When There Is No Way Up: Reconsidering Low-Paid Jobs As Stepping Stones

Gail Pacheco (NZWRI at AUT), Alexander Plum (NZWRI at AUT)

Magdeburg 2018

NEW ZEALAND WORK RESEARCH INSTITUTE

AUT UNIVERSITY NEW ZEALAND

SNZ Disclaimer

- Access to the data used in this study was provided by Statistics New Zealand under conditions designed to give effect to the security and confidentiality provisions of the Statistics Act 1975.
- The results presented in this study are the <u>work of the authors, not of Statistics NZ</u>.

Motivation

Background:

- Intensive discussion on inequality (e.g. OECD 2015, IMF 2017)
- Numerous studies on the effect of low pay employment on labour market prospects:
  - Low-paid face a high level of state dependence (see, beside others, Uhlendorff 2006, Cappellari 2007, Buddelmeyer et al. 2010, Clark & Kanellopoulos 2013, Fok et al. 2015, Cai et al. 2017)
  - Risk of staying low-paid employed is usually exceeded by the chances of becoming higher-paid employed
  - *Conclusion*: ‘a trajectory to ‘decent’ jobs’ [Fok et al. 2015, p. 892]

Motivation

Aim of this study:

Assessing the plausibility of assuming relatively constant wages within a year and determining the impact of this assumption on estimates of low pay persistence:

- Discussing the prevailing identification strategy which is based on earnings information for just one period within each year (‘point-in-time’ definition).
- Comparing the results with a model that uses a large administrative dataset with monthly earning information and accounts for the intensity of the low pay attachment.

Motivation

Findings:

1) Annual share of individuals affected by low pay is underestimated
2) Level of low pay attachment varies across individuals
3) Intensity of low pay attachment over time is highly correlated

$$\Downarrow$$

Conventional identification strategy *under*- and *over*estimates the persistence in low pay substantially

Literature Review

Table 1: Low pay persistence of related studies

Study	$P(\text{Lp}_t \mid \text{Lp}_{t-1})$	$P(\text{Hp}_t \mid \text{Lp}_{t-1})$
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
Uhlendorff (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.

Conceptual framework

Basic concept

- Dynamics of earnings model:
$$Y_{ik_m} = \mu_k + \alpha_i + \nu_{ik_m}$$
- An individual is identified as being low-paid in month m if their monthly wage is below threshold τ:
$$LP_{ik_m} = \mathbf{1}\left(Y_{ik_m} \leq \tau\right)$$
- On an individual level, the share of low-paid employed months can be derived as:
$$LP_{ik}^S = \frac{\sum_{m=1}^{M_{ik}} LP_{ik_m}}{12} \text{ with } LP_{ik}^S \in \{0, {}^1/_{12}, \ldots, 1\}$$
- The prevailing identifcation strategy is: $LP_{ik_{m^+}}$ of month $m^+ \in (1, \ldots, 12) \Longrightarrow \boldsymbol{LP_{ik}^S = LP_{ik_{m^+}}}$ **if** $\boldsymbol{\sigma_\nu^2 = 0}$

Conceptual framework

Correlation over time

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

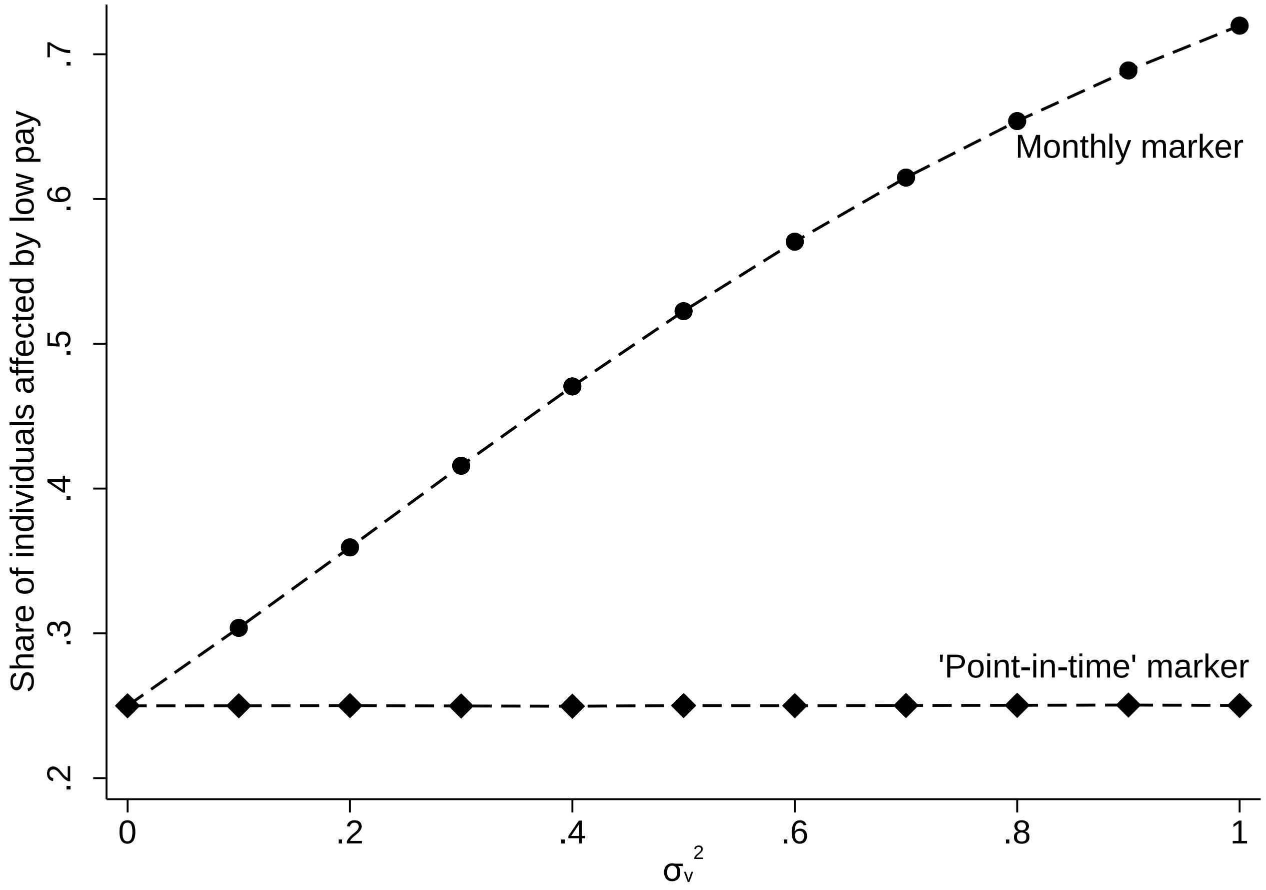
Conceptual framework

Simulation

- 5,000 individuals
- $Y_{ik_m} = 2{,}000 + 200\alpha_i + 200v_{ik_m}$ with $k \in \{1,2\}$, $\alpha_i = (0,1)$ and $v_{ik_m} = (0, x)$ with $x \in \{0, .1, \dots, 1\}$
- Low-paid if their wages belong to the lowest 25th percentile within the respective month
- 500 replications
- Two scenarios:
  - i) using the prevailing identification strategy, i.e. using information for one month in each year (the first month) – termed *'Point-in-time' marker*;
  - ii) using all monthly information, i.e. accounting for monthly variation in wages – *Monthly marker*

Conceptual framework

Simulation

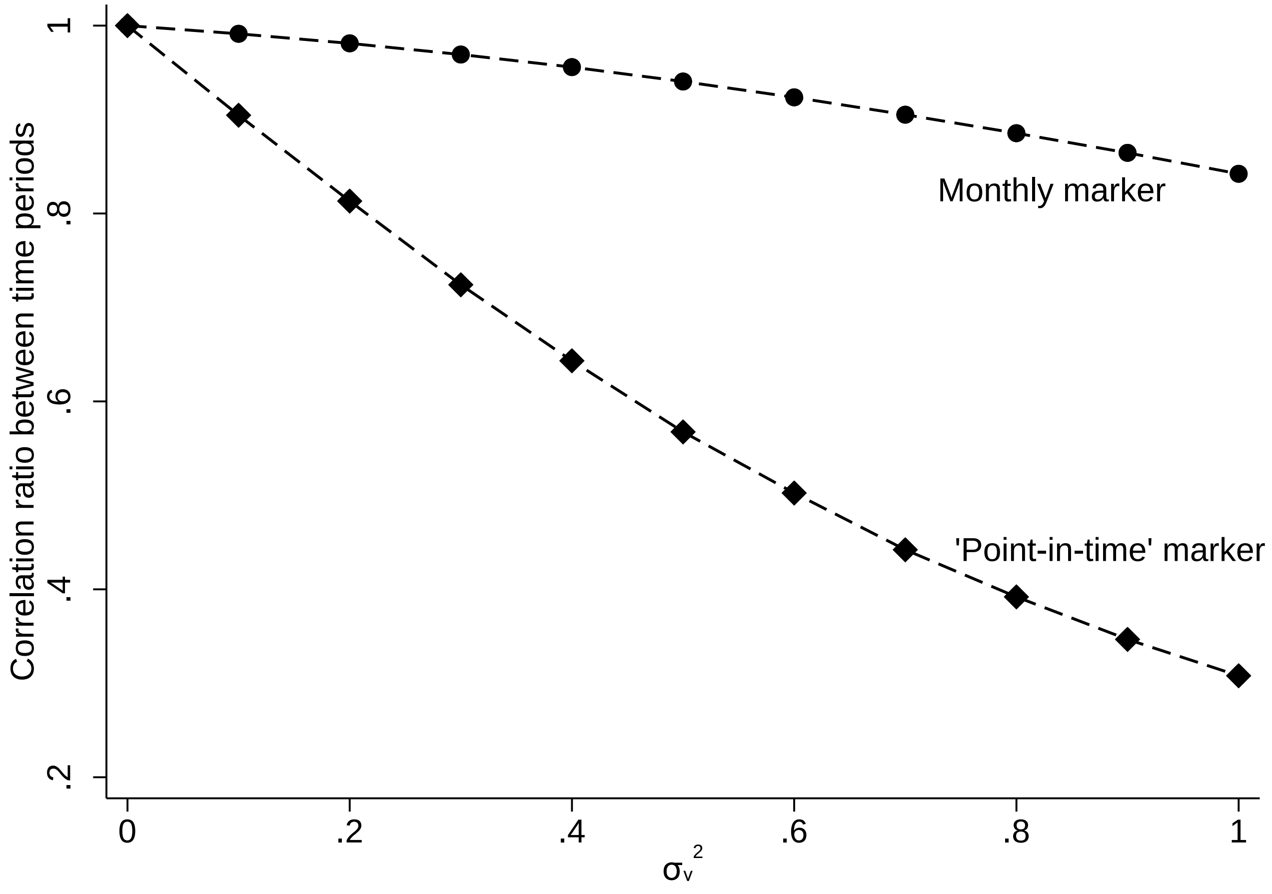


NEW ZEALAND WORK RESEARCH INSTITUTE

AUT UNIVERSITY NEW ZEALAND

Conceptual framework

Simulation



Descriptive Statistics

Statistics New Zealand’s Integrated Data Infrastructure (IDI):

- IDI links longitudinal microdata about individuals, households etc. from various sources
- Backbone is the Central Linking Concordance (CLC) which contains a list of all individuals with some characteristics (e.g. sex, date of birth)

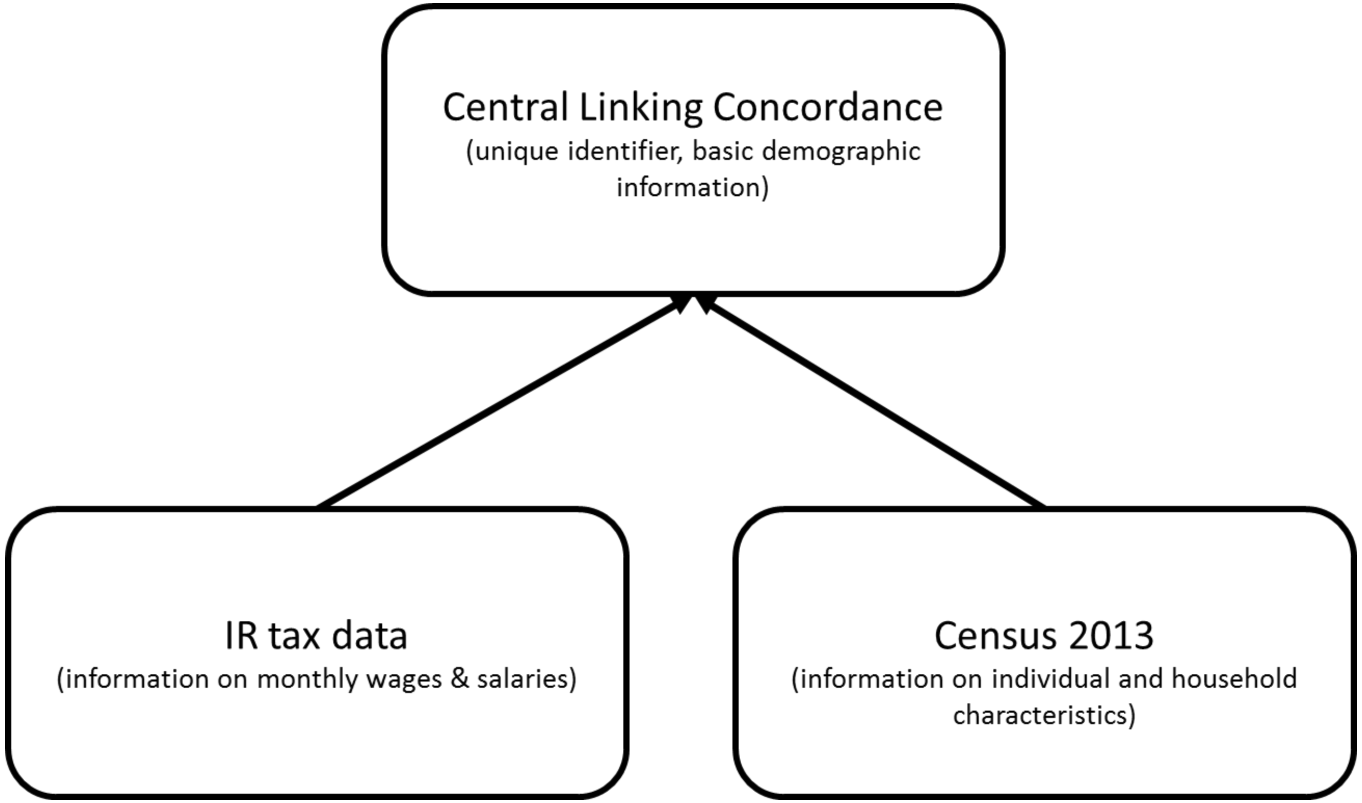
Inland Revenue tax data (IR):

- Information on person tax data from Inland Revenue
- Monthly data on gross earnings before tax that come from wages and salaries (geographic coverage: all New Zealand)

Census 2013:

- Information on individual and household characteristics

Descriptive Statistics



Source: own representation.

Descriptive Statistics

- The time period and population of interest exclusions are due to the following reasons:
  - To control for individual we use information provided by the 2013 Census => we only consider wage data over the years 2007 to 2013
  - As the IR tax data does not include information on working hours, we focus on prime aged men (NZ specific OECD data in the respective time frame under study indicates that approximately 95 percent of this age group of men are working fulltime).
  - The age restrictions employed also mitigate the influence of schooling or early retirement schemes on our analysis.
  - To further ensure the population of interest is restricted to full time workers, we exclude months in which the wage and salary total for the individual was below 30 times the respective minimum wage times 4.2 weeks.

Descriptive Statistics

- Men with their earnings belonging to the 10th lowest percentile are defined as low pay:
- Next, the level of low pay attachment per year is ascertained and the following three groups are created:
  - *Higher pay*: individuals with no low pay experience in a year.
  - *Weak low pay:* individuals who have worked in the low wage sector but for less than 6 months within a year.
  - *Strong low pay:* individuals who have worked at least 6 months of a year in the low wage sector.

Descriptive Statistics

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.

Descriptive Statistics

Table 3: Transition matrix of the labour market positions ('Point-in-time' marker)

	Higher pay $_t$	*Low-pay $_t$*	*Total $_{t-1}$*
Higher pay $_{t-1}$	96.53	3.47	90.05
Low-pay $_{t-1}$	31.37	68.63	9.95
Total $_t$	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.

NEW ZEALAND WORK RESEARCH INSTITUTE

AUT UNIVERSITY NEW ZEALAND

Descriptive Statistics

Table 4: Transition matrix of the labour market positions (Monthly marker)

	Higher pay$_t$	*Weak low pay$_t$*	*Strong low pay$_t$*	*Total$_{t-1}$*
Higher pay$_{t-1}$	93.19	6.60	0.20	77.12
Weak low pay$_{t-1}$	42.32	46.93	10.75	12.64
Strong low pay$_{t-1}$	2.18	12.53	85.29	10.25
Total$_t$	77.44	12.31	10.26	

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.

NEW ZEALAND
WORK RESEARCH INSTITUTE

AUT UNIVERSITY NEW ZEALAND

Econometric Model

Basic concept:

- First-order Markov process: lagged dependent variable has a genuine effect
- Controlling for unobserved heterogeneity (Heckman 1981a) and its correlation with the initial conditions (Heckman 1981b)
- Applying a dynamic random effects multinomial logit model (Uhlendorff 2006, Mosthaf 2014, Fok et al. 2015, Cai et al. 2017).
- To integrate out the RE we apply MSL (Halton draws).

Results

Table 5a: Predicted transition probabilities ('Point-in-time' marker)

	At $t = 0$		
	Total	*Higher Pay*	*Low Pay*
$P(Higherpay_t \mid Higherpay_{t-1})$	0.9643	0.9882	0.8058
	(0.0847)	(0.0104)	(0.1214)
$P(Lowpay_t \mid Higherpay_{t-1})$	0.0357	0.0118	0.1942
	(0.0847)	(0.0104)	(0.1214)
$P(Higherpay_t \mid Low\ pay_{t-1})$	**0.8664**	0.9226	**0.4185**
	(0.1936)	(0.0593)	(0.1800)
$P(Lowpay_t \mid Low\ pay_{t-1})$	**0.1336**	0.0774	**0.5815**
	(0.1936)	(0.0593)	(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.

Results

Table 5b: Predicted transition probabilities (Monthly markers)

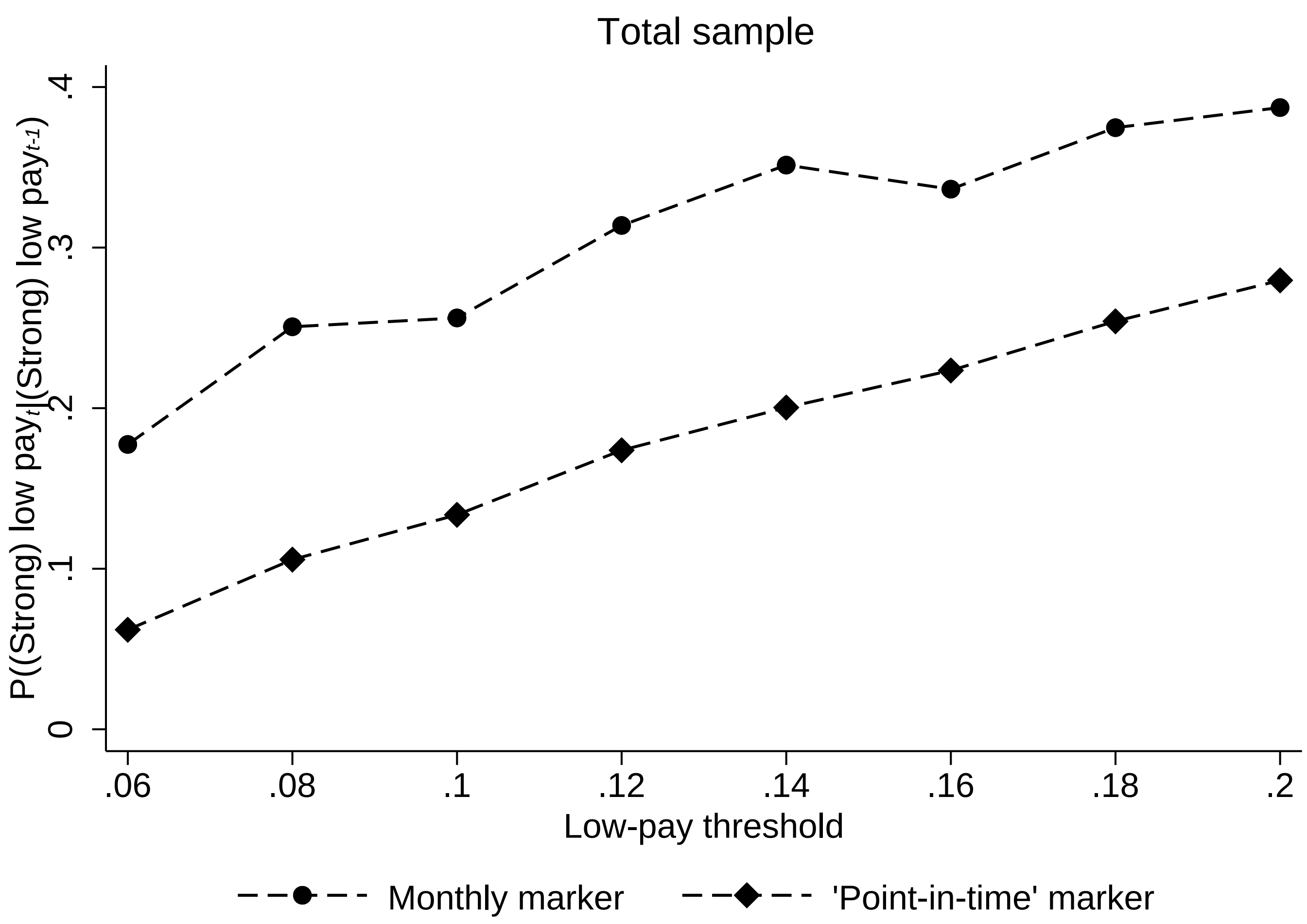
	At $t=0$			
	Total	*Higher pay*	*Weak lp*	*Strong lp*
$P(\mathit{Higher\ pay}_t \mid \mathit{Higher\ pay}_{t-1})$	0.8892	0.9617	0.7736	0.5825
	(0.1631)	(0.0266)	(0.1083)	(0.1482)
$P(\mathit{Weak\ low\ pay}_t \mid \mathit{Higher\ pay}_{t-1})$	0.1012	0.038	0.2199	0.3555
	(0.1386)	(0.0263)	(0.1027)	(0.1083)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

NEW ZEALAND WORK RESEARCH INSTITUTE

AUT UNIVERSITY NEW ZEALAND

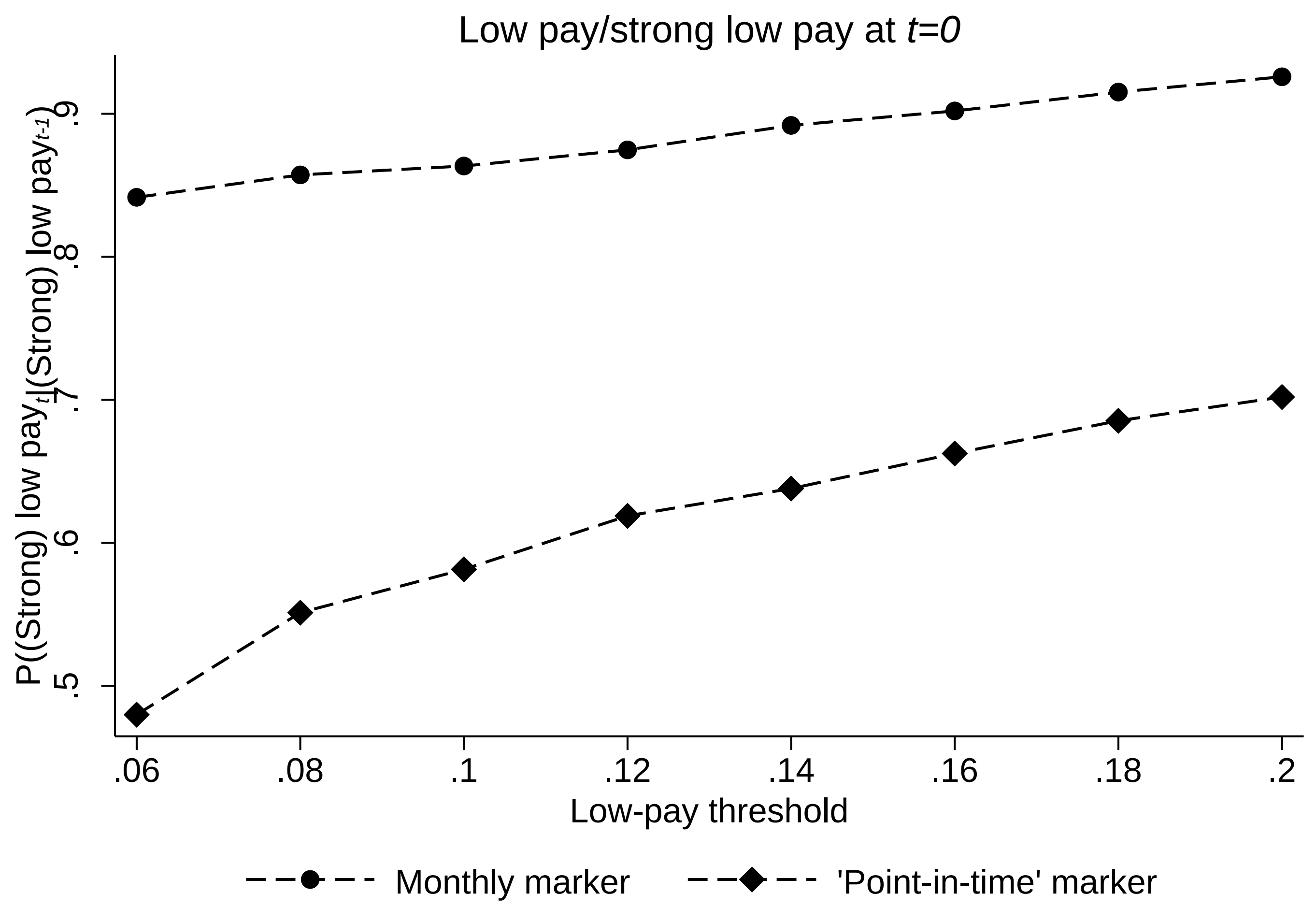
Results



NEW ZEALAND WORK RESEARCH INSTITUTE

AUT UNIVERSITY NEW ZEALAND

Results



Low pay/strong low pay at t=0
P((Strong) low pay_t|(Strong) low pay_t-1)
.5
.6
.7
.8
.9
.06
.08
.1
.12
.14
.16
.18
.2
Low-pay threshold
Monthly marker
'Point-in-time' marker

Robustness: Mean monthly wages

Table A1: Prevalence of low pay employment: monthly and mean monthly marker

		Mean monthly Marker		
		Higher pay$_t$	*Low pay$_t$*	Share$_t$
Monthly marker	*Higher pay$_t$*	100.00	0.00	77.44
	Weak low pay$_t$	94.80	5.20	12.31
	Strong low pay$_t$	9.18	90.82	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.

Robustness: Mean monthly wages

Table A2: Prevalence of low pay employment: 'point-in-time' and mean monthly marker

		Mean monthly Marker		
		Higher pay$_t$	*Low pay*$_t$	Share$_t$
'Point-in-time' marker	*Higher pay*$_t$	97.19	2.81	90.05
	Low pay$_t$	25.40	74.60	9.95
	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.

NEW ZEALAND WORK RESEARCH INSTITUTE

AUT UNIVERSITY NEW ZEALAND

Robustness: Mean monthly wages

Table 5b: Predicted transition probabilities (Mean monthly marker)

	At $t = 0$		
	Total	*Higher Pay*	*Low Pay*
$P(Higherpay_t \mid Higherpay_{t-1})$	0.9596	0.9976	0.7164
	(0.1288)	(0.0028)	(0.1857)
$P(Lowpay_t \mid Higherpay_{t-1})$	0.0404	0.0024	0.2836
	(0.1288)	(0.0028)	(0.1857)
$P(Higherpay_t \mid Low\ pay_{t-1})$	**0.8718**	0.9539	**0.1769**
	(0.2602)	(0.0470)	(0.1467)
$P(Lowpay_t \mid Low\ pay_{t-1})$	**0.1282**	0.0461	**0.8231**
	(0.2602)	(0.0470)	(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.

NEW ZEALAND
WORK RESEARCH INSTITUTE

AUT UNIVERSITY NEW ZEALAND

Conclusion

Findings:

1) Using the prevailing identification strategy, the heterogeneity of past low-pay cannot be detected at that granularity → low pay persistence is *over*- and *under*estimated
2) After accounting for the level of attachment to the low wage sector those with a strong attachment have very little chance of exiting this sector.
3) Strong doubts whether ‘any job is helpful’ with respect to climbing up the wage ladder.

Thank you very much for your time

Questions?