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Why are marginal workers unemployed: low productivity or high opportunity cost of employment?

Written by

Saman Darougheh
Research Economist

sdma@nationalbanken.dk
+45 3363 6126

15% of Danish workers account for 60% of unemployment. Using administrative data and a structural model, I investigate whether these workers are repeatedly unemployed due to lower productivity or higher opportunity costs—a distinction crucial for optimal unemployment insurance design.

Keywords

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Why are marginal workers unemployed: low productivity or high opportunity cost of employment?

Saman Darougheh*

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Abstract

15% of Danish workers account for 60% of unemployment. Are these workers unemployed more frequently because of their lower productivity or higher opportunity costs of employment? Using administrative data linking workers to their earnings, wealth, debt, health records, parental backgrounds, partners, job types, and firm-level value added, I find strong evidence that higher unemployment risk reflects lower productivity rather than higher pecuniary opportunity costs. A calibrated heterogeneous-agents model with segmented labor markets is consistent with these findings: productivity differences and non-pecuniary opportunity costs explain most of the unemployment gap. This matters for social policy: optimal unemployment insurance is higher than if marginal workers' unemployment was predominantly due to a high pecuniary opportunity cost.

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Why is it that the unemployed are unemployed? This fundamental question reflects two main competing views that have sharply different implications for policy. One view holds that the unemployed have high opportunity costs of employment—they search for high-wage jobs and are willing to wait longer to find them, whether due to generous benefits funding their consumption (pecuniary opportunity costs) or a strong preference for leisure during unemployment (non-pecuniary opportunity costs). Chodorow-Reich and Karabarbounis (2016) formalize this channel through the flow utility from unemployment. The contrasting view sees unemployment as driven by low productivity: workers want to work but cannot find jobs that match their productive capacity. These views suggest radically different policy responses. If high unemployment reflects high opportunity costs, reducing benefits could effectively lower unemployment rates by making workers willing to accept lower-wage jobs more quickly. However, if productivity gaps drive unemployment, such benefit cuts would merely penalize workers already struggling to find gainful employment, suggesting policies like retraining programs might be more appropriate.[1]

To make progress on distinguishing between these views, I build on recent research documenting large heterogeneity in unemployment risk across workers. Gregory, Menzio, and Wiczer (2025), Hall and Kudlyak (2019), and Ahn, Hobijn, and Şahin (2023) show that a minority of US workers face much higher unemployment risk than the median worker. Using Danish administrative data, I show that 15% of workers ("marginal workers") have unemployment rates of 35% and account for two-thirds of total unemployment. Understanding what drives their unemployment is therefore crucial – by studying how marginal workers differ from the remainder of the work force, we can understand the forces behind most unemployment in the economy.

The paper and its contributions are divided into three sections. First, in section 1, I use Danish administrative records, matched to the European Labor Force Survey, to compare marginal workers with the remainder of the Danish labor force – "stable workers". Denmark's comprehensive administrative data provides a unique opportunity to study this question, offering detailed individual-level information on employment histories, wealth, health, family networks, and firm outcomes. First, I estimate worker types by clustering workers using their realized employment histories, adapting the approach of Gregory, Menzio, and Wiczer (2022) to large administrative records with a shorter time-horizon.

[1]Another complementary explanation for cross-sectional differences in unemployment risk is employment in seasonal jobs, which the model will also speak to.

I then examine what distinguishes marginal workers from stable workers, focusing on two potential explanations. A high (pecuniary) opportunity cost of employment could arise from various factors, including savings, spousal insurance (Stephens, 2002), or parental support. However, all empirical evidence points to marginal workers having a *lower*, not higher, opportunity cost: they are less wealthy and more likely to be delinquent on debt payments, have fewer partners who on average earn less, and have parents with lower earnings. Indeed, I find evidence for both assortative mating (marginal workers partnering up with other marginal workers) and assortative parenting (marginal workers having marginal workers as parents). They are also more likely to be hospitalized and visit mental-health specialists more frequently: this is inconsistent with voluntary unemployment driven by high utility from non-employment. Instead, all empirical moments indicate lower productivity: they are (similar to their parents) on average much less educated, have lower Abowd, Kramarz, and Margolis (1999) —henceforth AKM— worker-fixed effects, and tend to work in less productive firms. Their higher incidence of temporary jobs and job loss for economic reasons further speaks against the notion of unemployment-by-choice. Whether marginal workers' lower productivity is worker-specific, match-specific, or due to selection towards less productive firms is relevant for policy interventions, but inconsequential for the decomposition analysis at the heart of this paper.[2]

The empirical results suggest that marginal workers have a lower pecuniary opportunity cost: if anything, their lower opportunity cost should incentivize them to find work faster, not more slowly, than stable workers. The findings suggest that instead, productivity differences appear to play a major role behind the large unemployment rate of marginal workers. However, a big drawback of the empirical approach is that we do not have direct empirical evidence on workers' non-pecuniary opportunity costs, a potentially important aspect of heterogeneity. In section 2, I therefore complement the empirical findings with a directed search model with worker heterogeneity.

The model shows that large differences in match surplus—whether from productivity or opportunity costs—are necessary to generate a high cross-sectional difference in unemployment rates. This echoes insights from Shimer (2005) and Ljungqvist and Sargent (2017), who emphasize that low match surpluses are

[2]The origin of the productivity gap would matter for policies that aim to improve their productivity – see for example Bagger, Moen, and Vejlin (2021) for a calibration to Danish data that includes worker effects, firm effects, and sorting.

necessary in search models to generate high volatility in unemployment rates over the business cycle. The model is similar to those proposed by Pries (2008), Ferraro (2018), and Gregory, Menzio, and Wiczer (2022), who calibrate models with worker heterogeneity to US data assuming only productivity differences; Pries (2008) emphasizes that the source of heterogeneity is irrelevant for unemployment dynamics. Following the latter two papers, we use directed search, which admits a block recursive equilibrium (Menzio and Shi, 2011).

The contribution to the existing theoretical literature is twofold. First, we develop a model that simultaneously incorporates both opportunity cost and productivity differences across worker types. This approach allows us to structurally estimate the relative importance of these factors in explaining unemployment disparities. Unlike previous work that assumes only productivity differences, our framework introduces a novel methodology for disentangling the sources of heterogeneity that drive unemployment inequality.[3]

The secondary innovation is that we propose an approach to structurally estimate these productivity and opportunity cost differences using data on consumption and unemployment rates. The challenge is that both productivity differences or opportunity cost differences could generate these large differences in match surpluses, and thus the observed unemployment patterns: lower productivity directly reduces job finding, while higher opportunity costs lead workers to search for higher wages that lengthen unemployment spells. While unemployment rates alone cannot identify the source of this heterogeneity, consumption patterns can. Intuitively, worker-type differences in average consumption indicate to what extent unemployment rate differences are driven by differences in productivity or opportunity costs: if a high unemployment rate is due to lower productivity, that worker type will consume less (than the other worker type) whereas, if the high unemployment rate is due to higher opportunity costs, that worker type will on average consume more. Finally, consumption *volatility* across employment states is indicative of the extent to which the opportunity cost of employment stems from pecuniary or non-pecuniary sources: for instance, if marginal workers' consumption is much higher during employment than during unemployment, this suggests that they have a high pecuniary

[3] In related work, Chodorow-Reich and Karabarbounis (2016) estimate the pecuniary and non-pecuniary opportunity cost of employment for a representative agent in the US labor market by, for example, measuring unemployment benefits directly in the data. The advantage of our approach is that consumption data are informative about the entirety of the pecuniary opportunity cost. These two approaches yield different results if, for example, an unemployed worker is receiving financial help from their parents or partner.

surplus from employment. In order to match their high unemployment rate, the calibrated model would then estimate that marginal workers have a high non-pecuniary opportunity cost – for instance, if they highly value the leisure associated with unemployment – to offset the low pecuniary opportunity cost. Thus, for a given worker-type-specific productivity, the higher the observed consumption volatility across employment states, the higher the non-pecuniary opportunity cost has to be to match the targeted unemployment rate.

The calibrated model reveals that marginal workers are less productive and have lower consumption during unemployment, but have a positive leisure shifter during unemployment. The natural question then is: to what extent do each of these factors shape marginal workers' unemployment rate? How much lower would their unemployment rate be, if they were as productive as stable workers? Through counterfactual analysis, I find that productivity differences explain most of the unemployment gap: when marginal workers are as productive as stable workers, their unemployment rate falls from 35% to 4%. Similarly, if marginal workers had no non-pecuniary opportunity cost, their unemployment rate would fall to 7%.

While the exact counterfactual unemployment rates are a result of modelling assumptions and the empirical moments that we calibrate to, a robust conclusion appears to be that both productivity differences and non-pecuniary opportunity costs by themselves are able to explain a large share of the unemployment rate difference between marginal and stable workers, whereas marginal workers' pecuniary opportunity cost is estimated to be lower than that of stable workers. These findings are qualitatively in line with the empirical results, and suggest that a large share of unemployment in the Danish economy is due to workers with lower productivity, and higher nonpecuniary opportunity costs.

Finally, I turn to unemployment insurance in section 3. Here, I analyze how optimal unemployment benefits depend on the determinants of marginal workers' unemployment. Optimal benefits are higher when marginal workers are less productive, or when they have high nonpecuniary opportunity costs. When they instead have high pecuniary opportunity costs, their marginal utility of consumption during unemployment is lowest, leading to lower optimal benefits. In the calibrated economy, optimal benefits are much larger than in each of the three scenarios analyzed in isolation: marginal workers both have lower productivity and a much lower pecuniary opportunity cost of employment, which together create a strong case for generous benefits. This result should be interpreted as precise policy prescriptions. It instead highlights the role of the determinants of unemployment – productivity or opportunity cost – in determining optimal unemployment benefits as the model uses a stylized unemployment insurance system to focus on the role of ex-ante worker heterogeneity. This focus complements other quantitative work on optimal unemployment insurance design in a Per Krusell, Mukoyama, and Şahin (2010) environment that emphasizes different aspects of the system. For instance, Birinci and See (2024) develop a detailed model with ex-ante homogeneous workers but carefully specified benefit take-up patterns.

1 Worker type heterogeneity in Denmark

This section classifies workers as "stable" or "marginal" workers based on systematically different unemployment patterns by using Danish administrative data. We focus on this binary classification as the minimum segmentation needed to demonstrate our key mechanisms, though the patterns we document would likely be even more pronounced with finer categorizations.[4]

A key result will emerge: marginal workers make up two-thirds of unemployment, despite only being 15% of the labor force.

Our classification approach goes beyond simple unemployment rates for two reasons. First, observed unemployment in any given period may reflect bad luck in matching rather than underlying worker characteristics. Second, unemployment is relatively rare, making it a noisy classifier on its own. We therefore incorporate additional labor market outcomes that correlate strongly with unemployment propensity, such as job duration and transition patterns, to more robustly identify systematic differences across workers.

Our analysis then proceeds in two stages that map directly to the key mechanisms of study. First, we examine differences in workers' opportunity costs of employment by analyzing their wealth, family support networks, and other outside options. Second, we investigate productivity differences between these groups using multiple measures including firm-level value added. This empirical evidence will not be used in the calibration of the model, but provides ancillary support that productivity gaps are likely to be the more important determinant of unemployment differences than differences in the opportunity cost of employment.

[4] Gregory, Menzio, and Wiczer (2025) apply this methodology to three worker types.

1.1 Estimating worker types

Our classification approach adapts the methodology of Gregory, Menzio, and Wiczer (2025) to Danish administrative data from 2008-2018.[5] It combines employment histories with machine learning: we first summarize each worker's labor market experience through a set of moments, then apply a k-means clustering algorithm to identify distinct worker types.[6]

The data tracks three possible labor market states: employed, unemployed (actively job searching), and non-employed (either unemployed or outside the labor force). We measure employment status using wage payment records (BFL), which also provide job spell durations. Unemployment status comes from social security benefit records (DREAM).

We apply two sample restrictions. First, we exclude workers with weak labor force attachment. Second, we restrict our sample to ages 30-65 to avoid misclassifying students with summer jobs. These restrictions halve the Danish labor force, leaving approximately 1.36 million workers.[7]

Table 1 presents the clustering results. The algorithm identifies two distinct groups: "stable" workers (86% of the sample) and "marginal" workers (14%). The differences are stark: 57% of stable workers maintain jobs lasting over two years, compared to only 29% of marginal workers. Stable workers typically experience brief non-employment spells (< 1 month) between jobs, suggesting a high share of job-to-job transitions. In contrast, marginal workers face much higher non-employment rates and an average 35% unemployment—nearly twelve times the rate of stable workers. Their frequent job changes suggest difficulty maintaining stable employment.

Demographically, the groups show similar age and gender distributions but differ in two key dimensions: marginal workers are twice as likely to have only a high school education or less, and twice as likely to be of non-Danish origin.

[5] The start date reflects data availability. We end two years before the pandemic to test for mean reversion.

[6] The algorithm groups workers to minimize within-cluster differences while maximizing between-cluster differences.

[7] Appendix A provides additional methodological details.

Table 1: Clustering of workers and descriptive characteristics

	Worker type	
	Stable	**Marginal**
Share	0.86	0.14
Clustering		
Match: 1– 3M	0.10	0.15
Match: 3– 6M	0.07	0.16
Match: 6–12M	0.09	0.18
Match: 12–24M	0.16	0.22
Match: 24+M	0.57	0.29
Nonemp: 0–1M	0.98	0.90
Nonemp: 1–3M	0.01	0.02
Nonemp: 3–6M	0.01	0.03
Nonemp: 6–12M	0.00	0.03
Nonemp: 12+M	0.00	0.03
#Jobs per month	0.02	0.05
Nonemployment rate	0.00	0.03
Unemployment rate	0.03	0.36
Worker characteristics		
Male	0.52	0.52
Age	46.09	44.87
Education: HS or less	0.15	0.28
Large city	0.58	0.57
Rural municipality	0.18	0.21
Danish citizen	0.94	0.88
Non-Danish origin	0.10	0.19

The top part of the table reports the 13 moments used to cluster the workers into two types, computed as described in Appendix A. The first five columns denote the share of matches of specific durations, in months. The next five columns denote the share of non-employment durations, in months. Job-to-job transitions are considered a non-employment duration of zero months. The bottom part of the table reports descriptive statistics for the two worker types.

1.2 Differences in the opportunity cost of employment

A natural explanation for marginal workers' unstable employment patterns might be higher opportunity costs of working—better outside options making them less attached to jobs. However, our evidence points in the opposite direction: marginal workers appear to have systematically worse outside options. Table 2 documents this pattern across multiple dimensions.

Wealth and debt obligations If workers use wealth to smooth consumption during unemployment, higher wealth would increase their opportunity cost of employment. However, marginal workers possess only one-quarter the net wealth (including housing) of stable workers. Their debt burden further constrains their options: while stable workers' absolute interest payments are 20% higher, marginal workers' relative interest payments constitute a much larger share of their wealth. Delinquency rates tell a similar story—marginal workers are twice as likely to have missed payments (27% versus 12%).

Spousal insurance Married individuals might rely on spousal income during unemployment spells. However, marginal workers appear disadvantaged in this dimension as well: they are 50% less likely to have partners (43% versus 61%), and those who do have partners tend to have lower human capital (50% higher likelihood of only high school education) and earn 20% less on average. We also find strong assortative mating—stable workers predominantly partner with other stable workers (91%), while marginal workers are more likely to partner with other marginal workers (22% versus 9% in the stable group).

Parental support The wealth disparity extends across generations. Parents of stable workers have approximately 50% higher net wealth than parents of marginal workers, and stable workers' parents are 40% less likely to experience financial delinquency. We also observe intergenerational persistence in worker type—16% of marginal workers have marginal-worker parents, compared to 10% of stable workers. While investigating the origins of worker types lies beyond our scope, this pattern suggests that early-life factors—whether through genetics or childhood upbringing—could play a major role in determining labor market outcomes.

Health outcomes Finally, the table also reports that marginal workers visit hospitals more frequently, especially for issues related to mental health – they are 25% more likely to visit psychologists and almost twice as likely to visit psychiatrists. These mental health patterns are difficult to reconcile with a story of voluntary unemployment driven by better outside options. If marginal workers had more attractive alternatives to employment, we would not expect to observe such elevated rates of mental health challenges. However, we note that the relationship between mental health and labor market outcomes is complex: while mental health issues suggest lower utility from non-employment, they could also directly affect worker productivity.

Table 2: Worker statistics related to the opportunity cost of employment

	Worker type	
	Stable	**Marginal**
Share	0.86	0.14
Worker wealth		
Net wealth ('000s DKK)	289.61	76.05
Stocks ('000s DKK)	63.94	22.52
Bonds ('000s DKK)	12.65	5.81
No loans found	0.43	0.43
Ever delinquent	0.12	0.27
Interest payments ('000s)	10.66	8.62
Worker relationship		
Has partner	0.61	0.43
Had partner	0.13	0.19
Partner: high school or less	0.11	0.16
L. earnings (partner)	12.58	12.37
L. earnings rel to partner	0.07	- 0.46
Partner cluster missing	0.47	0.50
Partner worker type: Stable	0.91	0.78
Partner worker type: Marginal	0.09	0.22
Mother		
Education: High school or less	0.36	0.41
Net wealth ('000s)	553.43	358.81
Loan missing	0.61	0.62
Ever delinquent	0.08	0.14
Missing cluster	0.84	0.85
Worker type: Stable	0.91	0.85
Worker type: Marginal	0.09	0.15
Father		
Education: High school or less	0.21	0.25
Net wealth ('000s)	1049.04	678.11
Loan missing	0.65	0.67
Ever delinquent	0.12	0.17
Age difference	29.20	29.05
Missing cluster	0.88	0.89
Worker type: Stable	0.90	0.83
Worker type: Marginal	0.10	0.17
Worker health		
Any hospital visit	0.51	0.58
Hospital visit: mental illness	0.03	0.04
Visit: psychiatrist	0.02	0.03
Visit: psychologist	0.02	0.03

The table reports average values for each worker type for the years 2008-2018. Net wealth *includes housing and debt. Delinquencies and interest payments are computed for observed non-housing debt* — No loans found *indicates the share of households for whom such debt is not observed.* Ever delinquent *includes delayed debt payments.* Partner *includes both marriages and registered partnerships.* Had partner *includes both divorces and death.* ***Health****: Data sources are SYIN and SSSY. Visit variables refer to share of population that ever had a visit.*

1.3 Differences in productivity

Table 3 presents several indicators suggesting marginal workers have lower productivity than stable workers. We examine this through multiple lenses: separation patterns, job characteristics, and direct productivity measures.

Job characteristics Marginal workers are 23% more likely to work part-time, with 21% of these workers preferring full-time employment (versus 17% of stable part-time workers). They are also 4.5 times more likely to hold temporary positions (20% versus 5%). Rather than indicating preferences for flexible work arrangements, these patterns suggest marginal workers face constrained labor market choices and have lower reservation wages.

Separation and wages Marginal workers are more than twice as likely to report economic reasons for their last job separation (14% versus 6% for stable workers). They earn systematically lower wages, even after controlling for observable characteristics. Both separations and wages are equilibrium outcomes that are not directly indicative of productivity or opportunity-cost differences, but the subsequent model will show that both outcomes are consistent with lower productivity of marginal workers.

Summary Taken together, our empirical findings strongly favor the low productivity scenario over the high opportunity cost scenario from our theoretical framework. Examining all measurable components of workers' outside options—wealth, family insurance networks, and financial resources—we find that marginal workers are systematically worse off than stable workers. Meanwhile, multiple indicators point to substantial productivity differences between worker types, from job separation patterns to direct productivity measures. One caveat is that we can only observe consumption-based components of workers' outside options: marginal workers could have higher non-monetary utility from non-employment, for instance through stronger preferences for leisure or higher disutility from work. To quantify the relative importance of productivity differences versus non-pecuniary utility differences, we turn next to a structural estimation of our model.

Table 3: Worker statistics related to productivity

	Worker type	
	Stable	**Marginal**
Share	0.86	0.14
Worker earnings		
Monthly hours worked	141.96	120.01
Hourly wage, log	5.33	5.14
Annual earnings ('000s DKK)	373.96	203.85
Public sector	0.35	0.30
Part-time	0.17	0.21
Parttime: cannot find fulltime	0.18	0.18
Temporary	0.05	0.20
Mincer resid.	- 0.02	- 0.12
AKM worker FE	0.02	- 0.09
Separation: economic reason	0.06	0.14

The table reports average values for each worker type for the years 2008-2018. Monthly hours worked*,* Annual earnings*,* Mincer residual*, and* AKM worker FE *are computed using administrative records on wage payments (BFL). The remaining statistics related to worker earnings are computed using the EU labor force survey, linked to the administrative records. Health-related statistics are computed using administrative records.* Temporary*: whether the job is a temporary job.* Separation: economic reason*: whether there was an economic reason for the most recent separation, reported by the worker. Mincer residuals and AKM worker fixed-effects are estimated on the entire population without sample restrictions.*

2 A structural estimation

In the previous section, we established the empirical patterns of worker heterogeneity and showed to what extent they correlate with productivity differences and pecuniary opportunity cost (OC) differences. While the evidence was suggestive, we could not provide any evidence on non-pecuniary opportunity costs, which are not observable in our administrative data.

We now develop a theoretical framework to understand the underlying mechanisms and estimate the worker-type differences structurally. This section presents a directed search model with two worker types – "marginal" and "stable" – that allows us to disentangle whether unemployment differences stem from productivity gaps or variations in opportunity costs.

The model generates large cross-sectional differences in unemployment rates by creating substantial differences in the match surplus between marginal and stable workers. Importantly, these surplus differences can arise either from productivity differences or differences in opportunity cost.

We first outline the model structure. Then, we demonstrate how different mechanisms can generate similar unemployment patterns: the observed differences in unemployment rates across worker types can be generated either through productivity differences or differences in the opportunity cost of employment (pecuniary or non-pecuniary). Critically, unemployment rates alone cannot identify which factor drives the heterogeneity.

We show that observing consumption patterns by employment status provides valuable identification power. By leveraging these consumption differences, we calibrate the model and structurally estimate the extent to which unemployment differences are due to productivity differences, pecuniary OC differences, or non-pecuniary OC differences.

In the model, workers differ ex-ante in their type $i \in \{s, m\}$, with labor force shares given by L_i. While time is continuous, we suppress time indices t until needed for exposition.

Summary Our model operates as follows.

2.1 Summary of the model

We develop a directed search model to formalize how differences in productivity and opportunity costs can generate the observed unemployment disparities between worker types. The model builds on the framework of Pries (2008), Ferraro (2018), and Gregory, Menzio, and Wiczer (2022), extending their approach to incorporate multiple sources of worker heterogeneity.

The key innovation in our model is that it allows for three potential sources of differences between worker types: (1) productivity, (2) pecuniary opportunity costs, and (3) non-pecuniary opportunity costs. This structure enables us to quantitatively assess which factors drive the large unemployment rate gap between marginal and stable workers.

The model operates as follows. Workers and firms interact in a labor market segmented by both worker type and wages. Firms post vacancies targeting specific worker-wage combinations, while unemployed workers strategically direct their search toward their preferred wage targets. Upon matching, the worker-firm pair draws a match-specific productivity, and production begins only if this exceeds the promised wage. The model generates equilibrium dynamics where workers face tradeoffs between wage levels and job-finding probabilities, while firms balance vacancy costs against expected production profits.

2.2 Firms

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

$$(\rho + \delta_i)J_i(z, w) = z - w, \tag{1}$$

where ρ is the discount rate, and δ_i is the type-specific separation rate.[8] Production begins only if match-specific productivity exceeds the promised wage ($z > w$). Let $G_i(z)$ denote the cumulative distribution function of productivity draws for type i. The expected value of matching with a type-i worker at wage w is:

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

Firms incur a flow cost c to maintain vacancies. With job-finding rate $f(\theta)$ and vacancy-filling rate $q(\theta)$, the value of posting a vacancy in submarket (i, w)

[8] A type-specific separation rate captures that workers of different type are employed in different types of jobs with different separation rates, for example seasonal work.

is:

$$\rho V_i(w) = -c + q(\theta_i(w))\hat{J}_i(w)$$
$$q(\theta) = \theta^{-\alpha}.$$

Free entry in each (i, w) submarket determines market tightness $\theta_i(w)$.

2.3 Workers

Workers derive utility from consumption of wages w when employed, and home production b when unemployed. Additionally, when unemployed, they also derive utility from leisure h_i. That is, the workers' pecuniary opportunity cost is determined by their home production b, whereas their non-pecuniary opportunity cost is given by the positive utility shifter h_i, consistent with utility from leisure.[9]

The utility function is given by $u(c) = u^{1-\sigma}/(1-\sigma)$, with the coefficient of relative risk aversion σ set to 2. Labor market segmentation occurs through directed search: workers observe tightness $\theta_i(w)$ in each submarket and direct their search toward the wage that maximizes their expected discounted payoff. The value functions for employed (E_i) and unemployed (U_i) workers satisfy:

$$\rho E_i(w) = u(w) + \delta_i(U_i - E_i(w))$$
$$\rho U_i = \max_{w'} u(b_i) + h_i + f(\theta_i(w'), w')(E_i(w') - U_i),$$
$$f(\theta, w') = \theta^{1-\alpha}(1 - G(w')).$$

Unemployed workers choose a target wage to search for, considering the effect that their target wage has on their job-finding rate $f(\theta_i(w'), w')$. In equilibrium, since workers prefer higher wages over lower wages, high-wage submarkets will be more congested, yielding a tradeoff between higher wages and higher job-finding rates.

[9]While h_i is framed here as a positive utility shifter during unemployment, consistent with the leisure value of non-employment, it need not be the only micro-foundation for a non-pecuniary opportunity cost. One could for example also consider the mental cost associated with working (such as stress) as a negative utility shifter during employment, which could be observationally equivalent in the structural estimation of this model, but would lead to very different policy prescriptions.

2.4 Steady state

Denote by w_i^* the wage decision of a worker of type i with wage w, and by $\mathcal{F}_i(w)$ the density of workers of type i with wages w.

A steady state is given by:

- a set of wage decisions of workers $\{w_i^*\}$,
- a set of market tightness $\{\theta_i(w)\}$,
- a set of distributions $\{\mathcal{F}_i(w)\}$

such that:

- the wage decisions and consumption decisions solve the workers' problem given finding rates and interest rate,
- the free entry condition holds for each submarket, $V(i, w) = 0$
- the distributions $\mathcal{F}_i(w)$ are consistent with the wage decisions and finding rates.

2.5 Identifying productivity vs. opportunity cost channels

We now address a fundamental identification challenge: unemployment rates alone cannot determine whether cross-worker differences stem from productivity gaps or variations in opportunity costs. This section develops a strategy to disentangle these competing explanations.

To illustrate this identification problem, we analyze a simplified version of our model and demonstrate how similar unemployment patterns can arise from distinct underlying mechanisms. To this end, we normalize stable workers' mean productivity z_s to zero, set their home production b_s to 0.9, and set their non-pecuniary opportunity cost h_s to 0. We calibrate the vacancy opening cost c to match stable workers' unemployment rate of 3% from the data, and eliminate heterogeneity in separation rates by setting $\delta_s = \delta_m$.

In this simplified environment, workers can differ along three dimensions:

1. Mean productivity (z_i): the average output a worker produces when employed
2. Pecuniary opportunity costs (b_i): the monetary value of home production during unemployment

3. Non-pecuniary opportunity costs (h_i): the utility value of leisure during unemployment

We examine three scenarios in which marginal workers differ from stable workers along exactly one dimension:

1. "Low productivity" scenario: marginal workers are less productive ($z_m < z_s$)

2. "High pecuniary OC" scenario: marginal workers have higher home production ($b_m > b_s$)

3. "High nonpecuniary opportunity cost" scenario: marginal workers have higher utility from leisure when unemployed ($h_m > h_s$)

In each scenario, we calibrate the relevant parameter (z_m, b_m, or h_m) to match the 35% unemployment rate for marginal workers observed in the data. The key finding is that all three scenarios can generate identical unemployment rate differences, making unemployment alone insufficient to identify the underlying heterogeneity.

Consumption patterns as identification tool While unemployment rates alone are insufficient for identification, consumption patterns provide powerful additional information. Figure 1 compares consumption across worker types and employment states under our three scenarios.

Stable workers' consumption is identical across all three scenarios: stable workers have significantly higher consumption during employment than during unemployment. For marginal workers, however, consumption levels differ substantially. In the "low productivity" scenario, marginal workers have low consumption during employment, since they can only be employed in lower-paying jobs. In the "high pecuniary OC" scenario, marginal workers enjoy higher consumption in both employment states. With higher home production, they have higher consumption when unemployed and search for higher-wage jobs that support elevated consumption when employed. In the "high non-pecuniary OC" scenario, consumption during unemployment matches the "low productivity" scenario (since the opportunity cost is non-pecuniary), but the higher utility from leisure induces workers to search for higher-paying jobs, leading to higher consumption during employment.

Figure 1: Consumption patterns across three scenarios

The figure shows how the dimension along which marginal and stable workers differ plays a role in the consumption differences across worker types and employment states. In the three scenarios, marginal workers are calibrated to the same high unemployment rate using either a lower productivity, a higher pecuniary opportunity cost, or a higher non-pecuniary opportunity cost.

It is also instructive to discuss these differences in terms of the surplus from unemployment. The model needs to generate a smaller surplus from employment for marginal workers in order to match their higher unemployment rate. In this model, the surplus from employment has two components: (i) the additional consumption during employment, and (ii) the lower utility from leisure h. If we were to observe similar consumption differences across employment states for our two worker types, the model would need to estimate a high utility from leisure for marginal workers h_m in order to lower their surplus from employment (relative to that of stable workers), and thus match their higher unemployment rate.

Therefore, consumption moments – together with information on unemployment rates – are not only informative about the worker's productivity and their pecuniary opportunity cost, but also about their non-pecuniary opportunity cost.

2.6 Quantitative estimation

Having established our identification strategy, we now apply it to estimate the structural model. Our empirical findings in Section 1 suggested that marginal workers' higher unemployment stems from lower productivity rather than higher opportunity cost of employment. The structural model allows us to formally test this hypothesis while also estimating non-pecuniary aspects of opportunity costs that were not directly observable in our data.

Our estimation proceeds in three steps. We first estimate empirical consumption patterns using administrative data. We then calibrate directly observable parameters using their empirical counterparts. Finally, we jointly estimate the remaining parameters to match key labor market moments.

2.6.1 Empirical consumption patterns

To construct empirical counterparts to the model's consumption moments, we use Danish administrative data on household finances. Here we have imputed consumption using each household's annual balance sheets.[10] The challenge is that we do not observe consumption by employment status, and therefore cannot directly compute the consumption gap by worker type $\Delta_{i,c}$. Instead, we rely on labor market information to compute for each worker the number of days in a year that they were unemployed, allowing us to compute their annual unemployment rate $u_{i,t}$. We then estimate the relationship between log annual consumption and annual unemployment rate to impute the extent to which consumption changes with employment status. That is, for each worker type $j \in \{m, s\}$, we estimate

$$c_{i,t} = \alpha_j + \beta_j u_{i,t} + T_t + I_i + \epsilon_{i,t}, \tag{2}$$

where $c_{i,t}$ and $u_{i,t}$ denote worker i's log consumption and unemployment rate in year t, and T_t and I_i denote time- and worker-fixed effects. Under this specification, the coefficient β_j directly captures the log consumption difference between full employment ($u_{i,t} = 0$) and full unemployment ($u_{i,t} = 1$) for worker type j. This means that β_j corresponds exactly to the consumption gap $\Delta_{j,c}$

[10] These balance sheets contain information on all labor and capital income. They are reliable as they are used for tax purposes, and the extent of the Danish gray labor market is limited.

that we target in our model calibration.[11]

2.6.2 Calibration

Our calibration strategy focuses on isolating differences in productivity and opportunity costs while keeping other labor market features constant across worker types. This approach helps us identify the key mechanisms driving unemployment differences.

Common parameters We standardize several parameters across worker types. We use a common matching function elasticity $\alpha = 0.5$ and identical vacancy posting costs c across all submarkets. We also maintain the same dispersion of match-specific productivity (σ_z) across types. This restriction focuses our analysis on mean productivity differences rather than differences in match quality dispersion.[12]

Type-specific parameters We allow four parameters to vary by worker type: separation rates (δ_i), home production values (b_i), leisure values (h_i), and mean productivity (z_i). Heterogeneous separation rates δ_i are essential since empirical rates show substantial differences across worker types. Without this heterogeneity, the model would attribute all unemployment rate differences to job-finding rates. We set these rates directly to their empirical counterparts, as measured in the matched employer-employee data. We further normalize stable worker's productivity and non-pecuniary opportunity cost: $h_s = 0$ and $z_s = 0$.

Estimated parameters This leaves us with five parameters to calibrate: the vacancy search cost c, the home production b_i of each worker type, and marginal workers' mean productivity and utility from non-employment, z_m and h_m. Consistent with the calibration strategy outlined earlier, c targets stable workers' unemployment rate u_s, while b_s targets their consumption gap, $\Delta_{s,c}$. The remaining marginal-worker specific parameters target the marginal workers' consumption gap $\Delta_{m,c}$, the average cross-type consumption difference $\hat{\bar{c}}$, and their average unemployment rate, u_m.

[11] The worker-fixed effects ensures that within-worker variation in consumption is used to estimate β_j. The time-fixed effects ensure that time-varying unemployment rates by worker-type (for example, if the unemployment rate of marginal workers increases more during recessions than the unemployment rate of stable workers) do not imply that we estimate β_j on different years for marginal and stable workers.

[12] For a different approach, see Gregory, Menzio, and Wiczer (2025).

2.6.3 Structural estimation results

Table 4, Panel A presents the parameter estimates under "baseline calibration". The calibrated model reveals that marginal workers have both lower productivity (approx 25%) and lower pecuniary opportunity costs b_i than stable workers, consistent with our empirical evidence. The calibrated model also estimates a higher non-pecuniary opportunity cost of unemployment, $h_m > 0$, which we could not measure empirically, but consistent with the notion that the fall of consumption in response to unemployment was similar for both worker types. Panel B reports that these calibrated parameters achieved a reasonable match between all moments and targets.

To quantify the relative importance of each factor – pecuniary OC, non-pecuniary OC, and productivity – in explaining unemployment differences, we conduct three independent counterfactual experiments. In each experiment, we change exactly one parameter of marginal workers to match the corresponding parameter of stable workers, while holding all other parameters constant.

Table 4, Panel C reports the findings from this exercise. First, equalizing productivity differences reduces marginal workers' unemployment rate from 35% to 3.9%, nearly matching stable workers' unemployment rate. Second, removing the non-pecuniary benefit yields a similar reduction to 5.9%. Finally, since marginal workers are estimated to have a lower pecuniary opportunity cost, equalizing home production actually *increases* their unemployment rate. In this counterfactual experiment, marginal workers are permanently unemployed. This is because their low productivity prohibits them from finding a high-paid job, whereas their high pecuniary and non-pecuniary OC lead them to search for a high wage – they prefer unemployment over employment at the low wages available. While this is an extreme prediction of a stylized model, it warns policymakers that too strong an improvement of marginal worker's income during non-employment (for example through unemployment benefits) might lead to significant disattachment from the labor market.

These experiments demonstrate that both productivity differences and non-pecuniary factors independently explain substantial portions of the unemployment gap.

Table 4: Model calibration and moments

Panel A: Calibrated parameters

		Calibrated parameter	
Common parameters			
c	Vacancy search cost	0.001	
α	Matching elasticity	0.500	
σ_z	Productivity dispersion	0.100	
ρ	Discount rate	0.003	
Type-specific parameters		Stable	Marginal
b_i	Income of unemployed	1.071	0.761
z_i	Log productivity	0.000	- 0.262
h_i	Utility from non-employment	0.000	0.230
δ_i	Exogenous sep. rate	0.005	0.030

Panel B: Targeted moments

	Moment	Target	Calibrated value
u_s	Unemployment (stable)	0.030	0.032
u_m	Unemployment (marginal)	0.350	0.350
$\Delta_{s,c}$	Consumption fall (stable)	- 0.178	- 0.172
$\Delta_{m,c}$	Consumption fall (marginal)	- 0.151	- 0.152
$\hat{\bar{c}}$	Consumption difference	0.329	0.330

Panel C: Counterfactual unemployment rates of marginal workers

	Scenario	Unemployment rate (marginal)
	Baseline	0.350
$z_m = z_s$	No productivity differences	0.039
$b_m = b_s$	No pecuniary OC differences	1.000
$h_m = h_s$	No nonpecuniary OC differences	0.059

Notes: Panel A shows the calibrated parameters of the model. Panel B shows the moments targeted in the calibration. All rates are at quarterly frequency. "Consumption difference" denotes the average difference of log consumption across worker types (stable minus marginal). "Consumption fall" is the volatility of consumption across employment states – the percentage fall of consumption when workers become unemployed.

3 Optimal provision of unemployment benefits

Having established that both productivity differences and non-pecuniary opportunity costs drive unemployment heterogeneity, we now examine the implications for optimal unemployment insurance policy. This section investigates how the underlying determinants of unemployment shape the appropriate level of benefits.

We analyze a stylized version of unemployment benefits in our model. Rather than attempting to precisely replicate the Danish system or make specific policy recommendations, we focus on how the optimal provision of benefits depends on the underlying causes of unemployment heterogeneity. The benefit system features a flat benefit g paid to unemployed workers in addition to their regular home production. We also note that since the model does not feature assets, households are not able to insure themselves against unemployment risk: the government intervention – providing unemployment insurance – is something that the private market cannot support. If households were able to self insure, optimal UI would likely be lower. Yet, the focus of this analysis is not the optimal level of unemployment benefits per se, but the extent to which it depends on the determinants of marginal workers' high unemployment rates.

3.1 Theoretical framework

We denote the welfare of worker type i as $\mathcal{W}_i = U_i + \int E_i(w)dH_i(w)$, where the first term captures the welfare of unemployed workers and the second term captures the welfare of employed workers. Total welfare is the population-weighted sum $\mathcal{W} = \mathcal{W}_m + \mathcal{W}_s$.

Benefits g are set to maximize total welfare and are financed through proportional labor taxation: $g(L_m u_m + L_s u_s) = \tau \sum_{i\in\{m,s\}} \int w dH_i^e(w)$, where τ denotes the proportional labor tax.[13]

We study optimal UI in four scenarios to isolate the role of different heterogeneity channels. The first three scenarios are identical to those discussed in section : workers either differ only in terms of productivity (low productivity scenario), home production (pecuniary OC scenario), or leisure utility (non-pecuniary OC scenario). In each of these three scenarios, the dimension of heterogeneity is calibrated such that marginal workers' unemployment rate is

[13] Since the analysis serves illustrative purposes, optimal UI maximizes steady state welfare excluding transitions.

35%.[14] Finally, we contrast these three illustrative scenarios with our calibrated model from the previous section.

3.2 Unemployment rates and welfare effects

Figure 2 illustrates how unemployment rates and welfare respond to benefit levels across all four scenarios.

Panel (a) shows type-specific unemployment rates as a function of benefits. Unemployment rates increase with UI benefits because the pecuniary opportunity cost of employment falls for two reasons: first, through higher income during non-employment, and second, through lower net employment income as wages are taxed more heavily to finance benefits. Consequently, workers target higher wages that are associated with lower job-finding rates.

Marginal workers, who have lower employment surplus in all scenarios, experience more dramatic unemployment increases in response to benefits than stable workers. While response rates differ slightly across scenarios, by benefit level $g = 0.03$, marginal workers reach 100% unemployment in all cases. In contrast, stable workers' unemployment increases more modestly, from 3% to approximately 4% between $g = 0$ and $g = 0.03$.

Panel (b) plots type-specific welfare components $\mathcal{W}_i$. Across all scenarios, stable workers' welfare decreases with higher benefits. This occurs because socialized unemployment insurance offers them little value: they face low unemployment risk and have adequate home production when unemployed. Meanwhile, they bear disproportionate costs through higher labor income taxes and cross-subsidization of high-unemployment workers. A social planner considering only stable workers' welfare would set benefits to zero.

Marginal workers' welfare increases with benefits through two phases. Initially ($g = 0$ to $g = 0.03$), they face offsetting effects: higher benefits versus increased tax burden. Beyond $g = 0.03$, they become permanently unemployed, receiving benefit increases without incurring additional taxes, creating a steeper welfare gradient. Welfare responses vary by scenario. The pecuniary OC scenario shows the weakest welfare gains due to marginal workers' already high home production diminishing the marginal utility of additional consumption.

[14] The scenarios can be thought of as a complement to the counterfactual exercise in Table 4, panel (c). There, the first row ($z_m = z_s$) asked: how much would unemployment change if we make marginal workers and stable workers alike in terms of mean productivity. Here, the "low productivity" scenario" asks: if marginal workers and stable workers were alike in all aspects but their mean productivity, what value of z_m would deliver the empirical unemployment rate u_m?

The calibrated scenario, with its substantially lower home production, yields the strongest welfare gains. Total welfare ($\mathcal{W}$) exhibits a non-monotonic pattern with distinct concave regions corresponding to marginal workers' employment transitions. Optimal benefit levels (marked by vertical dashed lines) differ significantly across scenarios: lowest in the pecuniary OC scenario, moderate in the non-pecuniary OC scenario, higher in the low-productivity scenario, and highest in the calibrated model combining low productivity with low pecuniary opportunity costs.

Table 5: Optimal UI in the four scenarios

	Low productivity		Pecuniary OC		Nonpecuniary OC		Calibration	
Optimal benefits g^*	0.016		0.012		0.069		0.093	
	g = 0	g = g*	g = 0	g = g*	g = 0	g = g*	g = 0	g = g*
Unemployment rate	0.08	0.11	0.08	0.10	0.08	0.20	0.08	0.23
Output	1.13	1.10	1.15	1.12	1.15	1.00	1.12	0.97
Mean productivity	1.23	1.24	1.25	1.25	1.25	1.25	1.22	1.25
Productivity loss	0.07	0.10	0.08	0.10	0.08	0.20	0.07	0.19
M. util. of unemp. (marginal)	0.87	0.85	0.69	0.68	0.87	0.77	1.73	1.37
M. util. of emp. (marginal)	0.83	0.83	0.66	0.66	0.66	nan	1.13	nan
M. util. of unemp. (stable)	0.87	0.85	0.87	0.85	0.87	0.77	0.87	0.74
M. util. of emp. (stable)	0.66	0.66	0.66	0.66	0.66	0.67	0.66	0.68

The table reports summary statistics for the four scenarios. ‘Mean productivity”: average productivity of the employed. “Productivity loss”: the loss of output associated with unemployment. Computed for each worker type as the product of the type-specific unemployment rate and the type-specific average productivity draw, and then summed up across worker types, weighted with their population shares. “M. util of emp/unemp”: the average marginal utility of employed/unemployed workers of a worker type. Marginal workers have an unemployment rate of 100% under optimal UI in the “Non-pecuniary OC” scenario and in the calibration, leading to not defined marginal utility of consumption of the employed.

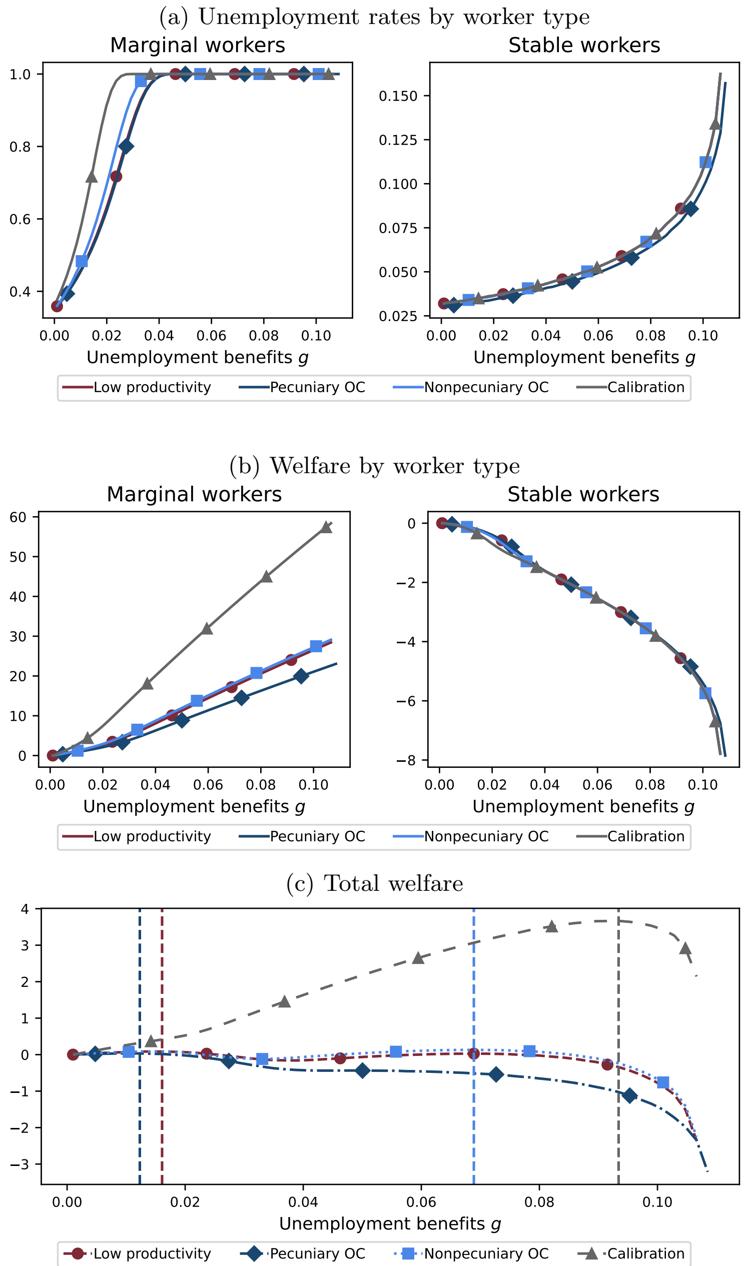

Figure 2: The effects of providing higher UI benefits

We study the effect of varying UI provision across the four scenarios. Panel (a): unemployment rates by worker type. Panel (b): worker-type-specific welfare. Panel (c): total welfare in the economy. Welfare in panels (b), (c) is relative to an economy without unemployment benefits. In panel (c), vertical dashed lines indicate welfare-maximizing benefit levels for each scenario.

3.3 Mechanisms determining optimal UI

What explains these substantial differences in optimal UI across scenarios? While we have already alluded to the importance of the marginal utility of consumption, three distinct mechanisms govern optimal benefit levels, which we analyze using Table 5. The first row confirms that optimal benefits g^* are significantly higher in the low productivity scenario (0.09) than in the pecuniary OC (0.01) or non-pecuniary OC (0.03) scenarios.

The Moral Hazard Effect UI affects search incentives by partially decoupling consumption from employment. Workers respond to higher benefits by targeting higher wages, which reduces job-finding rates and increases unemployment. While this raises average match productivity by increasing reservation wages, it also creates output losses through longer unemployment spells.

These moral hazard costs differ across scenarios. In the low productivity scenario, baseline output losses from unemployment are lower because marginal workers contribute less to production (see "Output" and "Productivity loss" rows). Additionally, while marginal workers' unemployment responds more strongly to benefits due to their lower employment surplus, this higher elasticity is less costly when these workers are less productive, lowering the moral hazard cost of UI.

The Insurance Value The insurance value of UI increases with the marginal utility gap between employment states. For marginal workers, this gap varies by scenario. In the pecuniary OC scenario, large consumption volatility exists because their home production doesn't raise unemployment consumption while their high wage-seeking creates high employment consumption. The other scenarios show smaller consumption volatility and weaker insurance motives. Table 5 confirms this pattern, showing marginal workers have the largest employment-unemployment marginal utility difference in the Non-pecuniary OC scenario, justifying higher optimal UI benefits.

The Redistributive Channel UI redistributes from low- to high-unemployment workers. The social planner has a redistributive motive to transfer resources from workers with low marginal utility of consumption to those with high marginal utility. This redistributive motive strengthens when marginal workers have significantly higher marginal utility of consumption than stable workers.

Unlike the insurance motive, which compares marginal utility across employment states within worker types, the redistributive motive compares marginal utility across different worker types. While the marginal utility of stable workers remains consistent across scenarios, unemployed marginal workers have much lower marginal utility in the pecuniary OC scenario than in the other two scenarios, weakening the redistributive justification for UI in that case.

Discussion Our analysis reveals that the costs and benefits of UI provision differ across the three illustrative scenarios, leading to different prescriptions. In the "pecuniary OC" scenario, the cost of providing UI is relatively high, the insurance motif is weak, and the redistributive motif is weak, leading to the lowest optimal UI at $g^* = 0.012$. In the "Low productivity" scenario, the cost providing UI is relatively lower, and the redistributive motif is stronger, leading to a higher optimal UI at $g^* = 0.016$. In the 'Non-pecunairy OC', a strong redistributive motif together with a very strong insurance motif lead to the highest optimal UI at $g^* = 0.069$. Our baseline calibration features both higher non-pecuniary OC, a lower productivity, and – instead of a higher pecuniary OC – a lower pecuniary OC. As a consequence, the optimally provided UI is highest in the calibration than in any of the discussed scenarios.

These results should be interpreted as highlighting the economic mechanisms at work rather than as precise policy prescriptions, since our model uses a stylized unemployment insurance system that abstracts from many institutional details. Nevertheless, they underscore the importance of understanding the underlying drivers of unemployment when designing social insurance programs. A model with assets – and where households thus self-insure against unemployment risk – would likely find lower optimal UI provision, since households are already self insuring against the risk of unemployment. Yet, it is reasonable to believe that the key findings – for instance, a lower optimal UI when unemployment is due to pecuniary opportunity costs – would be robust to such an extension.

4 Conclusion

The Danish labor market exhibits stark heterogeneity in unemployment risk: a small group of marginal workers, comprising only 15% of the labor force, accounts for 60% of total unemployment. Evidence from empirical analysis and structural estimation agree: these marginal workers are predominantly unemployed due to their lower productivity and higher non-pecuniary opportunity cost.

The non-pecuniary opportunity cost parameter in our model shifts the flow utility of the unemployed. While public narrative often frames this as "laziness", alternative interpretations exist. This parameter could instead represent higher mental costs of working (e.g. stress or other mental health challenges) rather than a preference for leisure. This interpretation is consistent with marginal workers' higher utilization of psychological and psychiatric services.

Future research should explore what determines marginal worker status. Our analysis points to several potential factors: parental background, education levels, and immigrant status. These channels suggest worker "type" may be shaped by factors preceding labor market entry. Understanding these mechanisms could clarify both the source of higher non-pecuniary costs and lower productivity. Another avenue for future research would be studying the asset decisions of marginal and stable workers, given their large differences in unemployment risk, both from a theoretical and empirical perspective. Such a framework would also lend itself to studying the optimal provision of UI, and the extent that it complements or substitutes self-insurance by worker type.

Given that productivity differences substantially drive unemployment disparities, policies improving marginal workers' productivity–such as adult vocational training or targeted retraining programs–should effectively reduce aggregate unemployment. Educational interventions like mentoring at-risk youth might prevent the formation of marginal worker characteristics.

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A Methodology

I choose my moments following Gregory, Menzio, and Wiczer (2022), 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 [15]. The next three moments compute the share of non-employment 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. I use data from 2008 to 2018 to summarize the workers' employment histories into the 11 moments [16]. The matched employer-employee data cover the universe of Danish employees, and are 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 [17] 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 they only contain 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.

Sample I focus on workers that are attached to the labor force by excluding workers that are employed less than five out of the ten years (see also Menzio

[15]The precise criteria are provided in Table 1

[16]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.

[17]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
3,169,414.000	In labor force during sample time
1,919,490.000	Within the age 30-60
1,752,138.000	At least two years in labor force
1,537,248.000	At least 12 months employed
1,518,443.000	Maximum nonemployment spell less than 2 years

Table A6: Sample restrictions and sample size

et al, 2022). I focus on workers in their primary working age, which I define as years 30-65 [18].'

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 non-employment 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 [19].

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. Since both $N = 2$ and $N = 3$ appear appropriate for the analysis, I choose $N = 2$ to facilitate the exposition.

[18] 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.

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

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Danmarks Nationalbank
Langelinie Allé 47
2100 Copenhagen Ø
+45 3363 6363

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