Stationarity In Labor-Income Process And State Dependence In Low Pay

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Work in progress

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Statistics NZ 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 work of the authors, not of Statistics NZ.

Motivation:

- Studies on wage dynamics: how persistent are wage shocks?
  - ➢ Unit-root process has strong implications
  - ➢ Numerous studies find that shocks to earnings are subject to having maximum persistence (see Meghir & Pistaferri 2004)
  - ➢ Gustavsson & Österholm (2014, p. 152) : ‘question the heavy use of unit-root processes for earnings’
- Estimating state dependence in low pay:
  - ➢ Genuine effect of low pay on the future labour market outcome
  - ➢ Studies show persistence in low pay

Motivation:

- How to link both strands of literature?
- Aim is to scrutinize prevailing empirical identification strategy to estimate state dependence in low pay.
- If wages are mean-reverting, which effect has adding additional past labour-market related information?
  - ➢ Unobserved heterogeneity
  - ➢ Goodness-of-fit statistics
  - ➢ Average partial effects (lagged dependent/covariates)
- Approach: 1) Simulation and 2) empirical example

Earnings process:

- Assume we have $i = 1, \ldots, N$ individuals who are continuously employed in month $m = 1, \ldots, 12$ of year $y = 1, \ldots, Y$. The wage w_{iy_m} the individual receives is:

$$w_{iy_m} = \mu + \alpha_i + \varepsilon_{iy_m}$$

- Main assumption is that wages are mean reverting. To hold, we assume that:

$$\varepsilon_{iy_m} = \rho\varepsilon_{i(y_m-1)} + u_{iy_m}$$

  with $\rho < 1$.
- With more time periods, we see that $\bar{w}_{it} \approx \mu + \alpha_i$ as $\mathrm{E}\left[\varepsilon_{iy_m}\right] = 0$

Earnings process:

- We assume that at each month m^+ the individual reveals $w_{iy_{m^+}}$
- $\text{lp}_{iy_m} = 1(w_{iy_m} < \tau)$
- Standard approach:

$$\text{lp}_{iy_{m^+}} = \mathbf{1}\left(a\text{lp}_{i(y-1_{m^+})} + a_1\text{lp}_{i(y=1_{m^+})} + a_i + \nu_{iy_{m^+}} > 0\right)$$

$$\Pr\left(\text{lp}_{iy_{m^+}} = 1|a_i, y = 1_{m^+}\right) = \Phi\left[a\text{lp}_{i(y-1_{m^+})} + a_1\text{lp}_{i(y=1_{m^+})} + a_i\right]$$

- However: $\text{lp}_{iy_m} = 1$ might not be constant across individuals and therefore be either a transient or a permanent position

Earnings process:

- $\text{int}_{iy} = \frac{\sum_m \text{lp}_{iy_m}}{12}$

$$\text{lp}_{iy_{m^+}} = \mathbf{1}\left(b\,\text{int}_{i(y-1)} + b_1\text{int}_{i(y=1)} + b_i + \theta_{iy_{m^+}} > 0\right)$$

$$\Pr\left(\text{lp}_{iy_{m^+}} = 1 | b_i, y = 1\right) = \Phi\left[b\,\text{int}_{i(y-1)} + b_1\text{int}_{i(y=1)} + b_i\right]$$

- We expect: $\text{int}_{i(y-1)}$ is a better indicator for $\overline{w}_{it}$ then $\text{lp}_{i(y-1_{m^+})}$

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Testing:

- First part: simulations
- Second part: empirical application to real world data
- Note:
  - ➢ Not testing whether the estimator is unbiased
  - ➢ Comparisons (e.g. goodness-of-fit statistics)

Simulation:

- We use the following model:

$$w_{iy_m} = 2000 + s_1\tau_i + s_2\kappa_i + s_3\delta_{iy_m}$$
$$\delta_{iy_m} = \rho\delta_{i(y_m-1)} + \upsilon_{iy_m}$$

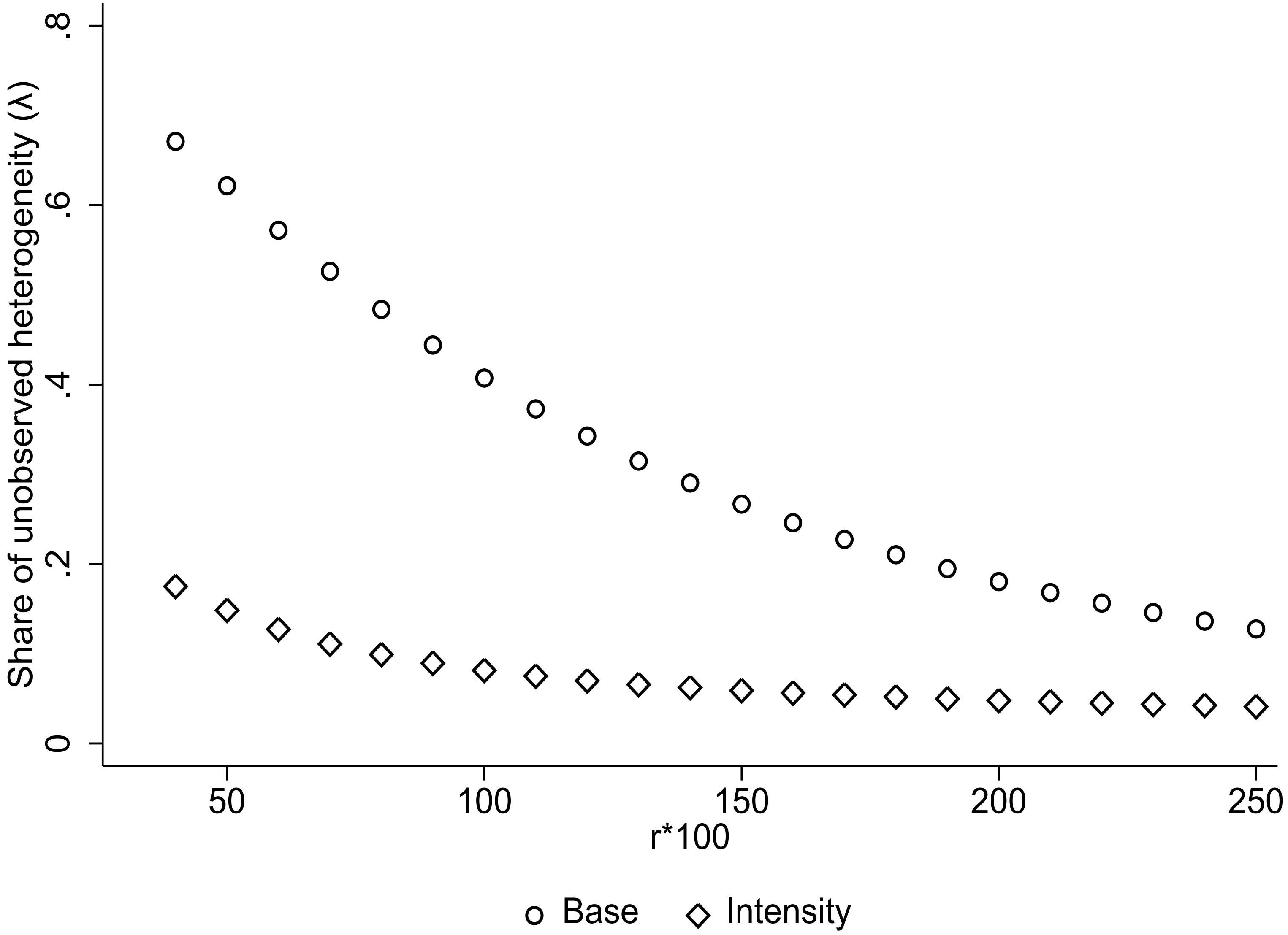
with $i = 1, \ldots, 500$, $m = 1, \ldots, 12$, $y = -20, \ldots, 20$, $\tau_i, \delta_{iy_m}, \upsilon_{iy_m} \sim N(0,1)$, $\kappa_i = 1(\omega_i < .4)$ with ω_i uniformly distributed random variates on $[0,1)$.

- m^+=10 and $\text{lp}_{iy_m} = 1$ if w_{iy_m} belongs to the lowest quartile
- $\text{int}_{iy} = \frac{\sum_m \text{lp}_{iy_m}}{12}$

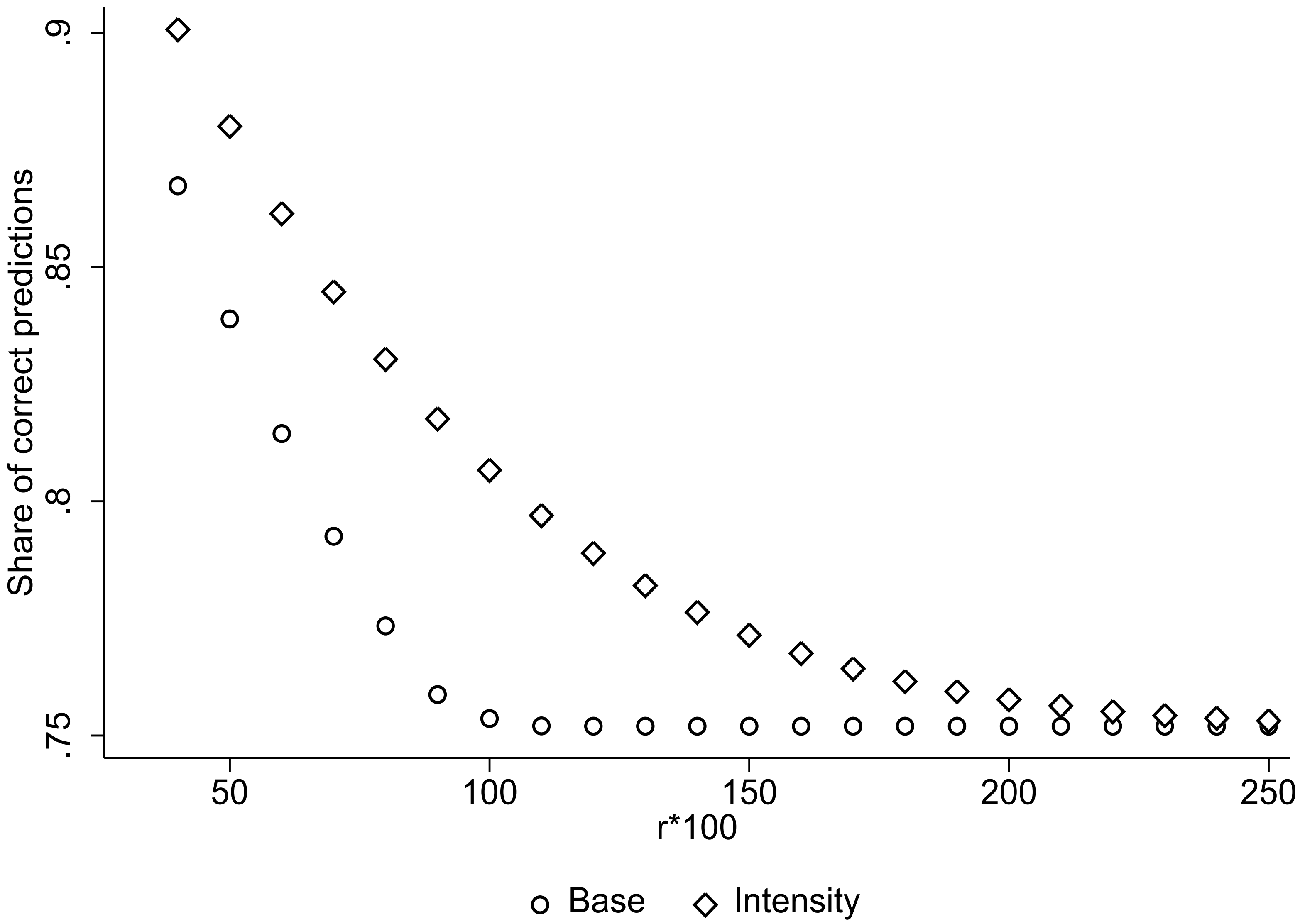
Simulation:

- 250 replications
- Running different models
  - ➢ Different levels of s_1, s_3 (s_2& $\rho = 0$)
  - ➢ Different levels of s_1, s_3, $s_2 \neq 0$ ($\rho = 0$)
  - ➢ One set of s_1, s_3 and different levels of ρ ($s_2 = 0$)
- Stata: **xtprobit**
- We present sample mean (std dev) of
  - ➢ Share of unobserved heterogeneity (λ)
  - ➢ Goodness-of-fit statistics (log likelihood, AIC, BIC, correct predictions)
  - ➢ Average partial effects (a, a_1, b, b_1)

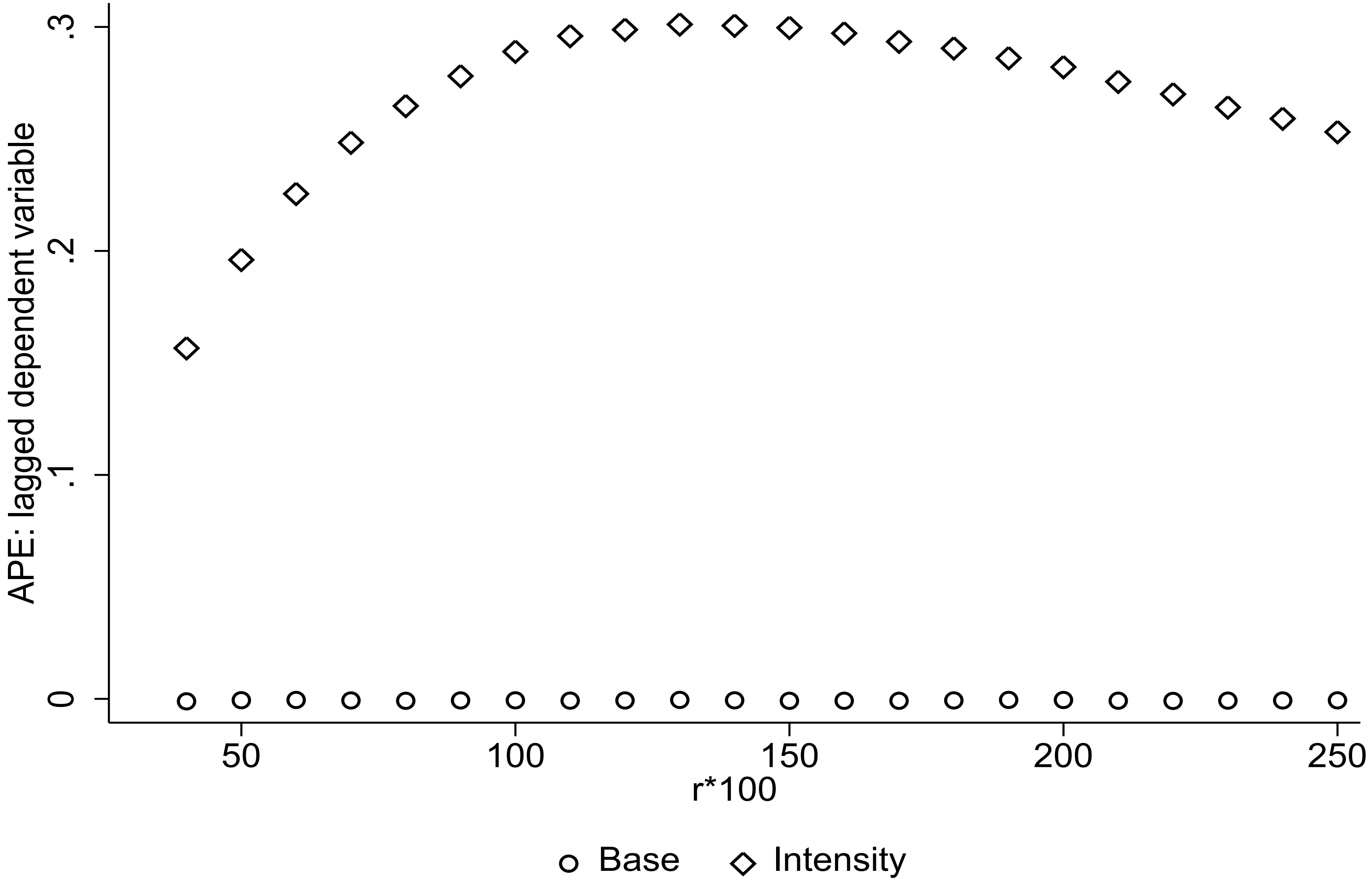
3. Simulation

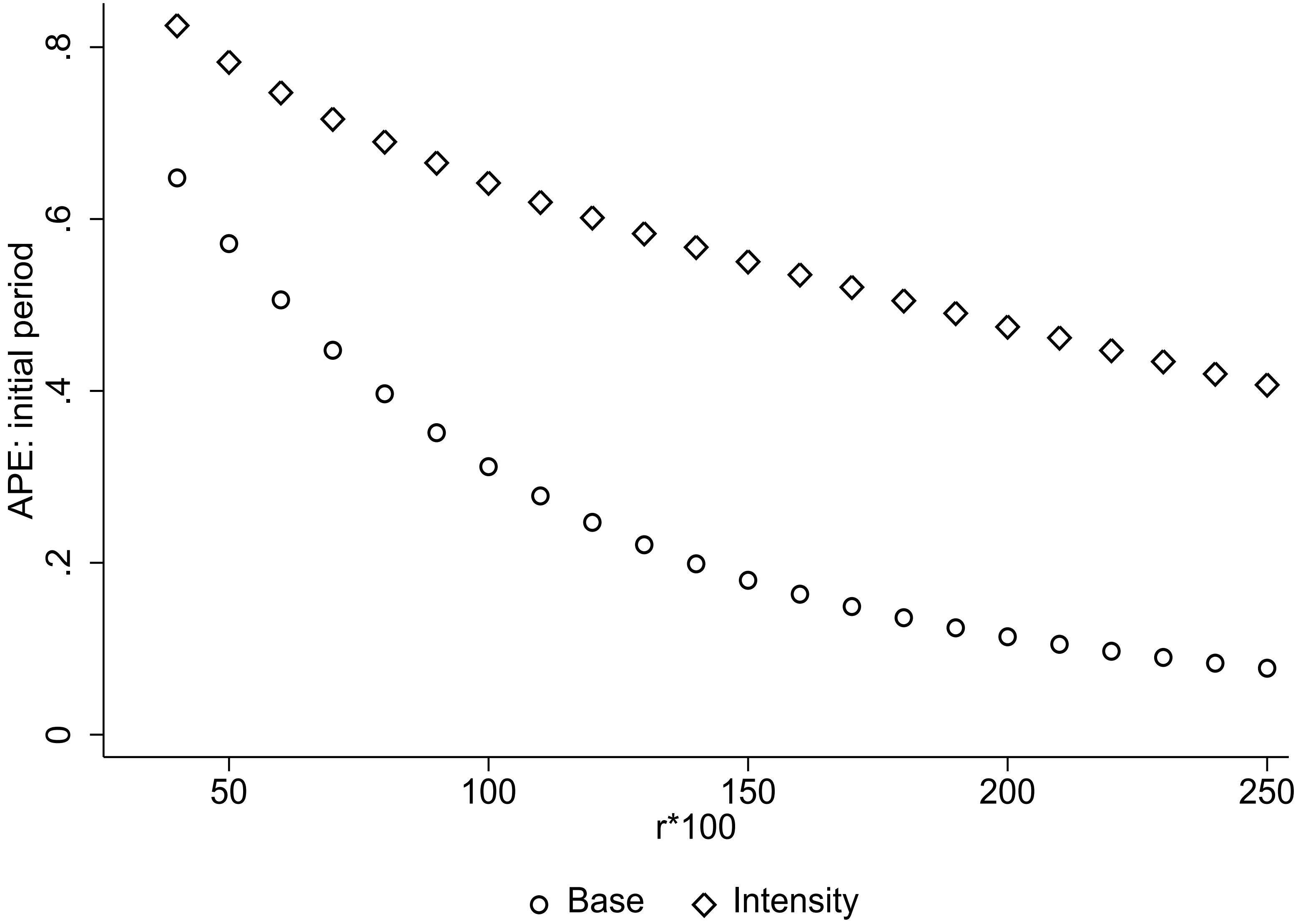


3. Simulation



3. Simulation





APE: initial period
0
.2
.4
.6
.8
50
100
150
200
250
r*100
Base
Intensity

Simulation:

- Unobserved heterogeneity (↓)
- GoF (↑)
- Average partial effects:
  - Lagged/initial period dependent variable (↑)
  - Covariate (↓)
- Difference diminishes in ρ

New Zealand low pay sector

- DIA affairs to identify male born in 1975/1976 and number of children
- IR tax records for the time frame 2008-2015 to identify income from wages and salaries, benefits, ACC claims
- 2013 Census to identify educational background (no qualification, Level 1-4, Level 5-6, bachelor and above) and ethnicity (only NZ European, Māori and Pacific Peoples)
- Labour market position based on the position within the wage distribution (≤ 25 percentile low pay; else higher pay)
- Keeping individuals who were continuously employed throughout the years
- $N = 71{,}064$

New Zealand low pay sector

- Are wages mean reverting?
- Simple DF test: yes (unit-root rejected for >90 percent)
- However, augmented DF test not that clear (open research task)
- But from previous simulations we know that if wages are not mean-reverting, time dimension hardly has any effect

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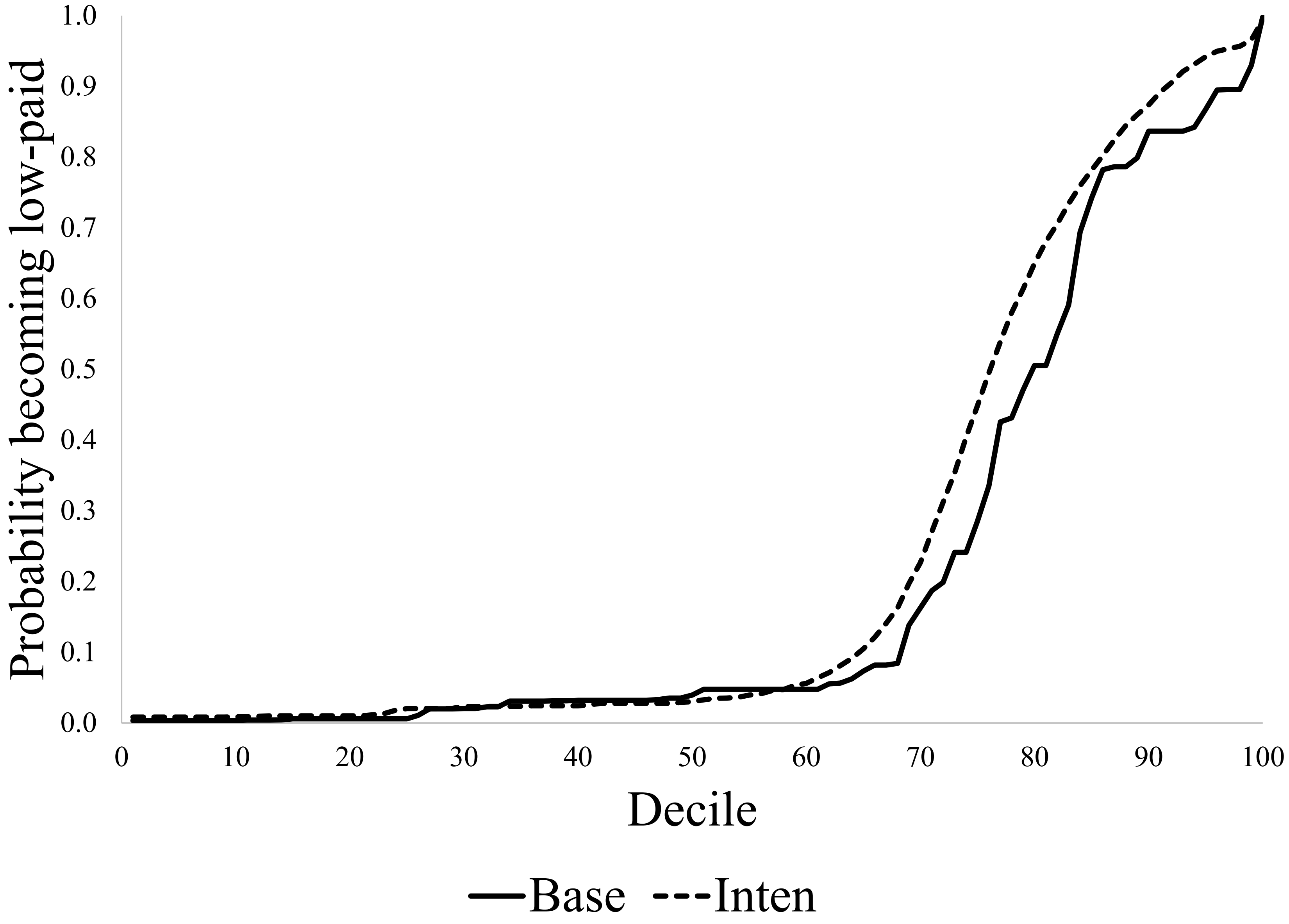
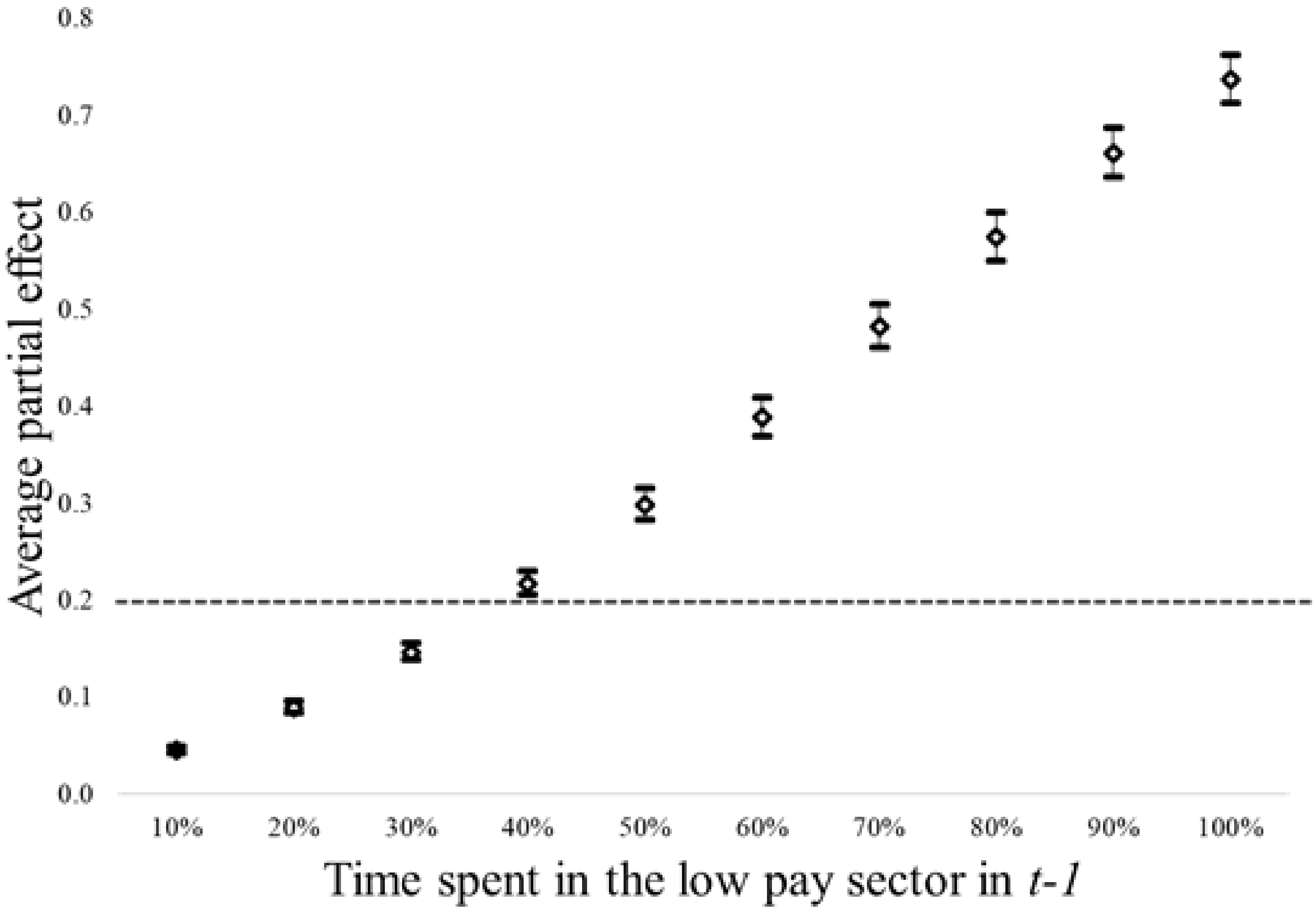
Econometric specification:

- Dependent variable: low-paid employed in October
- Covariates: qualification, ethnicity, number of children, receiving benefits, receiving ACC
- Two specifications:
  - ➢ *Basic*: Low pay in October past year/first year
  - ➢ *Inten*: Share of low paid months (0,1) in the previous year/initial year
- RE probit to control for unobserved heterogeneity

	Base	Inten	Inten^2	Inten^3	Inten^4	Categorical
λ	0.50	0.16	0.14	0.11	0.11	0.13
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
log likelihood	-21,268	-18,588	-18,461	-18,119	-18,099	-18,364
AIC	42,569	37,209	36,961	36,279	36,243	36,798
BIC	42,725	37,365	37,135	36,472	36,454	37,119
Correct predictions	0.845	0.886	0.887	0.886	0.886	0.886
N			71,064			

4. Empirical application




0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0.0
Average partial effect
10%
20%
30%
40%
50%
60%
70%
80%
90%
100%
Time spent in the low pay sector in t-1

4. Empirical application

	Base model	Intensity model
Highest qualification (reference: no qualification)		
Level 1-4	-0.009	-0.009
	[-0.025; +0.008]	[-0.018; -0.001]
Level 5-6	-0.039	-0.018
	[-0.056; -0.021]	[-0.027; -0.009]
Bachelor and above	-0.127	-0.063
	[-0.146; -0.109]	[-0.073; -0.053]
Ethnicity (reference: NZ European)		
Māori	+0.060	+0.018
	[+0.043; +0.078]	[+0.009; +0.028]
Pacific Peoples	+0.087	+0.022
	[+0.061; +0.112]	[+0.008; +0.035]
Benefit recipient (reference: receiving no benefits in $y-1$)		
Receiving 1-6 months	+0.083	+0.011
	[+0.032; +0.133]	[-0.028; +0.049]
Receiving ≥ 7 months	+0.258	+0.086
	[+0.143; +0.373]	[+0.010; +0.162]

Conclusion:

- Simulations indicate that if process is mean-reverting, the modelling of the lagged/initial period dependent variable matters:
  - Unobserved heterogeneity (↓)
  - GoF (↑)
  - Average partial effects:
    - Lagged/initial period dependent variable (↑)
    - Covariate (↓)
  - Difference diminishes in ρ
- Empirical application also points into this direction

Thank you for your attention!!!