marinescu & Steinbaum (2019); Datta (2022)
 - impact on wages: Azar et al. (2019); Benmelecg, Bergman & Kim (2020); Qiu & Sojourner (2022); Schubert, Stansbury & Taska (2020)
 - impact on monetary policy: Burya et al. (2022)
 - demand for skills: Hershbein & Macaluso (2018)



 the leading models of monopsony link firms' monopsony power to the unique bundle of amenities they provide in addition to wages (Card et al. (2018); Manning & Petrongolo (2021); Lamadon, Mogstadt & Setzler (2022), Dube, Naidu & Reich (2022))



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- however, the provision of these amenities is also the result of a decision made by the firms
- we present a new model of endogenous amenity provision when firms have monopsony power
 - Dube, Naide & Reich (2022): an alternative approach with specific utility and profit functions and different microfoundations



- we test the insights from the model on an important but relatively under-researched job feature: schedule flexibility
 - Mas & Pallais 2017, 2020; Datta, 2019; Datta, Giupponi & Machin, 2019; Eriksson & Kristensen, 2014; Goldin, 2014; Chen et al., 2019



- we test the insights from the model on an important but relatively under-researched job feature: schedule flexibility
 - Mas & Pallais 2017, 2020; Datta, 2019; Datta, Giupponi & Machin, 2019; Eriksson & Kristensen, 2014; Goldin, 2014; Chen et al., 2019
- new technology makes it easier than ever to offer alternatives to traditional [permanent, full-time, 9-5] jobs
 - only about 55% of jobs are traditional (Mas & Pallais, 2020)



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- new technology makes it easier than ever to offer alternatives to traditional [permanent, full-time, 9-5] jobs
 - only about 55% of jobs are traditional (Mas & Pallais, 2020)
- this might drive far-reaching changes to people's lives & the economy
 - smoothing income shocks, balancing work and caring duties
 - diminishing employment rights, precarious work



- despite this, little is known about the provision and preferences over schedule flexibility in real-world setting
 - ▶ focus on estimating WTP → one-off surveys and experiments
 - empirical research held back by data and measurement issues (Abraham & Amaya, 2019; Katz & Krueger, 2019)
 - e.g. zero-hour contracts are under-recorded by the main labour force survey (ONS)



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 - e.g. zero-hour contracts are under-recorded by the main labour force survey (ONS)
- we use the universe of online job vacancies and machine learning to construct an economy-wide and time-consistent measure of schedule flexibility
 - Hershbein & Kahn (2018); Deming & Kahn (2018); Clemens, Kahn & Meer (2020), Duchini et al (2020); Marinescu (2017), Javorcik et al (2020); Forsythe et al (2020); Turrell et al. (2018, 2019)



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- 2. analyse 46 million online job vacancies in the UK to measure schedule flexibility
- 3. provide new stylised facts about the prevalence and characteristics of flexible jobs
- 4. estimate a causal relationship between employer concentration and flexibility provision
- 5. identify whether schedule flexibility is an amenity or a disamenity by interepreting these empirical results through the lens of the theoretical model



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- 2. flexibility \nearrow already before the pandemic
- 3. flexible jobs also differ along other job characteristics
- 4. employers with monopsony power undersupply amenities and oversupply disamenities
- 5. salaried flexible jobs are a costly amenity, while non-salaried flexibility is a profitable disamenity

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Theory

Endogenous Amenity Provision in a Monopsonistic Labour Market

Data & Measurement

Theory

- a long history of studying how employers set wages when they have some market power
- we extend this question to non-monetary remuneration: what is the optimal level of amenities/disamenities when firms have monopsony power?
- the first model of amenity provision in a monopsony setting
 - Lamadon, Mogstadt & Setzler (2022) model the opposite: how the offer of job-specific dis/amenities generates monopsony power
 - Dube, Naidu & Reich (2022) use specific utility and profit functions and different microfoundations

Introduction	Theory 00●000	Data & Measurement	Patterns in Flexibility	Concentration Analysis	Conclusion 00

Set-up

- workers' utility depends on wages w and job features f: u(w, f)
- Firms' profits depend on output y, wage w and the profit/cost of the job feature δ(f): π = y − w + δ(f)
- there are 3 different types of job features:

	$u_{f}' > 0$	$u_f' < 0$
$\delta(f) > 0$	profitable amenity	profitable disamenity
$\delta(f) < 0$	costly amenity	

Introduction Theory Data & Measurement Patterns in Flexibility Concentration Analysis Conclusion

Bargaining

• when firm and worker meet, they bargain over optimal $\{w, f\}$

$$\underset{w,f}{\operatorname{arg\,max}} \quad \left[u(w,f) - \bar{U}\left(\sum s_i^2\right) \right]^{\beta} \left[y + \delta(f) - w \right]^{1-\beta}$$

• $\bar{U}(\sum s_i^2)$ = average outside option of a worker

- job search is frictional & granular (Jarosch, Nimczik & Sorkin (WP, 2021)): firms don't compete with themselves
- Workers' outside option falls when labour market concentration $(HHI = \sum s_i^2)$ if large



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Solution



Job Features and Employer Concentration



As HHI \downarrow = workers' outside option \uparrow :

► costly amenities ↑

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- ▶ profitable disamenities ↓
- ▶ profitable amenities ~ because close to a bliss point

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Job Features and Employer Concentration



Compared to perfectly competitive labour market:

- firms undersupply amenities
- and oversupply disamenities

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Data & Measurement



Data: Online Job Vacancies

- we measure flexibility on the basis of job vacancy text
 - BGT: text of 46+ million online job vacancies in the UK from 2014 onwards, from 6,500 job boards and company web pages
 - use machine learning to extract information about work arrangements



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 - not all jobs are advertised online
 - \blacktriangleright jobs posted online are disproportionately professional and \approx 30-40% missing wage info
 - only what firms state in the advert rather than realised arrangement



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- we complement it with one-off survey on job flexibility from Understanding Society, a UK household panel

Defining Schedule Flexibility

- any arrangement in which the timing of work is not fixed in the contract and has to be agreed at a later date between the employer and the employee
 - in practice: shift or rota work without a fixed pattern, "flexible working", "work will be organised according to the needs of the business"

Interaction with Other Job Features

- > prior literature: what matters is who has control over schedule
 - average worker is willing to take a 20% wage cut to avoid employer-set flexible schedule (Mas & Pallais, 2017)
 - however, identifying control from vacancy text is tricky: "Casual contract! Allows for flexibility" flexibility for whom?
 - and the survey responses from Understanding Society suggest that schedule control is a continuous rather than a binary measure

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 - however, identifying control from vacancy text is tricky: "Casual contract! Allows for flexibility" flexibility for whom?
 - and the survey responses from Understanding Society suggest that schedule control is a continuous rather than a binary measure
- control also matters because of its impact on variation in earnings: safe vs. risky flexible jobs

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Safe flexibility: schedule flexibility + salary



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Risky flexibility: schedule flexibility + pay by the hour



Patterns in Flexibility

Control and Renumeration Type



Data: Understanding Society

Classification by Machine Learning

- supervised machine learning approach:
 - 1. manually label 6,500 job vacancies for the dimensions of work arrangements of interest;
 - define the vocabulary and represent each job vacancy in a matrix format;
 - 3. train a machine learning model to classify work arrangements on the basis of vacancy text;
 - 4. apply the machine learning model to all 46 million job vacancies.
- using the whole text of the vacancy results in a significant improvement in accuracy and precision compared to keyword search



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Aggregate trends



- about ~ 30% of jobs are advertised as flexible
- an even split between safe and risky flexibility
- flex share has doubled since 2014

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Which jobs are flexible? Wages



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Which jobs are flexible? Occupations



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Which jobs are flexible? N. of required skills



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Which jobs are flexible?

- heterogeneity persists even within occupation and wage
- interaction between flexibility and remuneration type important

	Wage	N. of	skills	Permanent	
	(1)	(2)	(3)	(4)	(5)
Flexible=1	-0.072***	0.551***	0.572***	-0.027***	-0.030***
	(0.0013)	(0.0155)	(0.0154)	(0.0012)	(0.0011)
Non-Salaried=1	-0.022***	-1.200***	-1.213***	-0.453***	-0.454***
	(0.0043)	(0.0165)	(0.0165)	(0.0033)	(0.0032)
$Flexible=1 \times Non-Salaried=1$	-0.018***	-0.174***	-0.169***	0.089***	0.089***
	(0.0040)	(0.0178)	(0.0177)	(0.0024)	(0.0024)
Real wage (2019 prices)			0.401*** (0.0193)		-0.031*** (0.0020)
Constant	2.593***	5.005***	4.723***	0.138***	0.802***
	(0.0014)	(0.00987)	(0.0174)	(0.0011)	(0.0055)
Observations	16134476	16134476	16134476	16134476	16134476
<i>R</i> ²	0.3590	0.2086	0.2093	0.2732	0.2752

The regressions include controls for county, time, and 3-digit SOC code. Standard errors clustered at county-occupation level in parentheses. *p < 0.1, **p < 0.05, ***p < 0.01

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Welfare implications of schedule flexibility

both safe flex and risky flex jobs come with a wage penalty

Welfare implications of schedule flexibility

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- both safe flex and risky flex jobs come with a wage penalty
- ▶ is the wage penalty the result of workers' high WTP for flexibility?

Concentration Analysis

- or is it the result of lower bargaining power/worse outside options of workers that get these jobs?
- is the answer the same for safe and risky flex jobs?

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Concentration Analysis

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- is the answer the same for safe and risky flex jobs?

our strategy:

- estimate the causal relationship between flex provision and employer concentration
- use the theoretical model to interpret the findings: is flex a dis/amenity, costly/profitable?



Empirical Analysis

 use vacancy data to calculate employer power as HHI of vacancy postings (Marinescu & Azar (2019, 2020))

$$HHI_{c,o,t} = \sum_{i}^{l} s_{i,c,o,t}^{2}$$

where $s_{i,c,o,t}$ is firm *i*'s share of vacancies for occupation *o* in county *c* at year-quarter *t*



Empirical Analysis

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where $s_{i,c,o,t}$ is firm *i*'s share of vacancies for occupation *o* in county *c* at year-quarter *t*

 estimate the relationship between the share of a particular job feature and HHI in a given local labour market

$$\left(rac{\textit{flex vacs}}{\textit{all vacs}}
ight)_{\textit{c,o,t}} = lpha + eta \log \textit{HHI}_{\textit{c,o,t}} + \epsilon_{\textit{c,o,t}}$$



Identification Strategy

- issue 1: the concentration job feature relationship may be driven by systematic unobserved differences between regions and occupations
 - FE specification: control for occupation-county, county-time, and occupation-time FE



Identification Strategy

- issue 1: the concentration job feature relationship may be driven by systematic unobserved differences between regions and occupations
 - FE specification: control for occupation-county, county-time, and occupation-time FE
- issue 2: the within-market changes in employer concentration may not be exogenous
 - shift-share IV: instrument for HHI using nationwide firm-specific labour demand as the shifter

$$IV_{c,o,t} = \sum_{i} hiring_share_{i,c,o,t-1} * nationwide_hiring_{i,t}$$

	(1) FE	(2) IV	(3) IV	(4) IV	(5) IV				
Panel A: Flexible Vac	Panel A: Flexible Vacancies								
ln_hhi	0.0062*** (0.00159)	0.0574* (0.0328)	0.0838*** (0.0290)	0.117*** (0.0265)	0.0913*** (0.0304)				
ln_hhi									
ln_hhi									
ln_hhi									
N 1st-stage F statistic	232076	115314 34.881	115314 30.145	115314 6.859	115314 30.173				

Regressions control for county-SOC, county-time, and SOC-time FE. Standard errors clustered at county-occupation level in parentheses. (2) Firm-level shocks. (3) Firm-occupation-level shocks. (4) Firm-occupation-level shocks with leave-one-out sum. (5) Firm-occupation-level shocks wage control. *p<0.1. **p<0.05. ***p<0.01

						_
	(1)	(2)	(3)	(4)	(5)	
	FE	IV	IV	IV	IV	
Panel A: Flexible Vac	cancies					
In bhi	0.0062***	0.0574*	0 0020***	0 117***	0.0012***	
	0.0002	0.0574	0.0030	0.117	0.0913	
	(0.00159)	(0.0328)	(0.0290)	(0.0265)	(0.0304)	
Panel B: Risky Flexit	ole Vacancies					
In hhi	0.00481**	0.0920**	0.132***	0.195***	0.139***	
	(0.00157)	(0.0410)	(0.0364)	(0.0285)	(0.0378)	
	(0.00107)	(0.0110)	(0.0001)	(0.0200)	(0.0070)	
Panel C: Safe Flevih	le Vacancies					
Taner O. Sale Tiexib	e vacancies					
In hhi	0.00137	-0.0346***	-0.0479***	-0.0778***	-0.0477***	
-	(0.000920)	(0.0134)	(0.0135)	(0.0196)	(0.0135)	
	, ,	. ,	. ,	. ,	. ,	
ln_hhi						
N	232076	115314	115314	115314	115314	
1st-stage F statistic		34.881	30.145	6.859	30.173	

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	(1) FE	(2) IV	(3) IV	(4) IV	(5) IV				
Panel A: Flexible Vacancies									
ln_hhi	0.0062*** (0.00159)	0.0574* (0.0328)	0.0838*** (0.0290)	0.117*** (0.0265)	0.0913*** (0.0304)	$\Leftarrow \textit{profitable disamenity}$			
Panel B: Risky Flexib	ble Vacancies								
ln_hhi	0.00481** (0.00157)	0.0920** (0.0410)	0.132*** (0.0364)	0.195*** (0.0285)	0.139*** (0.0378)	$\Leftarrow \textit{profitable disamenity}$			
Panel C: Safe Flexib	le Vacancies								
ln_hhi	0.00137 (0.000920)	-0.0346*** (0.0134)	-0.0479*** (0.0135)	-0.0778*** (0.0196)	-0.0477*** (0.0135)	$\Leftarrow \text{costly amenity}$			
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	(1)	(2)	(=)	(1)	(=)				
	(1)	(2)	(3)	(4)	(5)				
	FE	IV	IV	IV	IV				
Panel A: Flexible Vacancies									
In hhi	0.0062***	0.0574*	0 0838***	0 117***	0.0913***	← profitable disamenity			
	(0.00150)	(0.000)	(0.0000)	(0.0005)	(0.0010				
	(0.00159)	(0.0328)	(0.0290)	(0.0265)	(0.0304)				
-									
Panel B: Hisky Flexit	ole Vacancies								
In bhi	0.00481**	0.0020**	0 132***	0 195***	0 130***	← profitable disamenity			
	(0.00401	(0.0320	(0.0264)	(0.000E)	(0.0270)				
	(0.00157)	(0.0410)	(0.0364)	(0.0265)	(0.0376)				
Panel C: Safe Flexibi	le Vacancies								
In hhi	0.00137	-0.0346***	-0 0479***	-0.0778***	-0.0477***	⇐ costly amenity			
	(0.000920)	(0.0134)	(0.0135)	(0.0196)	(0.0135)				
	(********)	()	()	(()				
Panel D: Permanent	Vacancies								
In hhi	-0.0110***	-0.0624*	-0 114***	-0 153***	-0 115***				
	(0.00173)	(0.0374)	(0.0274)	(0.0256)	(0.0273)				
	(0.00173)	(0.0374)	(0.0274)	(0.0200)	(0.0273)				
IN	232076	115314	115314	115314	115314				
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Regressions control for county-SOC, county-time, and SOC-time FE. Standard errors clustered at county-occupation level in parentheses. (2) Firm-level shocks. (3) Firm-occupation-level shocks. (4) Firm-occupation-level shocks with leave-one-out sum. (5) Firm-occupation-level shocks + wage control. * p<0.1. ** p<0.01

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Conclusion



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Conclusion

- vacancy text as a new source of data on job attributes
- schedule flexibility is prevalent & growing
- its welfare effects depend on interaction with other job attributes (remuneration type)

Representativeness of BGT data

Table: Summary statistics, 2014-2019

	BGT data	ONS data
number of vacancies (millions)	46	55.4
share with wage info (%) <£9 £9 - £15 £15 - £20	63.1% 22.1% 39.9% 17.3%	24% 36.7% 16.1%
>£20	20.8%	23.2%

Notes: ONS data on the number of vacancies comes from the Vacancy Survey. The ONS data in the rest of the table comes from the Annual Survey of Hours and Earnings. Data is pooled over the 2014-2019 period.



Representativeness of BGT data: occupations



Share of workers/vacancies in a given SOC 1-digit occupation group. Data from Annual Survey of Hours and Earnings pooled over years 2014-2019. BGT data excludes vacancies with missing occupation information.



Representativeness of BGT data: geography



Each point corresponds to the number of employees and vacancies in a specific county in 2019. Data from Annual Survey of Hours and Earnings.



Workers' outside option

The outside option of a worker bargaining with firm *j*:

$$U_j = \lambda \sum_{i \neq j} s_i u(w_i, f_i) + (1 - \lambda + \lambda s_j) u(b, 0)$$
(1)

$$=\lambda \bar{u} - \lambda s_j u(w_j, f_j) + (1 - \lambda + \lambda s_j) u(b, 0)$$
(2)

The average outside offer:

$$\bar{U} = \sum_{i} s_{i} U_{i}$$
$$= \lambda \bar{u} + (1 - \lambda) u(b, 0) - \lambda \sum_{i} s_{i}^{2} \left[u(w_{i}, f_{i}) - u(b, 0) \right]$$
(3)

 \bar{u} = the expected utility of jobs available on the market



Proposition 1

A unique interior solution to the bargaining problem exists for any type of job feature f if

- (i) there is some interval for $\delta(f)$ on which $\operatorname{sgn}(\delta'_f) \neq \operatorname{sgn}(u'_f)$
- (ii) the second derivative of the job feature profit function δ(f) is negative: δ["]_f < 0 ⇒ decreasing marginal profits (or increasing marginal costs)
- (iii) the second-order derivatives of the utility function u(w, f) are weakly negative: $u''_w \le 0, u''_f \le 0 \Rightarrow$ (weakly) diminishing returns for wages and amenities, (weakly) increasing marginal disutility of disamenities
- (iv) the sign of the second-order cross-derivative of the utility function is the same as the sign of marginal utility of job feature: $sgn(u'_{wf}) = sgn(u'_f) \Rightarrow$ wages and amenities are complements, wages and disamenities are substitutes

Propositions 2 & 3

Optimal $\{w^*, f^*\}$ bundle varies with worker outside option \overline{U} when at least one of u''_w, u''_{wf} is different from $0. \Rightarrow$ either u(w) is concave, or w, f must be substitutes/complements

If it is also true that

$$rac{u_{wf}^{\prime\prime}}{u_f^\prime} < rac{2}{eta[y+\delta(f^*)-w^*]}$$

the optimal quantity of job feature *f* increases in worker outside option \overline{U} when *f* is an amenity, and decreases when *f* is a disamenity. The size of this effect is larger when the amenity is costly rather than profitable. \Rightarrow the substitutability between *w*, *f* can't be too large



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Accuracy of our model

	Logistic R	egression	Model	Improvement to keywords			
Contract type	Precision	Recall	F	Precision	Recall	F	
Schedule flexible	0.8540	0.8083	0.8303	0.0005	0.4399	0.1855	
Permanent	0.9294	0.9736	0.9510	0.0471	-0.0067	0.0223	
Full-time	0.9162	0.8881	0.9019	0.1898	0.2236	0.1314	
Salaried	0.8604	0.8415	0.8503	-0.1032	0.3586	0.2070	

precision = 1 - false positives recall = 1 - false negatives F = an aggregate measure

back

Burning Glass vs Understanding Society



Burning Glass vs Understanding Society



Shock-level regressions

	(1)	(2)	(3)	(4)	(5)			
	FE	IV	IV	IV	IV			
Panel A: Flexible Vacancies								
ln_hhi	0.0062***	0.0574*	0.0838***	0.0966***	0.0913***			
	(0.00159)	(0.0345)	(0.0306)	(0.0213)	(0.0319)			
Panel B: Risky Flexil	ble Vacancies	;						
ln_hhi	0.00481**	0.0920*	0.132***	0.154***	0.139***			
	(0.00157)	(0.0480)	(0.0350)	(0.0199)	(0.0363)			
Panel C: Safe Flexib	le Vacancies							
ln_hhi	0.00137	-0.0346**	-0.0479***	-0.0570***	-0.0477***			
	(0.00092)	(0.0171)	(0.00915)	(0.0106)	(0.00906)			
Panel D: Permanent	Panel D: Permanent Vacancies							
ln_hhi	-0.0110***	-0.0624*	-0.114***	-0.128***	-0.115***			
	(0.00173)	(0.0330)	(0.0228)	(0.0273)	(0.0229)			
N	232076	913688	2369314	237450	2369314			
1st-stage F statistic		58.200	15.139	10.182	15.033			