

When There is No Way Up: Reconsidering Low-paid Jobs as Stepping Stones

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Motivation

Consensus in the economic literature that:

- Low-paid face a high level of state dependence (see, beside others, Uhlenborff 2006, Cai et al. 2017)
- Low-paid employment being more a *temporary* labour market position, operating as ‘a trajectory to ‘decent’ jobs’ [Fok et al. 2015, p. 892] rather than dead-ends.

However: past literature has relied on survey data

- Estimates are usually based on earnings information for just one period within each year (‘point-in-time’ definition)
- Bhuller et al. (2017) show in their Norwegian study on welfare benefit receipt dynamics that findings might change when using monthly information

Approach:

- Utilising monthly administrative data on wages and salary to differentiate workers between *strong* low-pay attachment (working at least 6 months of a year in the low wage sector) and *weak* low-pay attachment (less than 6 months)
- Compare findings with prevailing identification strategy

Conceptual framework

Basic concept:

- Dynamics of earnings model:

$$Y_{ikm} = \mu_k + \alpha_i + v_{ikm}$$

- An individual is identified as being low-paid in month m if their monthly wage is below threshold τ :

$$LP_{ikm} = \mathbf{1}(Y_{ikm} \leq \tau)$$

- On an individual level, the share of low-paid employed months can be derived as:

$$LP_{ik}^S = \frac{\sum_{m=1}^{12} LP_{ikm}}{12} \text{ with } LP_{ik}^S \in \{0, 1/12, \dots, 1\}$$

- The prevailing identification strategy is: $LP_{ik_{m^+}}^S$ of month $m^+ \in (1, \dots, 12) \Rightarrow LP_{ik}^S = LP_{ik_{m^+}}^S$ if $\sigma_v^2 = 0$

Correlation over time:

- $corr[LP_{ik-1}^S, LP_{ik}^S] = \frac{N(\sum_i LP_{ik-1}^S LP_{ik}^S) - (\sum_i LP_{ik-1}^S)(\sum_i LP_{ik}^S)}{\sqrt{[N \sum_i (LP_{ik-1}^S)^2 - (\sum_i LP_{ik-1}^S)^2][N \sum_i (LP_{ik}^S)^2 - (\sum_i LP_{ik}^S)^2]}}$
- $corr[LP_{ik-1_{m^+}}^S, LP_{ik_{m^+}}^S] = \frac{N(\sum_i LP_{ik-1_{m^+}}^S LP_{ik_{m^+}}^S) - (\sum_i LP_{ik-1_{m^+}}^S)(\sum_i LP_{ik_{m^+}}^S)}{\sqrt{[N \sum_i (LP_{ik-1_{m^+}}^S)^2 - (\sum_i LP_{ik-1_{m^+}}^S)^2][N \sum_i (LP_{ik_{m^+}}^S)^2 - (\sum_i LP_{ik_{m^+}}^S)^2]}}$
- It can be shown that $\left| \frac{\partial(corr[LP_{ik-1}^S, LP_{ik}^S])}{\partial \sigma_v^2} \right| < \left| \frac{\partial(corr[LP_{ik-1_{m^+}}^S, LP_{ik_{m^+}}^S])}{\partial \sigma_v^2} \right|$

Literature

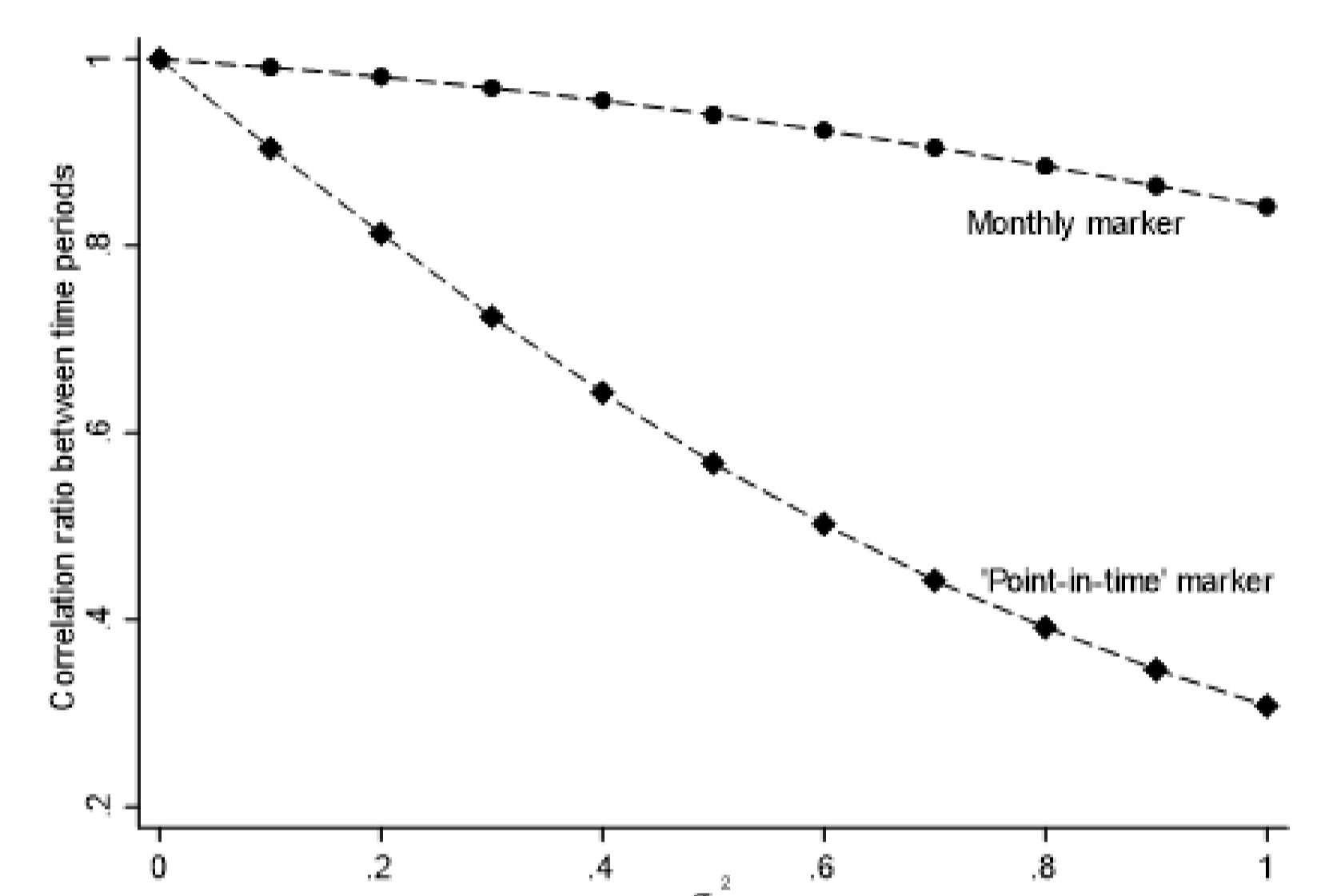
Table 1: Low pay persistence of related studies

Study	$P(LP_t LP_{t-1})$	$P(HP_t LP_{t-1})$
Cai et al. (2017, Table 2)	0.196	0.556
Cai et al. (2017, Table 6)	0.272	0.472
Mosthaf (2014, Table 5)	0.083 – 0.168	0.695 – 0.789
Uhlenborff (2006, Table 7)	0.050	0.888
Clark & Kanellopoulos (2013, Table 4)	0.033 (Spain) – 0.133 (Portugal)	-

Note: Cai et al. (2017) provides estimates based on the BHPS (Table 2) and Understanding Society data (Table 6). Mosthaf (2014) provides a range of estimates based on different qualification groups. Clark & Kanellopoulos (2013) provides a range of estimates based on data from twelve countries.

Model

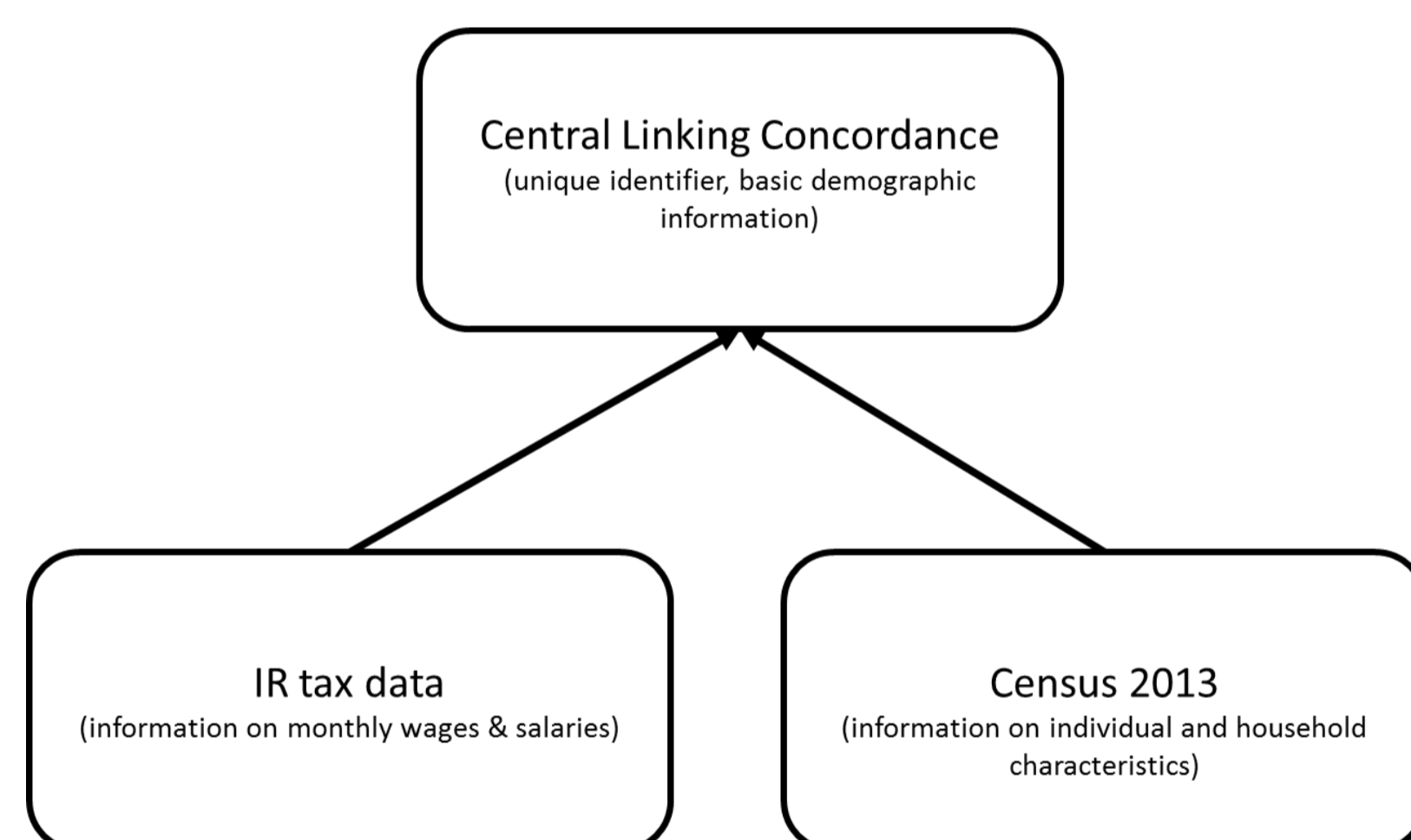
Figure 1: Simulation results (averages over 500 draws)



Note: The panel shows the correlation ratio between two time periods, for the monthly and ‘point-in-time’ markers. σ_v^2 = variation in monthly wages.

Data & Descriptives

Figure 2: Data sources



Source: own representation.

Notes:

- Focus on the time period of 2007 to 2013 and restrict our sample to male workers aged between 25 to 45 (inclusive) in 2007
- Those men with their earnings belonging to the 10th lowest percentile are defined as low pay.

Table 2: Prevalence of low pay employment

		‘Point-in-time’ marker		
		Higher pay _t	Low pay _t	Share _t
Monthly marker	Higher pay _t	100.00	0.00	77.44
	Weak low pay _t	81.81	18.19	12.31
	Strong low pay _t	24.78	75.22	10.26
	Share _t	90.05	9.95	

Notes: Data sourced from IDI (2018). Authors’ calculations. Based on a random subsample of population of interest $N = 47,496$. Time period = 2007 to 2013.

Econometric Model and Results

Econometric Model:

- We apply a dynamic random effects multinomial logit model (Uhlenborff 2006, Mosthaf 2014, Fok et al. 2015, and most recently Cai et al. 2017)
- Accounting for the *initial conditions problem* by following the suggestion of Wooldridge (2005)
- To integrate out the random effects, we use maximum simulated likelihood (MSL) with Halton draws.

Table 3: Predicted transition probabilities (‘Point-in-time’ marker)

	At $t = 0$		
	Total	Higher Pay	Low Pay
$P(\text{Higher pay}_t \text{Higher pay}_{t-1})$	0.9643 (0.0847)	0.9882 (0.0104)	0.8058 (0.1214)
$P(\text{Low pay}_t \text{Higher pay}_{t-1})$	0.0357 (0.0847)	0.0118 (0.0104)	0.1942 (0.1214)
$P(\text{Higher pay}_t \text{Low pay}_{t-1})$	0.8664 (0.1936)	0.9226 (0.0593)	0.4185 (0.1800)
$P(\text{Low pay}_t \text{Low pay}_{t-1})$	0.1336 (0.1936)	0.0774 (0.0593)	0.5815 (0.1800)

Notes: Data sourced from IDI (2018). Authors’ calculations. Based on a random subsample of population of interest $N = 47,496$. Time period = 2007 to 2013. Numbers in parenthesis refer to standard deviations.

Table 4: Predicted transition probabilities (Monthly markers)

	At $t = 0$			
	Total	Higher pay	Weak lp	Strong lp
$P(\text{Higher pay}_t \text{Higher pay}_{t-1})$	0.8892 (0.1631)	0.9617 (0.0266)	0.7736 (0.1083)	0.5825 (0.1482)
$P(\text{Weak low pay}_t \text{Higher pay}_{t-1})$	0.1012 (0.1386)	0.038 (0.0263)	0.2199 (0.1027)	0.3555 (0.1083)
$P(\text{Strong low pay}_t \text{Higher pay}_{t-1})$	0.0096 (0.0301)	0.0003 (0.0005)	0.0065 (0.0065)	0.0620 (0.0469)
$P(\text{Higher pay}_t \text{Weak low pay}_{t-1})$	0.7611 (0.2571)	0.8808 (0.0706)	0.5016 (0.1484)	0.2392 (0.1254)
$P(\text{Weak low pay}_t \text{Weak low pay}_{t-1})$	0.1856 (0.1603)	0.1140 (0.0654)	0.4358 (0.1117)	0.4222 (0.0513)
$P(\text{Strong low pay}_t \text{Weak low pay}_{t-1})$	0.0533 (0.1263)	0.0052 (0.0060)	0.0626 (0.0443)	0.3386 (0.1342)
$P(\text{Higher pay}_t \text{Strong low pay}_{t-1})$	0.4349 (0.2523)	0.5318 (0.1605)	0.1011 (0.0679)	0.0145 (0.0130)
$P(\text{Weak low pay}_t \text{Strong low pay}_{t-1})$	0.3089 (0.1069)	0.3317 (0.0840)	0.4018 (0.0760)	0.1219 (0.0476)
$P(\text{Strong low pay}_t \text{Strong low pay}_{t-1})$	0.2562 (0.2653)	0.1366 (0.0895)	0.4970 (0.1322)	0.8635 (0.0593)

Notes: Data sourced from IDI (2018). Authors’ calculations. Based on a random subsample of population of interest $N = 47,496$. Time period = 2007 to 2013. Numbers in parenthesis refer to standard deviations.

Robustness

Table 5: Predicted transition probabilities (Mean monthly marker)

		At $t = 0$		
		Total	Higher Pay	Low Pay
$P(\text{Higher pay}_t \text{Higher pay}_{t-1})$		0.9596 (0.1288)	0.9976 (0.0028)	0.7164 (0.1857)
	$P(\text{Low pay}_t \text{Higher pay}_{t-1})$	0.0404 (0.1288)	0.0024 (0.0028)	0.2836 (0.1857)
$P(\text{Higher pay}_t \text{Low pay}_{t-1})$		0.8718 (0.2602)	0.9539 (0.0470)	0.1769 (0.1467)
	$P(\text{Low pay}_t \text{Low pay}_{t-1})$	0.1282 (0.2602)	0.0461 (0.0470)	0.8231 (0.1467)

Notes: Data sourced from IDI (2018). Authors’ calculations. Based on a random subsample of population of interest $N = 47,496$. Time period = 2007 to 2013. Numbers in parenthesis refer to standard deviations.

Conclusions

⇒ Present evidence that low pay persistence differs with intensity of attachment to the low pay sector:

- ‘point-in-time’ marker: the likelihood of being low-paid in time period t if being initially low-paid and likewise in time period $t-1$ is 58.2 percent, while the likelihood of higher pay in t is 41.9 percent
- Monthly marker: for those with initially strong low pay attachment, the probability of staying strong low pay is 86.4 percent, while the probability of moving into higher pay is just 1.5 percent.

⇒ Prior empirical evidence has generally been supportive of the ‘work-first approach’ to work-force participation, ‘even if the jobs created are low-paid’ [Cai et al. 2017, p. 30].

⇒ Findings indicate that not every job contributes to the individuals’ human capital level (e.g. Stewart 2007).