What determines unemployment: low productivity or high outside options?

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Abstract

I show that unemployment risk is very heterogeneous in the cross section: 15% of the Danish labor force accounts for 60% of unemployment.I model this ex-ante heterogeneity in an Aiyagari-Bewley-Hugget economy with directed search. I calibrate the model to the cross-sectional unemployment risk using either heterogeneous productivity or heterogeneous outside options. The welfare cost of unemployment is significantly higher when it is caused by heterogeneous productivity.

Using detailed administrative data, I study whether the cross-sectional differences in Danish unemployment are driven by better outside options or lower productivity. I find ample evidence that higher unemployment risk is not driven by better outside options by focusing on wealth, debt, delinquency rates of high-risk individuals, their parents, and partners. Instead, higher unemployment risk is associated with several indices of lower productivity: high-risk individuals have lower wages, lower Mincer residuals, worse mental health and are less educated. Preliminary: the calibrated model – which is work in progress – suggests an increase in unemployment insurance relative to the status quo.

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1 Introduction

In this paper I study the determinants of cross-sectional differences in unemployment risk and their welfare implications.

First, I cluster the Danish labor force by their employment history, and estimate cross-sectional differences in unemployment risk. I show that a group of 15% of workers – “marginal workers” – make up 60% of the Danish unemployed. These marginal workers have an unemployment rate of 35%. This is in stark contrast to the remaining Danish labor force – “stable workers” – that have an unemployed rate of 3%.

Second, I show that in an Aiyagari-Bewley-Hugget-Imrohoglu environment with labor markets and directed search, cross-sectional differences in unemployment rates can be due to cross-sectional differences in either productivity or outside options. I use the model to establish that the welfare cost of unemployment is much higher when unemployment is due to differences in productivity.

Third, I use Danish administrative data on earnings, partners, parents, hospitalization, wealth, and credits, to establish whether the higher unemployment risk of marginal workers is due to better outside options, or lower productivity. I find that marginal workers have, if anything, worse outside options. The findings suggest that the welfare cost of unemployment is higher than previously thought, since it is concentrated on a minority of less productive workers with worse outside options.

In the first step, I use matched employer-employee data on the universe of Danish wage payments between the years 2008 to 2018 to compute summarize each workers employment history in a set of 12 moments. I then cluster workers into two groups using a k-means algorithm. I label the cluster with a lower and higher average unemployment rate as “stable workers” and “marginal workers”, respectively. The clustering exercise uncovers large heterogeneity in cross-sectional unemployment risk: marginal workers have an average unemployment rate of 35% (stable workers: 5%). These numbers are in line with previous findings for the United States (Gregory, Menzio, and Wiczer, 2021; Hall and Kudlyak, 2019; Ahn, Hobijn, and Şahin, 2023).

I then introduce a model that nests the consumption-savings decision from an Aiyagari-Bewley-Hugget-Imrohoglu environment with labor markets and directed search. In the model households belong to one of two ex-ante different types, marginal or stable. The job-separation risk is exogenous and identical across all households. The job-finding rate is endogenous: unemployed workers chooses a target wage at which to search for jobs. Each worker trades off a higher future income-stream from a higher wage against a higher job-finding rate from searching for a lower wage. In the model, the higher unemployment risk of marginal workers may be due to two factors: lower productivity, or higher outside-options. Less productive workers are, c.p., less likely to find a job for a given wage. In response, they lower their target wage – however not enough to completely offset the reduction in job-finding rates. Workers with higher outside options – modeled as a higher income stream during unemployment – have a higher unemployment rate for a different reason: they choose a higher target wage since the unemployment state is perceived as less costly.

I use either cross-sectional difference productivity or in outside options to match the empirically observed differences in unemployment rates. I then compute the welfare cost of unemployment for each worker type in each of the two calibrations. I show that the calibration choice is not innocuous: when marginal workers have better outside options, the welfare cost of unemployment is moderate and similar across both types. Instead, when marginal workers are less productive, their welfare cost of unemployment is much larger. This increase is such that the economy-wide average welfare cost of unemployment increases two-fold, despite marginal workers only making up 15% of the labor force.

After having established the relevance of the determinants of unemployment, I then use extensive data from Danish administrative registries to shed light on whether differences in productivity or outside options are responsible for the large cross-sectional differences in unemployment.

On outside options, I make progress by matching marginal workers to their partners and parents: these are potentially important devices to insure workers against the consumption loss associated with unemployment. I do not find evidence supporting the hypothesis that marginal workers have better outside options. In fact, they appear to have worse outside options: they have less wealth and higher delinquency rates. They are less likely to have a partner to rely on. Those that do have a partner, have a partner than earns less than the population average.

I then find several indicators that suggest that marginal workers are less productive. Worker productivity is notoriously difficult to measure. I first report classical wage-based measures: marginal workers have lower wages, lower Mincer residuals, and lower AKM worker fixed effects. Second, I use hospitalization data to show that marginal workers are significantly more likely to have mental-health related problems.

The findings suggest that the welfare cost of unemployment is higher than previously thought, since it is concentrated on a minority of less productive workers with worse outside options.

The remainder of this paper is as follows. Section 2 estimates worker types. Section 3 introduces the model, and discusses the welfare differences of the driver of unemployment. Section 4 studies outside options and productivity. Section 5 concludes.

2 Estimation of worker types

The goal is to separate workers with stable employment histories from those that less stable careers, e.g. move in and out of jobs frequently. To this end, I fix the sampling period of the analysis to the years 2008-2018[1]. I then estimate each worker's type based on their employment history during this time frame: I first summarize each worker's employment history in a set of moments. Workers are then clustered using a k-means algorithm[2].

A worker's employment history is constituted by episodes through which they are either employed, unemployed (actively searching for a job), or "nonemployed" (not part of the active labor force, for example due to parental leave or sickness). I measure employment/non-employment status using the wage payments in the BFL, which also allows me to estimate the duration of each job spell. I estimate unemployment status using social security benefits (DREAM).

I focus on the primary-aged workforce and exclude workers with low attachment to the labor force. I also exclude workers under the age of 30 to ensure that students (that frequently take summer jobs) are not missclassified as workers with a bad labor market history. These restrictions remove half of the Danish labor force from the sample, and leave me with ca. 1.36 million workers[3].

Table 1 summarizes the result of the clustering exercise: the algorithm separates the Danish workforce into three clusters, which I label as "stable" and "marginal". That table also lists the various moments that I have used for the clustering, together with the average value of each cluster during the sampling period (2008-2018)[4]. Note that 76% of workers are labeled "stable". 56% of

[1]The start is due to data availability. I end the sampling period two years ahead of the pandemic to test for mean reversion

[2]The clustering algorithm provides groupings of workers that minimize the difference in the moments within each cluster and maximizing the difference across worker types.

[3]Additional information regarding the methodology is provided in Appendix A.

[4]During that period, a cross-sectional out-of-sample prediction leads to a missclassification

	Worker type	
	Stable	**Marginal**
# Obs.	1 309 763	208 680
Share	0.86	0.14
Clustering		
Match: 1– 3M	0.11	0.17
Match: 3– 6M	0.08	0.17
Match: 6–12M	0.10	0.18
Match: 12–24M	0.16	0.21
Match: 24+M	0.56	0.27
Nonemp: 0–1M	1.00	0.97
Nonemp: 1–3M	0.00	0.00
Nonemp: 3–6M	0.00	0.01
Nonemp: 6–12M	0.00	0.01
Nonemp: 12+M	0.00	0.01
#Jobs per month	0.02	0.06
Nonemployment rate	0.00	0.01
Unemployment rate	0.03	0.35
Worker characteristics		
Male	0.52	0.52
Age	46.72	45.42
Education: HS or less	0.17	0.32
Large city	0.61	0.61
Rural municipality	0.18	0.20
Danish citizen	0.94	0.88
Non-Danish origin	0.10	0.19

Table 1: Clustering of workers and descriptive characteristics

these are employed in jobs that last more than two years, which is only true for 35% and 21% of unstable and marginal workers, respectively. Relative to the other two types, stable workers are much more likely to have nonemployment durations of less than one month between matches (implying a large share of job-to-job transitions). Unstable and marginal workers have much higher nonemployment and unemployment rates – the average unemployment rate of marginal workers is 50%! They also have a much higher number of jobs per month, suggesting that they keep cycling through jobs that do not last very long.

Table 1 also describes the demographics of the workers in each cluster. There are no stark differences in gender and age across the groups. A much smaller share of stable workers have only a high-school degree. They have a slightly higher tendency to live in large cities, and a slightly lower tendency to live in a rural municipality ("landkommun"): differences in employment and labor market developments between larger Danish cities and rural municipalities appear not to be driven by the worker types.

3 The welfare relevance of the determinants of unemployment

In order to explain cross-sectional heterogeneity in the unemployment rates and assess their welfare cost, I build a model that nests a Bewley-Aiyagari-Hugget economy with directed search. In this model, workers ex-ante differ in their type i. I will focus on an environment with two types, $i \in \{s, m\}$. The labor force share of each type is given by L_i. Time is continuous, but I will refrain from indicating time indices t until necessary for the ease of exposition.

Unemployed workers of each type receive benefits b_i and attempt to match with firms in order to receive wage income. The log productivity of worker-firm pair is a combination of a type component z_i, and a match specific component $\hat{z}$. Labor markets are segmented: each vacancy is indexed by a type-wage pair (i, w), directed towards a worker of type i, and promising wage w. Search is directed: workers of each type observe the tightness in each sub market $\theta(i, w)$, and decide to search for employment in the submarket that maximizes their expected discounted payment stream. Employed and unemployed workers of each type have access to an asset that promises interest rate r and exists in zero

in roughly 0.1% of the cases.

net supply.

The present-discounted value of a a firm with productivity z and promised wages w is given by

$$J(z,w) = \frac{z-w}{\rho+\delta}, \tag{1}$$

where ρ and δ denote the discount rate and the exogenous separation rate.

Upon matching with a worker, the match-specific productivity is observed. The worker-firm pair will only produce if $z > w$. Denote by $G_i(z)$ the c.d.f. of productivity draws for type i. The value of matching with a worker of that type and wage w is then given by

$$\hat{J}(i,w) = \int_w^\infty J(z,w)dG_i(z).$$

Opening a vacancy has a flow cost c. I denote the job-finding and vacancy-filling rates as $f(\theta)$ and $q(\theta)$, respectively. The value of opening a vacancy in sub market (i,w) is then given by

$$\rho V(i,w) = -c + q(\theta(i,w))\hat{J}_i(w).$$

A free-entry condition holds for each (i,w) sub market and will thus determine the market tightness $\theta(i,w)$.

The value functions for employed and unemployed workers, $E^i(w,a)$ and $U^i(a)$ are given by

$$\begin{aligned}\rho E^i(w,a) &= \max_c u(c) + \frac{\partial E^i(w,a)}{\partial a}(ra+w-c) + \delta(U(a) - E^i(w,a)) \\ \rho U^i(a) &= \max_{c,w} u(c) + \frac{\partial U^i(a)}{\partial a}(ra+b_i-c) + f(\theta(i,w))(E^i(w,a) - U^i(a)).\end{aligned}$$

Denote by $w^*(i,a)$ the wage decision of an unemployed workers of type i with asset level a, and by $c^*(i,a,w)$ the consumption choice of workers of type i with assets a and wage w. Denote by $H_i(a,w)$ the cdf of workers of type i over assets and wages. In equilibrium, we have zero net supplies of assets

$$\sum_{i\in\{\ell,h\}} L_i \int a dH_i(a,w) = 0, \tag{2}$$

which determines the equilibrium interest rate r.

A steady state is given by

- An interest rate r
- A set of market tightness $\{\theta(i,w)\}$
- A set of wage decisions of unemployed workers $\{w^*(i,a)\}$
- A set of consumption decisions $\{c_i^*(a,w)\}$
- A set of distributions $\{H_i(a,w)\}$

such that

- Assets are in zero net supply (2)
- The free entry condition holds for each sub market, $V(i,w) = 0$
- The wage decisions and consumption decisions are optimal
- The distributions are consistent with the wage and consumption decisions

Productivity versus outside options I now show that the model can be calibrated to the observed unemployment rates along two margins: benefits b_i, or mean productivities z_i. To do this, I fix a set of exogenous parameters. I then compare two alternative calibrations. In both calibrations, the unemployment rate of the stable workers is calibrated via the vacancy flow cost c. The calibrations differ in the fashion through which they match the unemployment rate of marginal workers. In the "low productivity" calibration, this is achieved by varying z_m. In the "high benefits" calibration, this is achieved by varying b_m.

The list of parameters is provided by Table 2.

Figure 1 compares the consumption decision for both agents across the two calibrations. As we can see, marginal workers consume more than stable workers in the outside option calibration, and their consumption fall from employment to unemployment is relatively small. The opposite of that is true when unemployment is due to consumption.

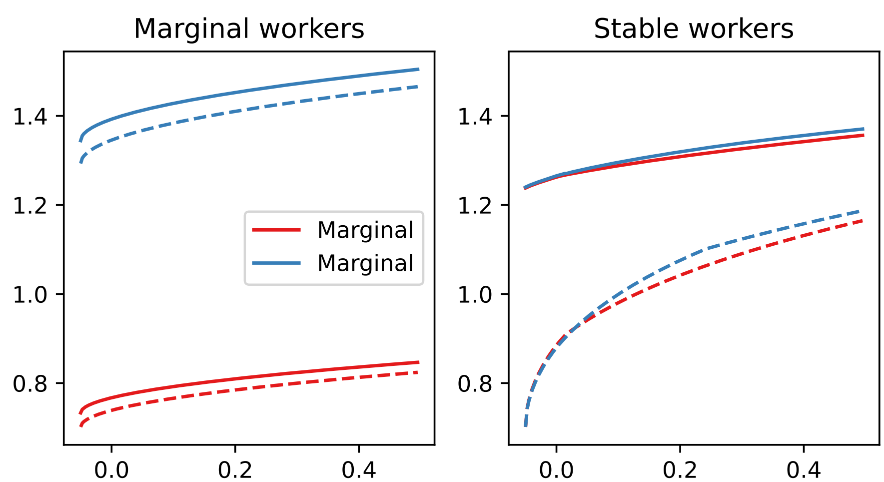
I then proceed to quantify the welfare cost of unemployment across both calibrations. Here, I ask the model: how much would average utility increase if the exogenous separation rate δ was set to zero, so that employed workers no longer faced unemployment risk? To be precise, I compute $(\hat{E}, \hat{U})$ for $\delta = 0$ – holding $f(\theta(i,w))$ at their previous levels. I then compute $\Delta c_i(a,w)$ as

$$E_i(a,w) - u(c_i^*(a,w)) + u\left(c_i^*(a,w) + \Delta c_i(a,w)\right) = \hat{E}_i(a,w). \tag{3}$$

Common parameters			Value
Exogenous separation rate	δ		0.04
Discount rate	ρ		0.01
Matching: elasticity	α		0.50
Productivity dispersion	σ_z		0.15
Log productivity (stable)	z_s		0.00
Income of unemployed (stable)	b_s		0.70
Specific parameters		**Low prod.**	**High out. opt.**
Vacancy search cost	c	0.00	0.00
Income of unemployed (marginal)	b_m	0.70	1.29
Log productivity (marginal)	z_m	-0.60	0.00

Table 2: Parameters

Figure 1: Optimal consumption



	Low productivity		High benefits	
Interest rate	-0.0297		-0.0323	
Cost of being marginal	82.0938		-24.1336	
By worker type	**Marginal**	**Stable**	**Marginal**	**Stable**
Unemployment rate	0.384	0.027	0.340	0.029
Asset holdings	-0.050	0.009	-0.050	0.008
Consumption (employed)	0.733	1.254	1.345	1.269
Consumption (unemployed)	0.701	0.767	1.293	0.762

Table 3: Moments

$\Delta_i(a, w)$ holds the additional consumption an agent of type (i, a, w) would need in order to be indifferent to the world in which $\delta = 0$ (holding firm decisions constant). It can be used to quantify the welfare cost of unemployment: the larger $\Delta_i(a, w)$, the more costly unemployment is to that worker.

Table 3 lists the average welfare cost of unemployment for both types of workers across both calibrations, and provides more detail about each calibration. In the "high benefits" economy, the welfare cost of unemployment is not very different across the two types. In fact, since marginal workers are unemployed because of their high outside options, their welfare cost of unemployment is lower than that of stable workers. In the "low productivity" economy, the welfare cost of unemployment is similar for stable workers. For marginal workers, this cost however increased significantly: they would necessitate a eight-fold increase of their consumption in order to be indifferent to the world without unemployment.

In this economy, marginal workers have a income stream during unemployment (b), and choose low wages as a result. They do not manage to build up sufficient amounts of assets to insure against the risk of unemployment, and consequently the consumption difference of employed and unemployed marginal workers is significantly higher than that in the economy with high outside options.

4 The drivers of Danish unemployment heterogeneity

In section 1, I estimated stable and marginal workers using Danish data. I showed that marginal workers have a significantly higher unemployment rate

	Worker type	
	Stable	**Marginal**
Share	0.86	0.14
Worker relationship		
Has partner	0.61	0.43
L. earnings (partner)	12.52	12.25
Partner worker type: Stable	0.91	0.77
Partner worker type: Marginal	0.09	0.23
Worker wealth		
Net wealth ('000s)	286.61	69.54
Ever delinquent	0.12	0.27
Interest payments ('000s)	10.67	8.76

Table 4: Outside-option related statistics

– 35% on average. Section 2 emphasized that the welfare cost of unemployment depends on the cause of unemployment: low productivity or high outside options. In this section, I will use the Danish administrative data and my previously estimated worker types to study several outcomes associated with either productivity or outside options. We will see that higher outside options cannot explain the higher unemployment rate of marginal workers. In fact, their outside options appear to be worse than those of stable workers. I then present several variables associated with productivity, suggesting that marginal workers are indeed less productive than stable workers.

4.1 Differences in outside options

Do marginal workers have worse employment histories because they – due to better outside options – are less attached to their jobs? One important measure of outside options is the employment status and the earnings of the partner: the secondary earner in a household can rely on the primary earner and perhaps needs not to be employed as much.

Table 3 shows that the opposite is true: marginal workers both have worse labor market histories and economically worse partners. First, 46% of marginal workers (63% of stable workers) have a registered partner[5]. The forty percent of marginal workers that do have partners have partners that earn significantly

[5]This analysis relies on registered partners with the Danish government, which can be either a registered partnership or a marriage.

less. The difference in log earnings of the partners of stable and marginal workers amounts to 0.2, suggesting an earnings difference of approximately 20%. This is, to some extent, because assortative mating: stable workers are more likely to have stable partners. The risk of having marginal workers as partners is highest for marginal workers.

Next, Table 3 shows wealth-related differences between marginal and stable workers. Stable workers almost have 300% higher wealth than marginal workers. These large wealth differences stand in contrast to small differences in interest payments: I find bank loans for 97% of stable and marginal workers[6]. The average interest payment of stable workers is only 20% higher than that of marginal workers. Finally, I look at delinquencies: throughout the episode from 2008-2018, the delinquency risk of marginal workers was 60% higher (37% vs 23%).

To conclude, it appears that the larger unemployment risk of marginal workers is not driven by better outside options: in fact, they appear to have worse outside options.

4.2 Differences in productivity

I now turn to productivity: are marginal workers less productive than stable workers?

Table 5 summarizes differences in earnings-related outcomes across the two clusters. Annual earnings of stable workers are almost twice times as high those of marginal workers – to some extent, this is due to differences in employment rates. Some of it however is also due to differences in hours: stable workers work 13% more hours than marginal workers. I match the administrative data to the EU Labor Force Survey to show that this is to some extent due to part-time jobs: marginal workers have a 4% higher rate of being employed part-time. Of these part-time employees among the marginal workers, 20% report that they are employed part-time because they could not find a full-time job (as opposed to prefer working part-time). Marginal workers are four times as likely to be employed on temporary jobs (15% vs 6%).

Is this because marginal workers are less productive? Worker-level productivity is historically difficult to measure. One approach is to estimate the so-called "Mincer residual": it contains for each worker their wage corrected for observable characteristics that are wage-related (for example age and edu-

[6] I focus on private bank lending that is not related to a mortgage.

	Worker type	
	Stable	**Marginal**
Share	0.86	0.14
Worker earnings		
Monthly hours worked	132	113
Annual earnings ('000s)	3651	1661
Part time	0.17	0.21
Part time: cannot find fulltime	0.18	0.20
Temporary	0.04	0.18
Mincer resid.	−0.02	−0.12
AKM worker FE	0.02	−0.09
Separation: economic reason	0.06	0.15
Worker health		
Any hospital visit	0.51	0.57
Hospital visit: mental illness	0.03	0.04
Visit: psychiatrist	0.04	0.09
Visit: psychologist	0.11	0.15

Table 5: Earnings differences by worker group

cation). This residual is often used as a proxy for productivity: workers that earn a higher wage (conditional on their observable characteristics) might do to because they are more productive, and hence are able to negotiate higher wages. Table 5 shows that the Mincer residual of marginal workers is 0.1 lower than that of stable workers[7]. If the Mincer residual was purely a result of productivity differences, this would imply a 10% lower productivity for marginal workers. This need not be due to worker productivity: marginal workers could for example be employed at firms that tend to pay lower wages. The so-called "AKM" worker fixed effect accounts for that: the difference in the AKM worker fixed effects between stable and marginal workers is also around 11%. Finally, the labor force survey also asks workers whether they last job ended due to an economic reason – because either the firm or the worker was not performing well. 15% of marginal workers (as opposed to 6% of stable workers) report that being the case.

Firm-level value added In order to show a direct relationship between worker type and output, I run a regression that attributes the log of value

[7]The Mincer residuals do not average to zero since they are estimated over the entire population.

	(1)	(2)	(3)	(4)	(5)	(6)
	log_va	log_va	log_va	log_va	log_va	log_va
Stable: log hours	0.391***	0.247***	0.257***	0.126***	0.117***	0.276***
	(97.73)	(97.39)	(102.17)	(54.64)	(29.48)	(93.35)
Marginal: log hours	0.114***	0.0713***	0.0717***	0.0450***	0.0829***	0.0652***
	(29.97)	(58.85)	(60.13)	(39.02)	(26.50)	(52.04)
Other: log hours	0.390***	0.260***	0.227***	0.102***	0.0954***	0.249***
	(100.50)	(104.68)	(95.76)	(43.59)	(26.22)	(85.59)
Log (firmsize)				0.580***		
				(86.09)		
Observations	1076480	1062513	1062513	1062513	133230	952088
Firm FE	No	Yes	Yes	Yes	Yes	Yes
Month FE	No	No	Yes	Yes	Yes	Yes
Firm size					Small	Large

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 6: Marginal workers contribute less to value added

added at firm i in quarter t to the stock of either employment or hours worked by worker type:

$$va_{i,t} = \alpha_i + \sum_j \beta_j x_{j,i,t} + \gamma_t + \epsilon_{i,t}$$

, where $x_{j,i,t}$ is the amount of labor of type j used by firm i in quarter t. I will study two specifications where x either is estimated using the number of employees or the total sum of hours provided.

Table 6 summarizes the results for value added. Column 1 reports the findings without the inclusion of either time or firm fixed-effects. A 1% increase in hours worked of stable workers is associated with an average of 0.37% of value added. With a coefficient of 0.094, marginal workers only add 1/4th of that to value added. These findings may to some extent be driven by selection of marginal workers into less productive firms: column 2 includes firm-fixed effects. This specification assigns each firm's average value added to α_i. Consequently, the point estimates are smaller. Yet, we still find that the effect of marginal workers on value added is 1/4ths of that of stable workers (0.06 vs 0.22). The results are robust to the inclusion of time fixed-effects (columns 3).

Caveats There are two threats to identification: first, other factors may determine both productivity and employment. For example, stable workers might be more perceptive to exogenous shocks that affect their company's future value added and search for alternative employment. Second, marginal and stable workers might be employed in different occupations. The impact of different occupations on contemporaneous value added might differ: some occupations might contribute less altogether, or their contributions will materialize further in the future. Together, this might imply that changes in the hours of marginal workers might simply reflect within-firm changes in the hours compositions of different occupations (with different degrees of productivity). In a model without occupational heterogeneity, the relevant question is whether marginal and stable workers *of the same occupation* are differently productive. To address this issue, one would optimally want an estimate of value added by occupation-firm which could then be broken down into the labor supplied by worker type into each occupation-firm. Since value added is not observed at the occupation level, I instead argue that short-run production functions are stable at the firm level: firms typically do not drastically change their input composition of occupations over short time horizons.

5 Conclusion

There is a significant cross-sectional difference in unemployment risk in Denmark. Marginal workers – workers with a high unemployment risk – have a higher unemployment risk despite having on average worse outside options. This suggests stark cross-sectional differences in productivity. I develop a Aiyagari-Bewley-Hugget-Imrohoglu economy with unemployment and directed search. In this economy, the welfare cost of unemployment is much larger when cross-sectional unemployment differences are driven by outside options. The model suggests the average consumption difference between employed and unemployed workers as an indicator for the welfare cost of unemployment.

The findings suggest that unemployment is more costly than previously thought, since it is concentrated on a minority of workers with significantly worse outside options.

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A Methodology

I choose my moments following Gregory, Menzio, and Wiczer (2021), but adapt them in order to use the higher precision and additional information provided by the administrative data. My first four moments compute the share of employment spells of a given worker that are of short, medium, long, and very long duration [8]. The next three moments compute the share of nonemployment spells that are of short, medium, and long duration. My final three moments contain averages across a worker's career: their number of jobs (per month), their non-employment to employment ratio, and their average unemployment rate (identified by social security benefits).

Data I enrich Danish matched employer-employee data (BFL) with data on social security benefits (DREAM) and additional information on each worker's background. The aim of the analysis is to first to characterize workers' types using their labor market histories before the Covid-19 episode, and then study how workers across different clusters were differently affected by the pandemic. I use data from 2008 to 2018 to summarize the workers' employment histories into the 11 moments [9]. The matched employer-employee data covers the universe of Danish employees, and is sourced from wage payments. Each individual wage payment is observed with the precise date. The drawback of this data is that wage payments may occur after the employment spell has ended.

I use social security payments (DREAM) to compute whether a worker is unemployed [10] Collection of unemployment benefits is highly standardized, and the pickup rate is estimated to be above 80%. The drawback of the DREAM data is that it only contains binary information on whether a worker has received some unemployment benefits. Workers may receive supplementary benefits while employed, and so relying on DREAM data alone can be misleading as well. As it turns out, the timing of unemployment benefits does not align well with non-employment episodes in the BFL, and the most robust approach is to use both data sources in isolation.

[8] The precise criteria are provided in Table 1

[9] The starting year is dictated by the availability of the BFL. Stopping two years short of the pandemic allows us to test the presence of mean reversal.

[10] DREAM contains many different reasons for benefits, for example various reasons of unemployment, health, etc. The aggregated available data contains a single code per worker-week. Codes are ranked in terms of priority, and workers who receive benefits for different reasons are stored with the highest-ranked code. I use codes 112-118 to characterize a worker as unemployed.

# Obs	Sample restriction
3 169 414	In labor force during sample time
1 919 490	Within the age 30-60
1 752 138	At least two years in labor force
1 537 248	At least 12 months employed
1 518 443	Maximum nonemployment spell less than 2 years

Table 7: Sample restrictions and sample size

Sample I focus on workers that are attached to the labor force by excluding workers that are employed less than 5 out of the 10 years (see also Menzio et al, 2022). I focus on workers in their primary working age, which I define as years 30-65 [11].'

The moments I compute each worker's employment and non-employment spells using the BFL alone. The final moment, the worker's average unemployment rate, is computed using DREAM, in order to address workers that may have larger nonemployment histories that are driven by temporary exits out of the labor force. In order to harmonize the different types of moments, I reweight moments s_1-s_4 by 1/4 and moments s_5-s_7 by 1/3, and then standardize each moment.

The clustering I cluster workers into N groups using a k-means algorithm. I also compute the accuracy of the algorithm using an out-of-sample validation exercise: I first split the set of workers into three groups, $\{a, b, c\}$. I then cluster workers in groups a and b independently. Finally, I predict the cluster of workers in group c using the clusters generated by both groups a and b and compute the prediction error as the share of workers who are placed into different clusters [12].

The out-of-sample prediction error for both $N = 2$ and $N = 3$ is less than 0.1%, and much lower for larger numbers of groups. I chose $N = 3$ as my number of clusters, in order to isolate clearly the workers that have the worst

[11] The goal is to study workers that have involuntary unstable careers. I set the high minimum age in order to ensure that most students, who typically also have unstable employment histories, are excluded from the sample.

[12] I always rank clusters by their nonemployment-to-employment ratio, which ensures that clusters from independent clustering exercises are aligned in the sense that lower-ranked clusters have "better" employment histories.

employment histories and render my findings comparable to the literature. I then re-run the k-means algorithm using the entire cross section of workers. I label the three groups "stable", "unstable", and "marginal" workers.

B Welfare cost of unemployment

Let the value function of an employed and unemployed be given by

$$\begin{aligned}
\rho U(a) &= \max_{c,w} u(c) + f(w)(E(w,a) - U(a)) + \frac{\partial U(a)}{\partial a}\dot{a}(c) \\
\dot{a}(c) &= b + ra - c \\
\rho E(w,a) &= \max_{c} u(c) + \delta(U(a) - E(w,a)) + \frac{\partial E(w,a)}{\partial a}\dot{a}(c) \\
\dot{a}(c) &= w + ra - c
\end{aligned}$$

Consider an alternative environment with $\delta = 0$. Denote the corresponding E, U with hats.

How much better is $\hat{E}$?

Define

$$\hat{E}(a,w) = E(a,w) + a$$