The Return to Big City Experience: Evidence from Danish Refugees

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Outline

Introduction

The Danish Refugee Program of 1986-1998 and Data

Documenting The Treatment Effect

Mechanisms

Sorting in a Spatial Model of Earnings Dynamics

Introduction

- **Urban wage premium**: Workers earn higher wages in cities even after controlling for observables
  - Is the urban wage premium only due to selection across areas?
  - If not, which mechanisms explain the urban wage premium?

- **Problem**: Hard to pin down premium and mechanisms due to endogeneity of location choice

- ***This Paper***: Combine Danish administrative data & natural experiment to study the anatomy of the urban wage premium for a particular population

Outline of the Paper

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    - *Assignment to a big city led to a causal difference of* ***0.8%*** *per year of experience in hourly wages,* ***2.1%*** *for earnings*

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2. Use rich administrative data to provide evidence on mechanisms driving the premium
    - *Establishment and occupation sorting explains* ***60%*** *of the difference*
3. Quantify contribution of sorting on unobserved ability
    - *Natural experiment identifies key model parameter*
    - *Sorting* ***within cities*** *important in explaining observed patterns*

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  - Eligible to work immediately upon assignment
- Used before Damm & Dustmann (2014), Damm (2009)

Group Averages - Natives and Refugees

Comparison by:	Group		Assignment (Refugees only)	
	Natives	Refugees	Copenhagen	Non-Copenhagen
Age	36.72	28.24	28.67	28.08
Married	0.47	0.28	0.28	0.28
No. of children	0.68	0.54	0.47	0.57
Age of youngest child	7.43	3.46	3.63	3.40
Age of oldest child	10.01	7.27	7.20	7.30
Missing education	0.00	0.19	0.19	0.19
$\leq$ 10 years of education	0.31	0.27	0.23	0.28
12 years of education	0.50	0.34	0.34	0.34
$>$ 12 years of education	0.17	0.20	0.23	0.19
Observations	1,335,545	20,493	5,530	14,963

Note: Statistics are males only. Married is an indicator taking value 1 if the individual is married. Missing education, 10 years of education, 12 years of education, and $\geq$ 12 years of education are all indicator variables.

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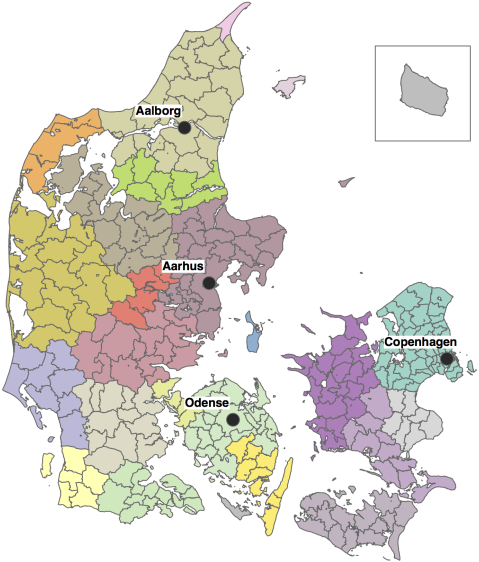
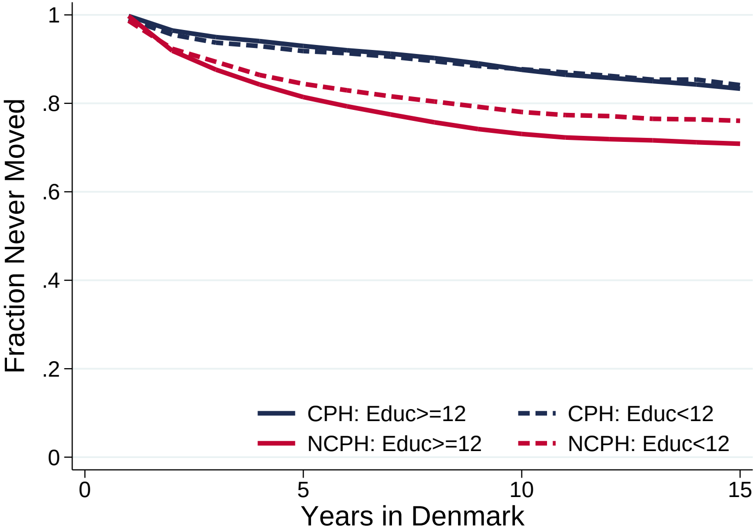
Commuting Zones of Denmark 1986



Persistence of Initial Assignment by Education Groups



Outline

The Treatment Effect of Initial Assignment

- We stratify the sample by location of initial assignment, and follow refugees over time
- **Document**: The causal effect of initial assignment to a big city on
  1. Wage- and earnings-experience profiles
  2. Extensive margin of labour supply
- **Interpretation**: The causal effect of initial assignment to a big city on population-level labor market outcomes

Wage- & Earnings-Experience Profiles by Initial Assignment

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- We estimate a simple linear model by initial assignment

$$y_{it} = \mu_t + \beta_1 Exp_{it} + \beta_2 InitCop_i + \beta_3 \left(InitCop_i \times Exp_{it} \right) + \boldsymbol{X}'_{it}\boldsymbol{\theta} + \epsilon_{it}$$

  where

  - y_{it} is log hourly wages or earnings
  - μ_t is time fixed effects
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- Non-parametric results very similar Non-parametric results

Wage- & Earnings-Experience Profiles by Initial Assignment

	(1)	(2)	(3)	(4)	(5)	(6)
	$logwage_{it}$	$logwage_{it}$	$logwage_{it}$	$logearnings_{it}$	$logearnings_{it}$	$logearnings_{it}$
Exp_{it}	0.0228***	0.0250***	0.0211***	0.0759***	0.0784***	0.0750***
	(0.00142)	(0.00159)	(0.00126)	(0.00322)	(0.00370)	(0.00341)
$InitCph_i$	0.000477	0.00858	-0.00892	-0.0725***	-0.0543**	-0.104***
	(0.0101)	(0.00883)	(0.0136)	(0.0184)	(0.0190)	(0.0237)
$InitCph_i \times Exp_{it}$	0.00810***	0.00736***	0.00813***	0.0214***	0.0186***	0.0261***
	(0.00148)	(0.00163)	(0.00134)	(0.00303)	(0.00330)	(0.00312)
Observations	97,402	57,994	39,408	107,297	63,870	43,427
R^2	0.056	0.062	0.055	0.155	0.158	0.156
Sample	All	Educ≥12	Educ<12	All	Educ≥12	Educ<12
Nationality FE	Yes	Yes	Yes	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
Assignment Controls	Yes	Yes	Yes	Yes	Yes	Yes

Robust standard errors clustered at the level of initial commuting zone. Standard errors in parentheses. * p<0.05, ** p<0.01, *** p<0.001.

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Extensive Margin of Labour Supply

	(1) $neveremployed_i$	(2) $neveremployed_i$
$InitCph_i$	0.00259	0.0371***
	(0.00882)	(0.0111)
Age at Arr.	0.0188***	0.0196***
	(0.000602)	(0.000539)
No. Kids at Arr.	0.0347**	-0.0285**
	(0.0126)	(0.0111)
Married at Arr.	-0.0691***	-0.0295*
	(0.0113)	(0.0140)
Observations	11,138	9,434
R^2	0.141	0.175
Sample	Educ$\geq$12	Educ$<$12
Nationality FE	Yes	Yes
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What is Driving the Dynamic Urban Wage Premium?

We consider the following channels to explain the dynamic urban wage premium:

1. More experience at high-wage establishments
2. Differential sorting into occupations
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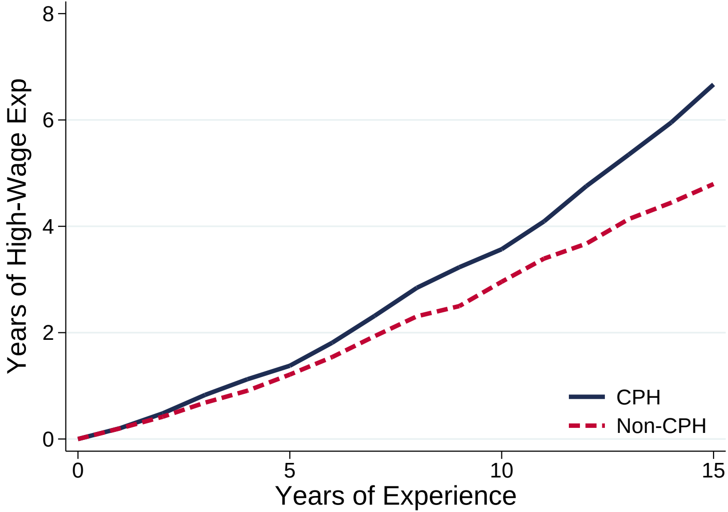
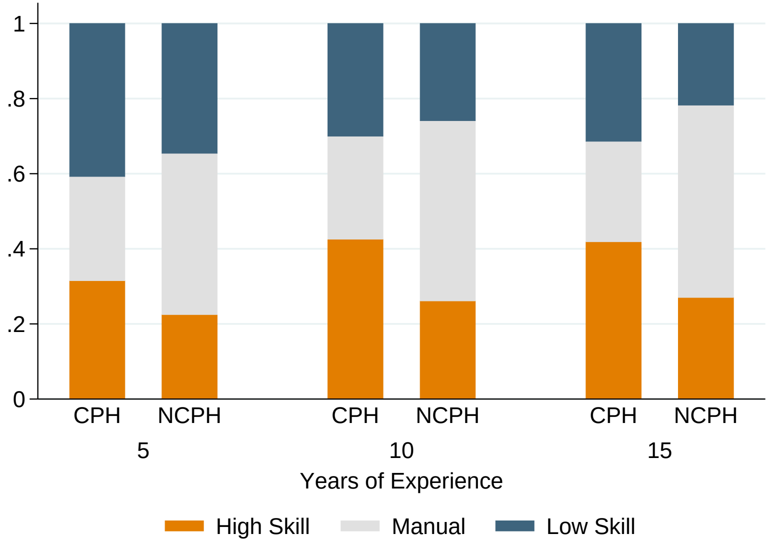
Accumulation of Experience at High-Wage Establishments



Differential Sorting into Occupations by Initial Allocation



High-Wage Establishment Experience & Occupational Ladder

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Exp_{it}	0.0250***			
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$HighExp_{it}$		0.0259***	0.0217***	0.0225***
		(0.00121)	(0.00124)	(0.00138)
$OtherExp_{it}$		0.0206***	0.0186***	0.0157***
		(0.00203)	(0.00140)	(0.00126)
$InitCph_i$	0.00858	-0.00241	0.00597	0.00580
	(0.00883)	(0.00676)	(0.00538)	(0.00533)
$InitCph_i \times Exp_{it}$	0.00736***	0.00566***	0.00354**	0.00278*
	(0.00163)	(0.00148)	(0.00115)	(0.00101)
Observations	57,994	57,994	48,183	44,135
R^2	0.062	0.137	0.188	0.224
Sample	Educ≥12	Educ≥12	Educ≥12	Educ≥12
High-Wage Firm FE	No	Yes	Yes	Yes
Occupation FE	No	No	Yes	Yes
Industry FE	No	No	No	Yes
Assignment Controls	Yes	Yes	Yes	Yes

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Motivation for Spatial Model to Understand Sorting Within

- Want to understand contribution of sorting *within* cities on unobserved ability in driving these patterns

- At least three reasons why such sorting could matter:
  1. Who gets experience *at all* may differ fundamentally within a city and without, even with identical populations in both locations
  2. Correlation between type and working at certain establishments/occupations
  3. Complementarities between worker type and establishment type

- Estimate a spatial model with unobserved heterogeneity to quantify role of sorting following Baum-Snow & Pavan (2012)

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  - Either work or receive unemployment benefit
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- **Locations**:
  - Copenhagen and remainder, $j = \{CPH, NCPH\}$
  - Agents dropped in a random location at year 0
  - Agents can change locations each period subject to frictions
- **Earnings** driven by:
  - Establishment productivity
  - Experience
  - Individual ability (unobserved to econometrician)

Earnings and Value Functions

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- The wage earned by a type h worker, conditional on having a job at a establishment of type f is given by:

$$\ln w_j(h, \mathbf{x}, f) = \bar{w} + \theta^h + \psi^f + \Phi^{h,f} + \sum_f \beta_1^{h,f} x_f + \beta_2 \Big(\sum_f x_f \Big)^2 + u$$

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- Value of starting in a location with a job given by:

$$\begin{aligned}\bar{U}_t^E(j, h, \mathbf{x}, f) &= \delta_j^h \bar{V}_t^{UE}(j, h, \mathbf{x}) \\ &\quad + (1 - \delta_j^h) \Big[(1 - \lambda_j^{h,f'}) \mathbb{E}_u \max\{ \bar{V}_t^E(j, h, \mathbf{x}, f \mid u), \bar{V}_t^{UE}(j, h, \mathbf{x}) \} \\ &\quad + \lambda_j^{h,f'} \mathbb{E}_{u,u'} \max\{ \bar{V}_t^E(j, h, \mathbf{x}, f \mid u), \bar{V}_t^{UE}(j, h, \mathbf{x}), \bar{V}_t^E(j, h, \mathbf{x}, f' \mid u') \} \Big]\end{aligned}$$

where $\lambda_j^{h,f}$ is the probability of receiving an offer from type f and δ_j^h denotes the job destruction probability

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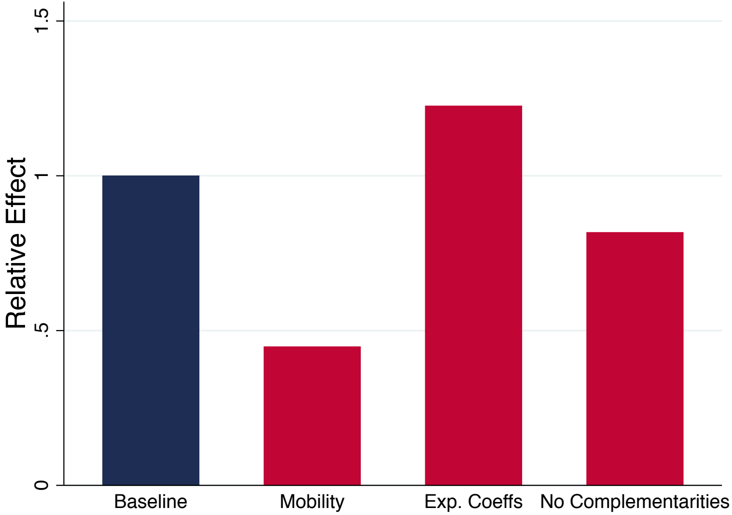
Treatment Decomposition



▸ Sequential Decomposition

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- **Key results**:
    1. Causal big city experience premium of **0.8%** in hourly wage and **2.1%** in earnings
    2. **60%** of dynamic premium can be explained by experience at high-wage establishments and high-skill occupations
    3. Structural decomposition suggests effect of assignment to cities depends crucially on unobserved types

Outline

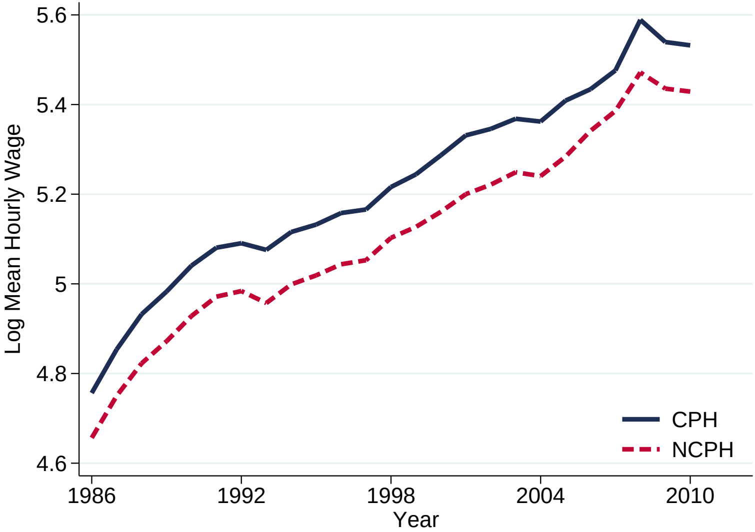
Appendix

Initial Years of Education - Balancing Tests

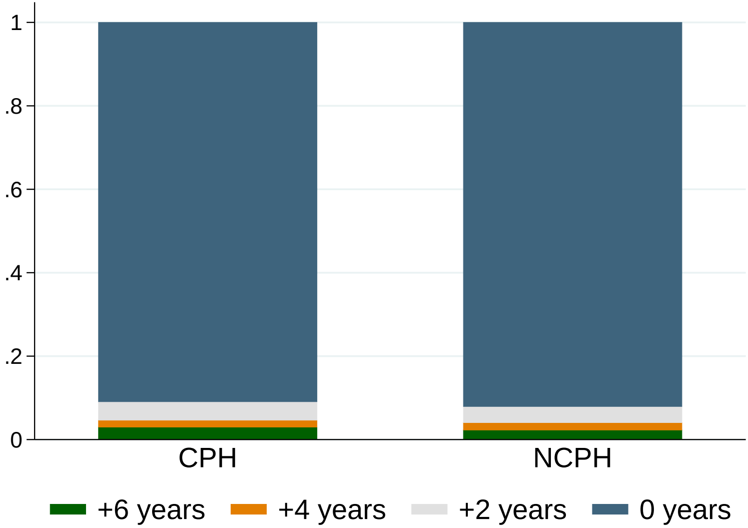
	$yearseduc_i$	$yearseduc_i$
CPH	0.164***	0.0980
	(0.0491)	(0.0571)
Married	0.213***	0.145*
	(0.0617)	(0.0691)
No. of children	-0.121***	-0.0549*
	(0.0218)	(0.0247)
Age	0.431***	0.233***
	(0.0191)	(0.0243)
Constant	5.046***	9.434***
	(0.369)	(0.482)
Observations	11,812	7,386
Sample	All	Educ≥12

Individuals with missing education information are dropped from the regression. Robust standard errors clustered at the level of initial commuting zone. Standard errors in parentheses. * p<0.05, ** p<0.01, *** p<0.001.

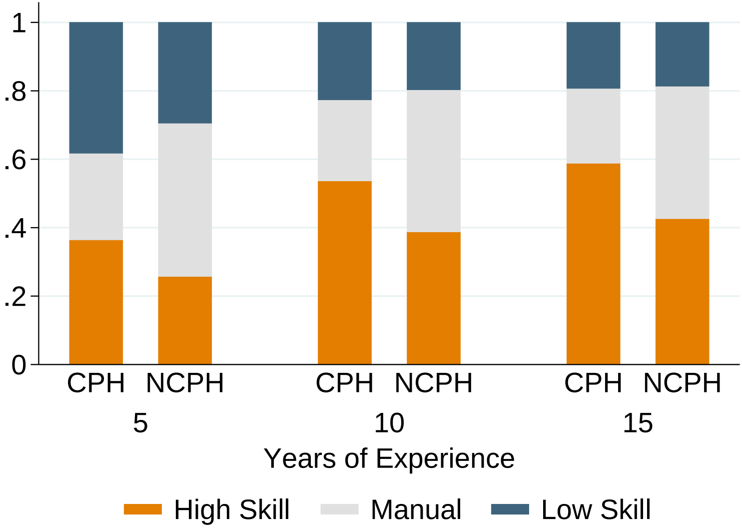
Aggregate Hourly Wage Trends - CPH and NCPH



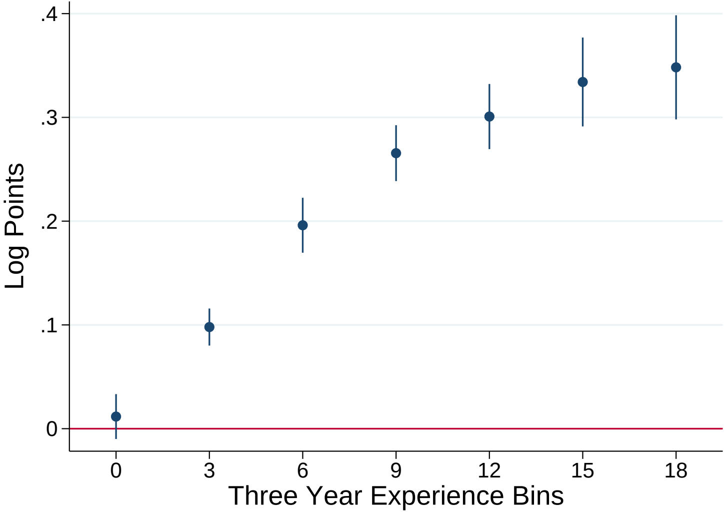
Differential Take-up of Education



Occupation Distribution of Natives



Non-Parametric Average Return to Experience - Wages



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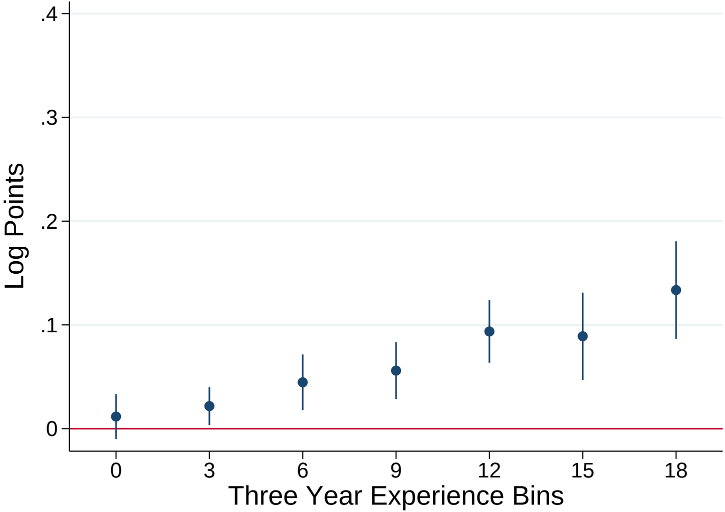

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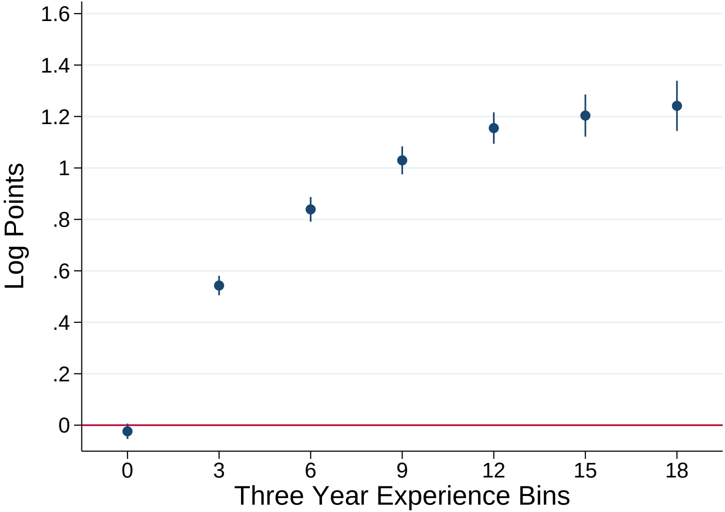
Non-Parametric Average Return to Experience - Earnings



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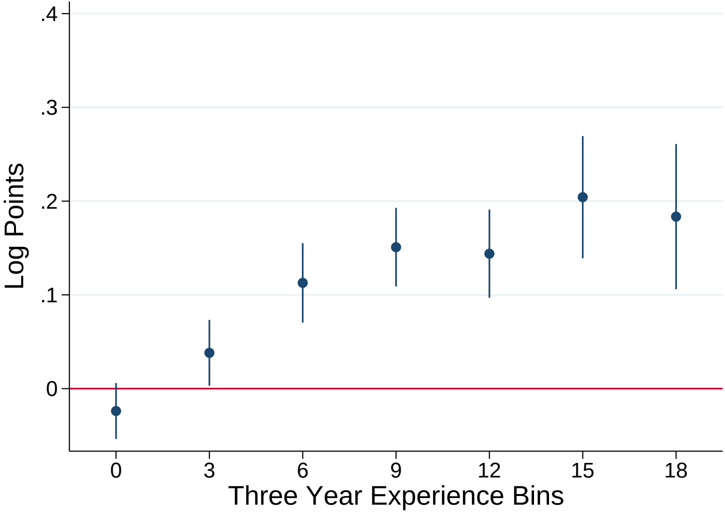

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- Value for working given by

$$V_j^E(h, \mathbf{x}, f, t \mid u, \eta_j, \eta_{j'}) = a_j + \ln w(\cdot)$$
$$+\rho \max_{j,j'} \{ \bar{U}_j^E(h, \mathbf{x}+1, f, t+1) + \eta_j, \bar{U}_{j'}^{UE}(h, \mathbf{x}, t+1) - \tau + \eta_{j'} \}$$

here $\bar{U}_j^E(\cdot)$ is the value function for E prior to labor market shocks realizing, likewise for UE

Value Function Prior to Labor Market Shocks Realizing

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- Gumbel assumption on u allows use to solve for these in closed form

Maximum Likelihood Estimation

- Likelihood of observing a sequence of wages and transitions, given unobserved type h and parameter vector θ by

$$P(Y^i|h;\theta) = P(Y_1^i|h;\theta)\prod_{t=w}^{T} P(Y_t^i|Y_{t-1}^i, h;\theta)$$

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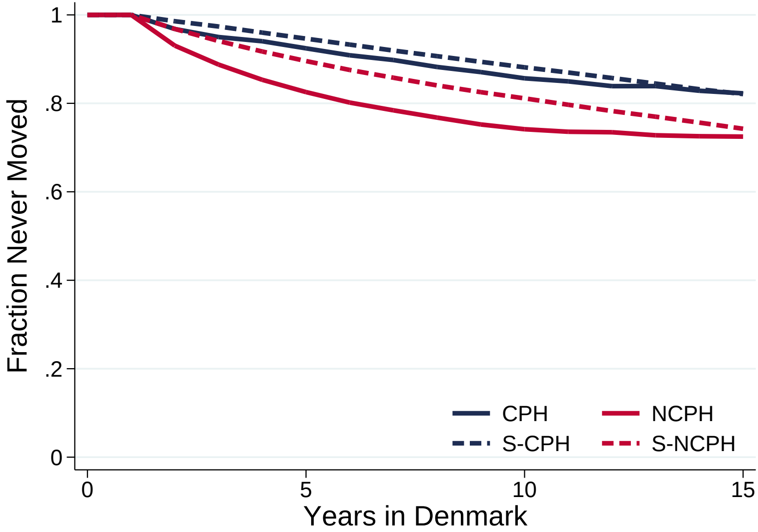
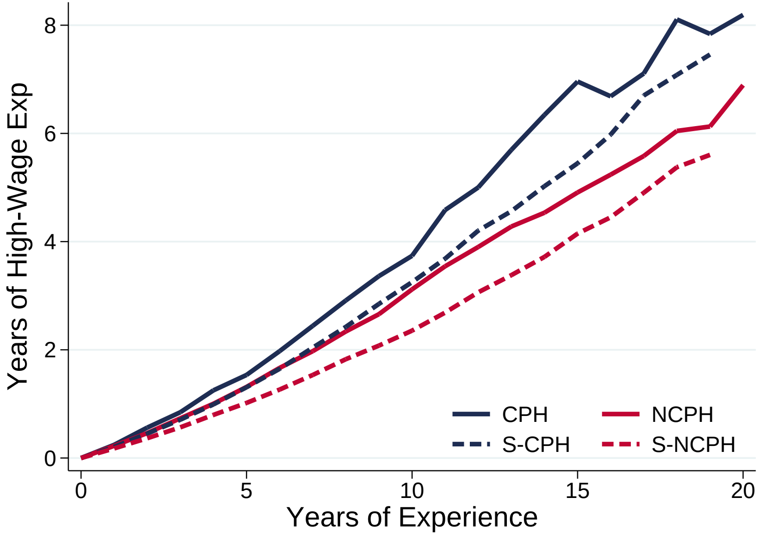
- An individual's contribution to the overall likelihood function is given by weighted average across unobserved types

$$L(\theta) = \chi_L P(Y^i|L,\theta) + (1-\chi_L)P(Y^i|H,\theta)$$

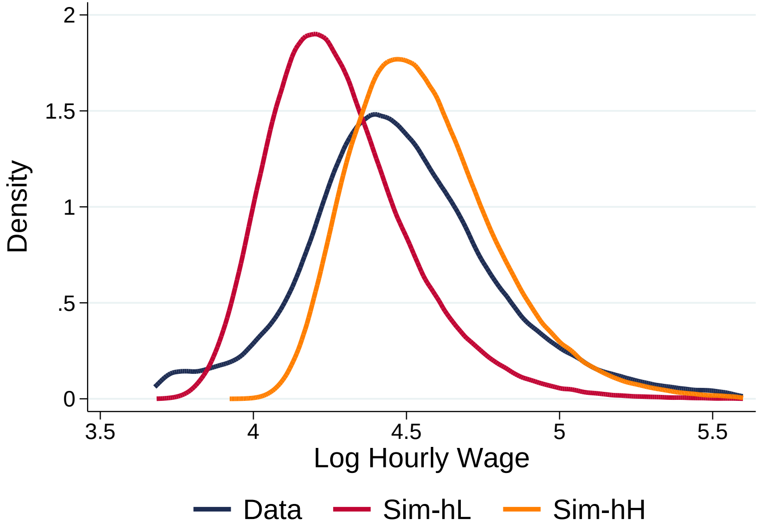
Model Fit - Actual and Simulated Moving Profiles



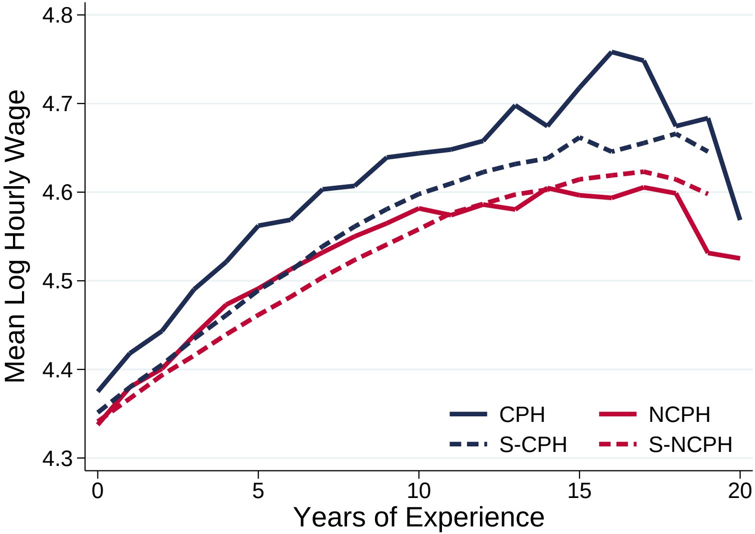
Model Fit - Actual and Simulated Experience Accumulation



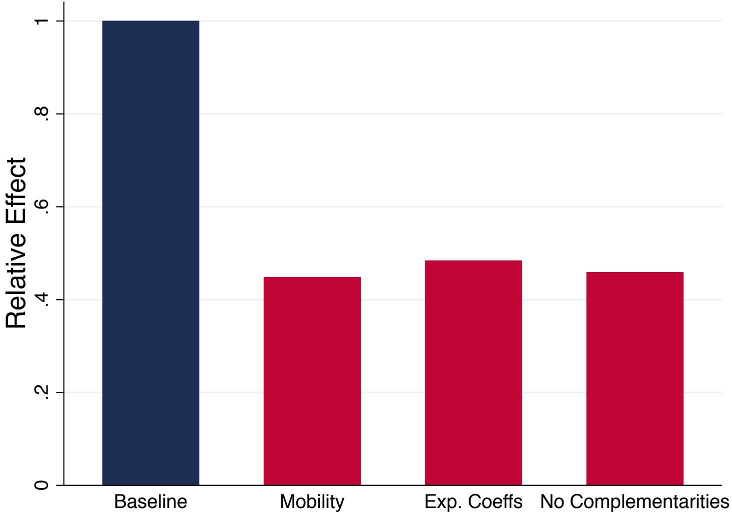
Model Fit - Actual and Simulated Wage Densities



Model Fit - Wage-Experience Profiles



Treatment Decomposition - Sequential



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