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When there is no way up: Reconsidering low-paid jobs as stepping stones

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

Abstract

Several studies have shown significant persistence in low pay, along with a greater probability of moving out of low pay and into higher pay in the future. Low-paid jobs are therefore often deemed stepping stones, rather than dead-ends. However, using point-in-time information past literature has usually only considered changes in labour market status at the annual level and not accounted for within-year changes of an individual’s low pay position. Using population-wide administrative data with monthly earnings information, this study accounts for changes in an individual’s low pay position and shows that attachment to the low pay sector is highly heterogeneous. The empirical evidence points to workers that have a strong attachment to the low pay sector facing a very high probability of staying low-paid employed; and the likelihood of their low pay jobs being stepping stones towards higher pay are found to be negligible.

Keywords: Low pay; Pay persistence; Dynamic random effects models; Administrative data

JEL classification: J62, J31, C33, C55

1. Introduction

In recent years public (and academic) debate regarding rising levels of inequality has surged (see for example IMF 2017), often fuelled by an increasing or stagnating share of low pay employment. The average low pay incidence in the OECD in 2015 was approximately 16 percent, though with remarkable gender and country differences.[1] Related to this, the number of studies analysing the labour market prospects of low-paid employed has increased noticeably, often asking to what extent low-paid employment may operate in the capacity of a 'stepping stone' towards improved labour market outcomes versus remaining stuck in a low pay cycle (in this scenario low pay employment would equate to a dead-end).[2] Against the background of rising inequality, Stewart & Swaffield (1998) emphasized the importance to determine the level of persistence in low pay: 'this could have come about either because the incidence of permanent low pay has increased or because transitory fluctuations in earnings have increased (or a combination of the two)' [p. 24].

When analysing the labour market prospects of low-paid employed, there is a general consensus that these individuals face a high level of persistence (see, beside others, Uhlendorff 2006, Cappellari 2007, Buddelmeyer et al. 2010, Clark & Kanellopoulos 2013, Fok et al. 2015, Cai et al. 2017). However, this consensus is also accompanied by the finding that the risk of staying low-paid employed is usually exceeded by the chances of becoming higher-paid employed. Thus current literature generally points to 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 (e.g. Uhlendorff 2006, Buddelmeyer et al. 2010, Cai 2014, Mosthaf 2014, Fok et al. 2015, Cai et al. 2017).[3]

Much of the past literature has relied on survey data. Due to data limitations, estimates are usually based on earnings information for just one period within each year, for example a specific month (point-in-time definition). However, current research indicates that the type of time aggregation might have an impact on estimated level of state dependence. For example, Bhuller et al. (2017) show in their Norwegian study on welfare benefit receipt dynamics, that persistence increases when switching from a model that uses information at the monthly level to one at the annual level. The aim of this study is to contribute to the literature investigating persistence in low pay (as well as stepping stone effects) and utilise monthly administrative data on wages and salary. We compare our findings with the prevailing identification strategy and show that not accounting for monthly variation in wages across the year has a severe impact

[1] This number refers to full-time employees. Data retrieved on 19 April 2018 from the OECD: http://stats.oecd.org/

[2] Another recent strand of literature is looking at the wage growth rates of low-paid employed (e.g. Gladden & Taber 2009, Sørensen & Vejlin 2014), however transitions between low pay and higher pay cannot be modelled straightforward.

[3] To identify a 'stepping-stone' effect of low pay, most studies compare the probability of becoming higher paid conditional on the previous labour market position (e.g. Cai et al. 2017). High intertemporal transition probabilities from low pay at $t-1$ to higher pay at t form the basis to conclude that 'that low paid jobs are stepping stones to better jobs' [Uhlendorff 2006, p.18].

on the estimated size of low pay persistence, and thus the likelihood of stepping up out of the low pay sector.

So far, most studies on low pay only provide scarce theoretical explanation on the effect of low pay on labour market prospects. On the one hand, low pay might have a positive effect on the human capital level (Mosthaf 2014) and signal the willingness to work (Knabe & Plum 2013) and thus act as a stepping stone. At the same time, being previously employed in some kind of 'bad job' might be perceived as a negative productivity signal (McCormick 1990, Acemoglu 2001). Layard et al. [1991: 249] popularized this concern by the famous remark: "While unemployment is a bad signal, being in a low-quality job may well be a worse one."

From an empirical perspective, studies have generally showed that 'being low paid does not have any adverse effects on future employment prospects' [Uhlendorff 2006, p. 17], with a greater probability of transitioning into higher pay relative to staying low-paid. Based on the finding that low pay jobs operate as a gateway to higher pay the policy implication is promotion of 'a 'work-first' strategy' [Fok et al. 2015, p. 892] as the blueprint for attempting to enter higher-paid employment.

To analyse the above labour market dynamics empirically, information on individual earnings and characteristics are required. Surveys (like the British Household Panel Survey (BHPS), the German Socio-Economic Panel (SOEP), and/or the Household Income and Labour Dynamics in Australia Survey (HILDA)) are often employed for these empirical exercises, as they provide a rich set of individual and labour market related information. However, one limitation of such survey data is that earnings information are collected with respect to one time point in a year. Though not discussed in the low pay literature, it is implicitly assumed that earnings variation within a year does not have a major effect on estimation results.

However, if wages are not constant within a year, the intensity with which an individual is employed in the low wage sector might also not be constant and this might raise concerns regarding the identification of low pay status. For example, an individual might be identified as low-paid employed at the interviewed month in a survey as their wage was below the low pay threshold. But if their wage dynamics meant that was one of only a few months on low pay, and that most of the year they were earning above the threshold, then accounting for monthly variation in wages illustrates the weak attachment this individual has to the low pay sector. Likewise, it is possible for someone to be classified as not low-paid employed in the interviewed month, even if that individual has spent most of the remaining months of the year in the low wage sector, and thus has a strong low pay attachment. Our study provides evidence that wages vary across the year, and especially at the lower tail of the earnings distribution: e.g. the mean variation coefficient of the 10^{th} percentile is found to be 1.8 times higher compared to the one of the 50^{th} percentile[4].

[4] In Appendix **A1** we present descriptive evidence on within-year wage variation at the individual level, which especially operates at the lower tail of the wage distribution.

The aim of this study is to assess empirically the plausibility of assuming relatively constant wages, as well as the impact when this assumption is not realized on estimates of low pay persistence (and likewise on the stepping stone effect). For this reason, we employ population-wide monthly administrative data on individual wages and salaries to estimate low pay persistence. This unit record information is sourced for the time period of 2007 to 2013 from the Integrated Data Infrastructure (IDI) in New Zealand (NZ). The IDI contains micro data from a range of government agencies and enables the researcher to join these on the individual level. For the purposes of this study, tax data from Inland Revenue are used, which covers the entirety of the NZ working population. The main advantage of these data is that accurate information are provided on a monthly basis and that survey related issues like panel attrition (e.g. Lillard & Panis 1998) and measurement error associated with self-reporting (Pavlopoulos et al. 2012) do not need to be addressed. Furthermore, the high number of observations aids in providing a detailed picture of labour market movements.

In a similar vein to past literature, we focus on prime aged male workers. We initially determine the intensity of low pay attachment for each worker by calculating the number of low pay months experienced within each year relative to the total number of employed months. Based on these constructed ratios, three groups are formed to indicate strength of attachment to the low pay sector: those without any low pay experience (higher pay); those spending less than half of their employed months in the low pay sector (weak low pay); and the final group spending at least fifty percent of their employed time in low pay (strong low pay). We find a noticeable variation in low-pay attachment across the working population, with some workers on low pay for just a few months in a year, whereas others spend most of their employment in the low wage sector. Moreover, the correlation of low pay sector attachment over time appears rather stable and is substantially higher after accounting for monthly variation in pay, compared to the traditional method of comparing wages of a single month (via survey data) across consecutive years.

To derive the impact of labour market position on future labour market outcomes, we apply dynamic random-effects multinomial logit estimators. The regression results indicate that there is substantial heterogeneity in the risk of facing low pay depending on past strength of attachment to the low pay sector. More specifically, we find that an individual has a significantly higher risk of strong low pay attachment, if they experienced strong low pay attachment in the past, compared to their counterparts who experienced weak low pay attachment, or higher pay. These findings lead us to the conclusion that in contrast to the existing literature, for a considerable share of low-paid employed their jobs do not operate as a gateway to higher pay and thus cannot be considered as stepping-stones.

The remainder of this paper is structured as follows: Section 2 provides an overview of the current literature on low pay dynamics; Section 3 encompasses an overview of the administrative data and presents key descriptives; Section 4 describes the econometric model; while results are shown in Section 5, followed by conclusions.

2. Literature Review

The number of studies on low pay has increased substantially in recent years. Many have focussed on persistence in low pay (e.g. Clark & Kanellopoulos 2013) or comparing future unemployment risk of the low-paid relative to those unemployed (for example, see Stewart 2007, Buddelmeyer et al. 2010). Recent attention has been directed towards understanding the transition probability of low-paid employment to higher pay (e.g. Mosthaf 2014, Fok et al. 2015, Cai et al. 2017), and it is the aim of this section to provide a brief overview of country specific empirical findings in this space.

Table 1 provides estimates regarding low pay dynamics on two fronts: low pay persistence (i.e. $P(\mathrm{Lp}_t|\mathrm{Lp}_{t-1})$), and predicted transition probabilities of entering higher pay (i.e. $P(\mathrm{Hp}_t|\mathrm{Lp}_{t-1})$). Throughout this paper, we will refer to these two probabilities as persistence in low pay, and the stepping stone effect (respectively).

Table 1: Low pay persistence of related studies

Study	$P(\mathrm{Lp}_t\|\mathrm{Lp}_{t-1})$	$P(\mathrm{Hp}_t\|\mathrm{Lp}_{t-1})$
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
Cai (2014, Table 2A)	0.113	0.772
Cai (2014, Table 2B)	0.191	0.697
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. Note that both probabilities do not necessarily sum to one as the authors might account for further transitions into other labour market positions, e.g. into unemployment (see Uhlendorff 2006) and/or self-employment (see Cai et al. 2017).

For the case of the United Kingdom (UK), Cai et al. (2017) uses data from both the BHPS and Understanding Society to examine persistence in low pay, as well as the stepping stone effects of low pay. They find that men who were on low pay in $t-1$, have a probability of between 19.6 percent and 27.2 percent (depending on dataset used) of being on low pay in the following year t. Interestingly, these estimates are far exceeded by the probability of being on higher pay conditional on being low-paid in the preceding year. Based on the BHPS analysis, the probability of moving up towards higher pay is 55.6 percent, and with respect to the Understanding Society data, this probability is estimated at 47.2 percent.

Within the German context, Mosthaf (2014) uses data from the Integrated Employment Biographies Sample (IEBS) for the years 2000 to 2006. While this is an administrative data set with rich employment information available on a daily basis, wage changes within the year cannot be observed precisely, and as such the author builds ‘a panel data set with yearly observations at the reference day June 30’ [p.164]. This data source also lacks information on hours worked, and as a consequence an individual is identified as low-paid if he earns less than two thirds of the median gross wage of all full-time employed individuals. After applying dynamic multinomial logit models with random effects the author detects persistence in low pay to range between 8.3 percent and 16.8 percent depending on level of educational qualification. The comparable probabilities for exiting from low pay towards higher pay range between 69.5 and 78.9 percent. As expected, the higher the level of educational attainment, the greater the probability of stepping up from low pay into higher-paid jobs.

In another Germany study, Uhlendorff (2006) uses data from the SOEP for the years 1998 to 2003 and applies two different measures to identify low-paid employed: gross wages below two thirds of the median hourly wages and the first quintile of the wage distribution. Based on the first low pay threshold, the probability of remaining low-paid in the subsequent year is 5 percent, while the probability of moving from low pay to higher pay is substantially higher at 88.8 percent. Importantly, the authors recalculate the transition probabilities after accounting for the initial condition. As Stewart & Swaffield (1999, p.24) also explain, to not condition on initial labour market status and assume exogeneity of the initial labour market position would "result in a selection bias in the estimates". After Uhlendorff (2006) recalculate the probabilities conditional on being initially low-paid, the estimates found are 40.83 and 48.92 percent, respectively. Thus, still indicating a higher likelihood of exiting low pay towards higher pay.

Using the first 12 waves of the Household, Income and Labour Dynamics in Australia (HILDA) Survey, Cai (2014) also applies the two different thresholds to define low pay status as suggested by Uhlendorff (2006). Independent of the threshold used, persistence in low pay is detected – but this risk is exceeded by a much better chance of entering higher pay. The author concludes that low pay 'has a stepping-stone effect towards higher pay' (Cai 2014, p. 486).

Finally, broadening the scope of empirical evidence to that by Clark and Kanellopoulos (2013) for the wider European context, data from the European Community Household Panel (ECHP) is analysed for twelve countries over the period 1994 – 2001. After applying the OECD threshold of two-thirds of the mean hourly wages and random effects probit estimation, the authors find evidence for 'positive, statistically significant state dependence in every single country' [p. 122]. This ranges from 3.3 percent in Spain to 13.3 percent in Portugal. While the authors do not explicitly provide the probabilities of moving towards higher pay out of low pay, it can be inferred from the low pay persistence estimates given that they focus on a binary outcome variable – low pay or higher pay. Hence, we can expect that $P(Hp_t|Lp_{t-1}) = 1 - P(Lp_t|Lp_{t-1})$, which means that the probability of exiting the low-pay sector exceeds the risk staying on low pay in all twelve countries investigated.

In summary, the general consensus from the current literature (described above) points towards persistence in low pay, accompanied by a greater probability of a 'stepping stone effect' out of low-pay.[5]

[5] Though not listing the transition probabilities of low-paid employed, other studies (e.g. Knabe & Plum 2013, Fok et al. 2015) confirm that low pay acts as a stepping stone to higher pay.

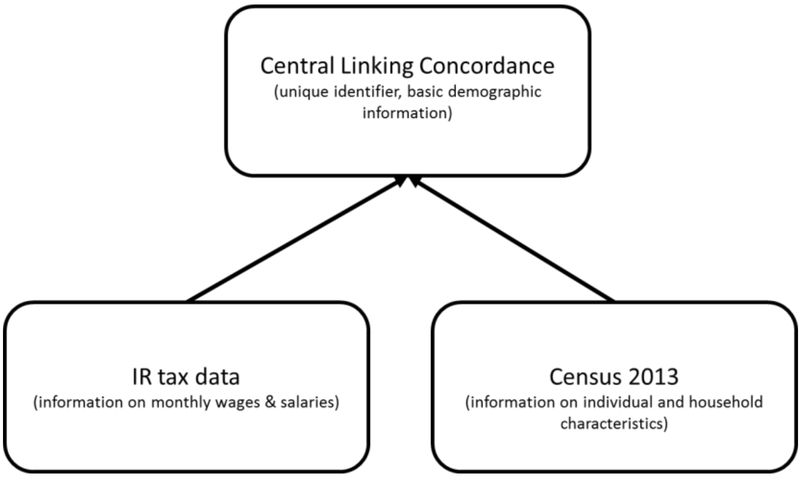
3. Data and Descriptive Statistics

3.1. Data

To empirically analyse persistence in low-paid employment we use administrative data from Statistics NZ's Integrated Data Infrastructure (IDI).[6] The IDI contains population-wide longitudinal microdata about individuals, households, and organisations. These data are sourced from government, and non-government agencies, as well as Statistics NZ surveys. The data are confidentialised by means of assigning a unique identifier for each individual.

The spine of the IDI is the Central Linking Concordance (CLC), which contains a list of all unique identifiers, along with the corresponding basic demographic information for each individual – gender, date of birth, and ethnicity. The unique identifier enables the researcher to link across multiple datasets within the IDI. For our purposes, and as shown in Figure 1, we link the CLC with two sources – tax data from Inland Revenue (IR) to gauge wage and salary information over time, and the 2013 Census survey (which provides a range of individual and household characteristics).

Figure 1: Data sources



Source: own representation.

The IR tax data are available from 1 April 1999 for the entirety of the NZ population. It includes monthly information on all sources of income. There are seven potential categories - i) wages & salary, ii) withholding payments, iii) benefits, iv) student allowance, v) paid parental leave, vi) pensions (superannuation) and vii) claimants compensations. For our analysis we use the gross wages before tax that come from wages and salaries. As an employee might be holding multiple jobs or change jobs within a month, there could be more than one entry per month per individual. As we are considering monthly wages, we aggregate all wage sources each month.

We focus on the time period of 2007 to 2013 and restrict our sample to male workers aged between 25 to 45 (inclusive) in 2007. The time period and population of interest exclusions are due to the following reasons:

[6] See Appendix **A2** for details of the disclaimer associated with use of the IDI.

- To control for individual characteristics in the forthcoming empirical analysis we use information provided by the 2013 Census. Therefore, we only consider wage data over the years 2007 to 2013 to ensure that no substantial changes on the individual level have occurred.
- As the IR tax data does not include information on working hours, we focus on a relatively homogenous sample (with respect to hours worked) of prime aged men. NZ specific OECD data[7] 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.

As long-term unemployed have different labour market prospects compared to short-term unemployed, Stewart (2007) restricts in his study the sample to individuals 'who have an intervening spell of employment' [p. 520] between two points in time. Following this approach and to avoid any influence from changes in the sample composition caused by entrants and exits to the sample, we restrict our sample to men who are observed receiving wages and salaries in minimum four months per year and for at least 70 periods across the period 2007 to 2013. Finally, the individual has to be employed each year in the month October, as this month will be treated as the interview month.[8]

To identify the low-paid employed, one strategy is using the OECD (1997) threshold of two-thirds of the median monthly. However, the wage distribution might not be constant over all months within a year. Therefore, an individual might be identified as exiting the low-pay sector because the threshold changed, though the position within the wage distribution did not change. To exclude influence of changes in the wage distribution, those men with their earnings belonging to the 10th lowest percentile are defined as low pay. This share is in line with the latest OECD estimate of low pay incidence for men in NZ (for 2015) of 12.8 percent. In a robustness analysis we switched to the OECD (1997) approach but the findings hardly changed.

To identify labour market transitions, we construct the following three markers:

(1) Point-in-time marker: following the dominant prevailing identification strategy of utilising annual information from surveys. This marker refers to the labour market position in a specific month of each year (here: October). Thus, changes in the labour market transitions between two consecutive years uncover the pecuniary movement in the month October between two successive years.

[7] Retrieved from OECD Stats homepage (https://stats.oecd.org/) on 18 June 2018. The OECD classifies persons who usually work 30 hours or more in the survey reference week as full-timers.

[8] We do not explicitly account for non-employment as we cannot identify whether the individual was searching for a job during that time. In a robust estimation we have trimmed the sample to individuals what were continuously employed throughout the year, but findings were qualitatively unaffected. As the estimation procedure is time intensive, we draw a 20 percent random subsample of $N = 144{,}942$.

(2) Mean monthly marker: this marker refers to the year specific mean monthly wage across the employed months. This approach helps to minimize the effect of the 'transitory earnings component' (Baker & Solon 2003).

(3) Monthly marker: to construct this marker, we first derive the share of months an individual is employed in the low pay sector for each year (in relation to total number of employed months). Accordingly, this number ranges between zero (not working at all in the low pay sector in any of the employed months) and one (working in all employed months in the low pay sector). Under this framework, we differentiate between two types of low pay status relative to higher pay. An individual is considered as experiencing weak low pay attachment if the share of low-paid months is below 50 percent[9]; and strong low pay attachment if working at least half of the employed months in the low pay sector.[10] Further, to be designated as higher pay, the individual would be observed as having no low pay months. Due to the low number of transitions between higher pay and a high share of low pay months, we refrained from a more detailed differentiation beyond two types of low pay attachment.

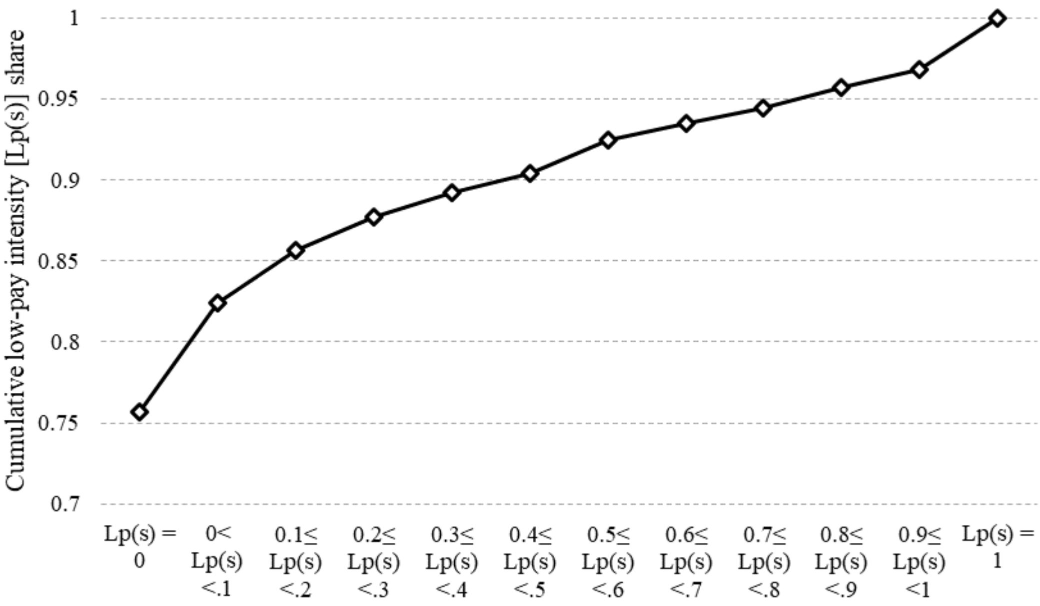
3.2. Descriptive profile

In Figure 2 we have calculated for each individual $i \in \{1, \dots, N\}$ in year $t \in \{1, \dots, T\}$ the annual low pay intensity LP_{it}^{s}, which is the number of months being employed in the low pay sector divided by the total number of employed months. Figure 2 shows the average cumulative distribution of low-pay intensity for the sample period of 2007 to 2013. We can see that on average, 75 percent of individuals do not have any low pay experience in a calendar year. Interestingly, Figure 2 illustrates a linear relationship between LP_{it}^{s} and its cumulative distribution. This pattern indicates that there is no evidence of clustering at certain levels of low pay intensity.

[9] Note, that as our sample is restricted to those receiving wages and salaries for a minimum for four months per year, to be classified as weak low pay, the minimum threshold is one low-paid month per year.

[10] This approach does not differentiate between consecutive and cyclical low pay months. To investigate this topic requires a different identifications strategy (e.g. Buhler et al. 2017) and remains an open task for future research.

Figure 2: Distribution of LP_{it}^{s}



Notes: Data sourced from IDI (2019). Authors' calculations. Based on a random subsample of population of interest $N = 144{,}942$. Time period = 2007 to 2013.

Next, we cross tabulate the wage groups defined using information on monthly variation (monthly marker) against the categories that would be formed under the prevailing point-in-time identification strategy; as well as, for comparison purposes, the mean monthly marker (Table 2a and Table 2b respectively). For this purpose, we use the labour market position of the month of October in a year.

Under the prevailing point-in-time markers, 10 percent of the sample is classified as low-paid. However, after accounting for monthly variation in wages and salary, we find that the number of individuals with some kind of low pay attachment (whether weak or strong) more than doubles to 25 percent. Just over half of these individuals have a weak attachment, with the remainder classified as strong attachment.

Focusing on the comparison between the prevailing strategy in prior literature (utilising point-in-time markers) and monthly markers, in Table 2a, provides further insights. Unsurprisingly, all individuals classified as higher pay using monthly information are also placed in that category using point-in-time information. Interestingly, at the other end of the spectrum, of those classed as having strong low pay (using monthly information), just over a fifth of these workers would be labelled as higher pay based on point-in-time markers.

Table 2a: 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	75.70
	Weak low pay$_t$	83.90	16.10	14.72
	Strong low pay$_t$	20.37	79.63	9.58
	Share$_t$	90.00	10.00	

Notes: Data sourced from IDI (2018). Authors' calculations. Based on a random subsample of population of interest N = 144,942. Time period = 2007 to 2013.

Table 2b: Prevalence of low pay employment

		Mean monthly Marker		
		Higher pay$_t$	*Low pay$_t$*	Share$_t$
Monthly marker	*Higher pay$_t$*	99.99	0.01	75.70
	Weak low pay$_t$	91.66	8.34	14.72
	Strong low pay$_t$	8.55	91.45	9.58
	Share$_t$	90.00	10.00	

Notes: Data sourced from IDI (2018). Authors' calculations. Based on a random subsample of population of interest N = 144,942. Time period = 2007 to 2013.

Next, to describe the correlation in labour market position over time, transition matrices are generated for point-in-time marker (Table 3a), mean monthly marker (Table 3b) and monthly marker (Table 3c). Each matrix provides the probability of being in one labour market position at time t conditional on the labour market position at $t-1$ and provide some first indication on persistence in low pay.

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

	Higher pay$_t$	*Low-pay$_t$*	*Total$_{t-1}$*
Higher pay$_{t-1}$	95.86	4.14	90.00
Low-pay$_{t-1}$	37.32	62.68	10.00
Total$_t$	90.01	9.99	

Notes: Data sourced from IDI (2018). Authors' calculations. Based on a random subsample of population of interest $N = 144{,}942$. Time period = 2007 to 2013.

Table 3b: Transition matrix of the labour market positions (Mean monthly Marker)

	Higher pay$_t$	*Low-pay$_t$*	*Total$_{t-1}$*
Higher pay$_{t-1}$	97.64	2.36	90.00
Low-pay$_{t-1}$	21.21	78.79	10.00
Total $_t$	90.00	10.00	

Notes: Data sourced from IDI (2018). Authors' calculations. Based on a random subsample of population of interest $N = 144{,}942$. Time period = 2007 to 2013.

Table 3c: 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$_{t-1}$	90.67	8.61	0.72	75.53
Weak low pay$_{t-1}$	47.16	40.53	12.30	14.90
Strong low pay$_{t-1}$	5.45	19.31	75.24	9.57
Total$_t$	76.03	14.39	9.58	

Notes: Data sourced from IDI (2018). Authors' calculations. Based on a random subsample of population of interest $N = 144{,}942$. Time period = 2007 to 2013.

When applying point-in-time markers, the probability of being higher pay conditional on experiencing higher pay in the preceding year is very high (95.86 percent). A similar result is found when applying (mean) monthly markers – conditional probability of 90.67 (97.64) percent.

The nuances between **Error! Reference source not found.** and **Error! Reference source not found./Error! Reference source not found.** emerge when we focus on individuals with experience in the low pay sector. For example, based on the point-in-time markers, conditional on experiencing low pay in the prior year, an individual appears to be less likely to be higher pay (37.32 percent) than low pay (62.68 percent) in the subsequent time period. When applying the mean monthly marker, low pay persistence increases (78.79 percent) and less individuals manage to switch into higher pay (21.21 percent). Moreover, after accounting for monthly variation in wages, it is evident that the transition probabilities are markedly different for those with weak versus strong low pay attachment. As shown in **Error! Reference source not found.**, for those experiencing weak low pay, these individuals are equally likely to experience weak low pay in the next year, as they are to have higher pay (both probabilities just over 40 percent). In contrast, for individuals with a strong attachment to the low pay sector, they have a conditional probability of 75 percent to experience a high number of low pay months in the following year.

It should also be noted from **Error! Reference source not found.** that transitions from one extreme to the other appear to be rare. For example, the share of individuals moving from higher pay to strong low pay is below one percent, and the figure for those moving in the opposite direction is just below three percent.

4. Econometric Model

To identify persistence in low pay, we apply a first-order Markov process: underlying assumption is that the lagged version of the dependent variable has a genuine impact on the outcome variable.[11] Such dynamic models have been applied in numerous low pay studies and

[11] To estimate transition probabilities, this approach has been applied in several different contexts, for instance unemployment persistence (e.g. Arulampalam et al. 2000), state dependence in low income (e.g. Biewen 2009) or the interrelation of poor health and non-employment (Haan & Myck 2009).

thus is following in the footsteps of Uhlendorff (2006), Mosthaf (2014), Fok et al. (2015), and most recently Cai et al. (2017).

4.1. Point-in-time marker and mean monthly marker

In the case of point-in-time marker (pit) and mean monthly marker (mm), we consider the following outcome variables: y_{it}^{pit} equals 1 if individual i was in October of year t on low pay and 0 else; y_{it}^{mm} equals one if the mean monthly wage across all employed months belongs to the lowest percentile and 0 else. [12] Thus, the probability being on low pay is

$$P\left(y_{it}^{pit} = 1 | y_{it-1}^{pit}, X_i, \alpha_i^{pit}\right) = \frac{exp\left(X_i\beta_{pit} + y_{it-1}^{pit}\gamma_{pit} + \alpha_i^{pit}\right)}{1 + exp\left(X_i\beta_{pit} + y_{it-1}^{pit}\gamma_{pit} + \alpha_i^{pit}\right)} \tag{1a}$$

and

$$P(y_{it}^{mm} = 1 | y_{it-1}^{mm}, X_i, \alpha_i^{mm}) = \frac{exp(X_i\beta_{mm} + y_{it-1}^{mm}\gamma_{mm} + \alpha_i^{mm})}{1 + exp(X_i\beta_{mm} + y_{it-1}^{mm}\gamma_{mm} + \alpha_i^{mm})} \tag{1b}$$

X_i refers to a vector of explanatory variables. These include ethnicity, educational attainment, age, marital status and binary indicators for long-term disability and English-speaking household[13]. Moreover, a categorical variable on the number of employment spells in included which runs from 4 to 12. y_{it-1}^{pit}, resp. y_{it-1}^{mm}, is a vector of dummy variables with respect to the lagged labour market position. Additionally, as individuals may differ in unobservables such as motivation or ability (Heckman, 1981a), to control for unobserved heterogeneity we include a time-invariant error term α_i^{pit}, resp. α_i^{mm}.

A key issue in this type of specification is that the labour market position in the initial period might not be randomly distributed, due to a correlation between the time-invariant error term and the initial conditions (Heckman 1981b).[14] As Skrondal & Rabe-Hesketh (2014) have pointed out, not accounting for unobserved heterogeneity and its correlation with the initial labour market position might result in biased estimations. To take care of the 'initial conditions problem', we follow the suggestion of Wooldridge (2005) by applying a conditional random-intercept model:[15]

$$\alpha_i^{pit} = y_{i0}^{pit}\lambda_{pit} + \kappa_i^{pit} \tag{2a}$$

and

[12] Due to the lack of relevant information, a further decomposition of the labour market position (e.g. unemployed, inactive, self-employed) is not possible.

[13] The ethnicity categories are NZ European, Māori, Pacific, Asian, and other ethnicities. The age variable refers to the age in 2007 and the categories are 25-30, 31-35, 36-40 and above 40. The educational levels are Level 1-4 certificate, Level 5-6 certificate, and tertiary or higher (i.e. Bachelor, Master or Doctorate Degree). Note that as we use data from the 2013 Census, none on the individual or household level are time-varying.

[14] As a robustness estimation we also restricted the sample to those individuals who were on low pay in 2007. However, this does not affect the results.

[15] In Wooldridge (2005) it is suggested to include the time means of the explanatory variables, however as we only consider time constant explanatory variables this aspect is dropped.

$$\alpha_i^{mm} = y_{i0}^{mm}\lambda_{pit} + \kappa_i^{mm} \tag{2b}$$

It is assumed that the random effects are normally distributed $\kappa_i^{pit} \sim N\left(0, \sigma_{\kappa_{pit}}^2\right)$, resp. $\kappa_i^{mm} \sim N\left(0, \sigma_{\kappa_{mm}}^2\right)$. The likelihood function now takes the following form:

$$L_i^{pit} = \int_{-\infty}^{\infty} \prod_{t=1}^{T} \left\{ \frac{exp\left(X_i\beta_{pit} + y_{it-1}^{pit}\gamma_{pit} + y_{i0}^{pit}\lambda_{pit} + \kappa_i^{pit}\right)}{1 + exp\left(X_i\beta_{pit} + y_{it-1}^{pit}\gamma_{pit} + y_{i0}^{pit}\lambda_{pit} + \kappa_i^{pit}\right)} \right\} f\left(\kappa^{pit}\right) d\kappa^{pit} \tag{3a}$$

and

$$L_i^{mm} = \int_{-\infty}^{\infty} \prod_{t=1}^{T} \left\{ \frac{exp(X_i\beta_{mm} + y_{it-1}^{mm}\gamma_{mm} + y_{i0}^{mm}\lambda_{mm} + \kappa_i^{mm})}{1 + exp(X_i\beta_{mm} + y_{it-1}^{mm}\gamma_{mm} + y_{i0}^{mm}\lambda_{mm} + \kappa_i^{mm})} \right\} f(\kappa^{mm}) d\kappa^{mm} \tag{3b}$$

The integrals can be approximated with Gauss–Hermite quadrature.

4.2. Monthly marker

To estimate state dependence in the low pay intensity, we construct the monthly marker that differentiates between higher pay, weak and strong low pay attachment. In the following, we consider three labour market positions: j is equal to 1 if the individual has higher pay (i.e. no low pay months), 2 if the individual has weak low pay attachment and 3 if the individual has strong low pay attachment (as defined in Section 4).[16] Thus, the probability of individual $i \in \{1, \dots, N\}$ to be in the labour market state y_{it} at time point $t \in \{1, \dots, T\}$ can be written as (already implementing the suggestion of Wooldridge (2005)):

$$P\left(y_{it} = j | y_{it-1}, X_i, \kappa_{ji}\right) = \frac{exp(X_i'\beta_j + y_{it-1}'\gamma_j + y_{i0}'\lambda + \kappa_{ji})}{\sum_{k=1}^{3} exp(X_i'\beta_j + y_{it-1}'\gamma_j + y_{i0}'\lambda + \kappa_{ji})} \tag{4}$$

The reference category is higher pay, and therefore coefficient vectors β_1, γ_1 and α_{i1} in equation (4) are set equal to zero. It is assumed that the random effects are normally distributed $\kappa_{ji} \sim N\left(0, \sigma_{\kappa_j}^2\right)$ and are correlated by ρ_κ. The likelihood function for individual i takes the following form:

$$L_i = \int_{-\infty}^{\infty} \prod_{t=1}^{T} \prod_{j=2}^{3} \left\{ \frac{exp(X_i'\beta_j + \mathrm{Emp}_{it-1}'\theta_j + y_{it-1}'\gamma_j + y_{i0}'\lambda + \kappa_{ji})}{1 + \sum_{j=2}^{3} exp(X_i'\beta_j + \mathrm{Emp}_{it-1}'\theta_j + y_{it-1}'\gamma_j + y_{i0}'\lambda + \kappa_{ji})} \right\}^{d_{ijt}} f(\kappa) d\kappa \tag{5}$$

Note that d_{ijt} equals 1 if individual i is in state j at time point t and zero otherwise. To integrate out the random effects, we use maximum simulated likelihood. Using random numbers based on prime numbers (also called Halton draws, see Train 2009), two times R standard uniform distributed draws are derived and transformed by the inverse cumulative standard normal distribution. For each draw, the likelihood is derived for each observation, multiplied over all individuals and time-points and finally averaged over all draws (using 75 draws):

[16] As the outcome variable is a count variable (number of low pay months), we also applied a bivariate random-effects probit model (e.g. Stewart 2007). However, findings were not affected.

$$MSL = \prod_{i=1}^{N} \frac{1}{R} \sum_{r=1}^{R} \left\{ \prod_{t=1}^{T_i} P_{it}(\kappa_1^r, \kappa_2^r) \right\} \tag{6}$$

5. Results

5.1. Estimation results

Initially, we present the estimated coefficients using the prevailing strategy of point-in-time markers for low pay status (Table 4, first column). Individuals are differentiated into low pay and higher pay according to their labour market position in the month October, and a random effects logit model is applied. In line with the extant literature in this space, our regression results in Table 4 indicate that being low-paid in the previous period significantly increases the risk of being low-paid in the next time period, compared to the reference category of being higher-paid at $t-1$. Moreover, being low-paid employed in the initial period of our sample timeframe (2007) is also associated with a greater risk of experiencing low pay employment in the future, relative to experiencing higher pay. When we turn to mean monthly marker (Table 4, second column), a change is especially apparent: the seize of the coefficient referring to the effect of past low-pay experience nearly doubles.

Table 4: Regression results on low pay persistence (point-in-time marker & mean monthly marker)

	point-in-time marker *Low pay$_t$*	mean monthly marker *Low pay$_t$*
Labour market position at $t-1$		
Higher pay$_{t-1}$	*reference category*	*reference category*
Low pay$_{t-1}$	1.724***	3.233***
	(0.042)	(0.057)
Labour market position at $t=0$		
Higher pay$_{t=0}$	*reference category*	*reference category*
Low pay$_{t=0}$	2.858***	3.290***
	(0.073)	(0.112)
Explanatory variables	✓	✓
σ_κ	2.947***	3.197***
	(0.123)	(0.182)
Log Likelihood	-24 809.755	-17 398.916
N	124 236	124 236

Notes: Data sourced from IDI (2018). Authors' calculations. Based on a random subsample of population of interest $N = 144{,}942$. Time period = 2007 to 2013. Numbers in parenthesis refer to standard errors. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels respectively. Explanatory variables include ethnicity, age, educational attainment, marital status, number of employment spells and binary indicators for long-term disability and English-speaking household.

We next turn to estimation results using dynamic random effects multinomial logit models, where monthly variation in low pay is accounted for, via the intensity of attachment to the low pay sector (weak versus strong). As shown in Table 5, higher pay is again used as the reference category.

Table 5: Regression results on low pay persistence (Monthly marker)

	Weak low pay$_t$	*Strong low pay$_t$*
Low pay status at $t-1$		
Higher pay$_{t-1}$	*reference category*	
Weak low pay$_{t-1}$	1.192***	2.394***
	(0.030)	(0.060)
Strong low pay$_{t-1}$	2.733***	5.772***
	(0.060)	(0.082)
Low pay status at $t=0$		
Higher pay$_{t=0}$	*reference category*	
Weak low pay$_{t=0}$	1.312***	1.901***
	(0.040)	(0.075)
Strong low pay$_{t=0}$	1.681***	3.506***
	(0.067)	(0.124)
Explanatory variables	✓	✓
$\sigma_{\kappa_1}^2$	1.330***	
	(0.055)	
$\sigma_{\kappa_2}^2$	3.394***	
	(0.198)	
$\rho_\kappa \sigma_{\kappa_1} \sigma_{\kappa_2}$	1.755***	
	(0.094)	
Log Likelihood	-53 435.076	
N	124 236	

Notes: Data sourced from IDI (2018). Authors' calculations. Based on a random subsample of population of interest $N = 144{,}942$. Time period = 2007 to 2013. Numbers in parenthesis refer to standard errors. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels respectively. Explanatory variables include ethnicity, age, educational attainment, marital status, number of employment spells and binary indicators for long-term disability and English-speaking household.

Estimated coefficients in Table 5 indicate that there is persistence in attachment to the low pay sector. Irrespective of whether the labour market status in the preceding time period was weak or strong low pay, an individual will be more likely to experience either of these outcomes, relative to the reference category of higher pay. Furthermore, the magnitude of our coefficients indicate that the likelihood of experiencing low pay employment correlates with the intensity of attachment.

With respect to the coefficients that capture the effect of initial labour market position, we find indications that those with a weak low pay status in 2007 are either more likely to stay in this labour market position over the sample timeframe, or become strongly attached to the low pay sector, compared to an individual without any low pay experience in that initial year. A similar pattern is observed for those who were strongly attached to the low pay sector in 2007, with more pronounced effects estimated.

Note that in both Table 4 and Table 5 we find evidence of unobserved heterogeneity, the variances of the random effect error terms are of noticeable size and highly significant. Moreover, we can see in Table 5 that the random effects are significantly positive correlated, indicating that an individual who is more likely of weak low pay is also more likely of strong low pay compared to higher pay, keeping all other aspects constant.

5.2. Transition probabilities

We next calculate the probability of being in a particular labour market state at time point t conditional on the labour market position at $t-1$ and the initial labour market position in $t=0$. For Table 6, it is provided for each of the two possible labour market positions at $t-1$ based on point-in-time marker and mean monthly marker information – low pay and higher pay.

Table 6: Predicted transition probabilities (point-in-time marker & mean monthly marker)

	point-in-time marker		mean monthly marker	
	At $t=0$		At $t=0$	
	Higher Pay	*Low Pay*	*Higher Pay*	*Low Pay*
$P(Higherpay_t \mid Higherpay_{t-1})$	0.984	0.801	0.992	0.845
	(0.018)	(0.111)	(0.011)	(0.102)
$P(Lowpay_t \mid Higherpay_{t-1})$	0.016	0.199	0.008	0.155
	(0.018)	(0.111)	(0.011)	(0.102)
$P(Higherpay_t \mid Low\ pay_{t-1})$	0.920	0.449	0.852	0.219
	(0.066)	(0.126)	(0.099)	(0.099)
$P(Lowpay_t \mid Low\ pay_{t-1})$	0.080	0.551	0.148	0.781
	(0.066)	(0.126)	(0.099)	(0.099)

Notes: Data sourced from IDI (2018). Authors' calculations. Based on a random subsample of population of interest $N = 144{,}942$. Time period = 2007 to 2013. Numbers in parenthesis refer to standard deviations.

Referring to the point-in-time marker, for those who were on higher pay in the initial period (1st column of Table 6), the chances staying on low pay are very little – on average 8 percent – and is exceeded by the chances switching to higher pay (92 percent) if on low pay at $t-1$. Therefore, for this group low paid jobs might be considered as a gateway to higher paid ones. When conditioning on being on low pay at $t=0$ there is clear evidence of persistence in low pay (2nd column of Table 6), accompanied by a somewhat lower probability of moving onto higher pay. The likelihood of being on low pay in time period t if low-paid in time period $t-1$ and low-paid initially is 55.2 percent, and for these individuals, the likelihood of higher pay in time period t is 44.9 percent. These numbers are on a comparable level to that found for Germany by Uhlendorff (2006) of 40.8 and 48.9 percent respectively[17]. Therefore, in line with

[17] These figures are based on Threshold 1 in Uhlendorff (2006) which equates to two thirds of the median wage, while Threshold 2 which is based on the first quintile provided similar figures of 43.1 and 48.4 percent. Numbers do not sum to 100 as the author also accounts for the risk becoming non-employed.

the international evidence in this space (see Table 1), when utilising the prevailing identification strategy there is evidence of sizable stepping stone effects for low pay workers.

When applying the monthly mean marker, the effect of past low pay experience on the labour market prospects changes clearly. First, for those who were initially on higher pay, the upward mobility declines: the chances staying on low pay nearly doubles to 14.8 percent. More interestingly, referring to those who were on low-pay at $t = 0$, the change is even more apparent: the chance staying on low pay increases on average by 23 percentage points to 78.1 percent. This difference is especially striking as in both markers, by construction the seize of the initially low paid employed equals. Hence, for those who were initially on higher pay, low pay might still be considered as a stepping stone to higher pay, the positive effect noticeably declines for those initially on low pay.

The difference between both identification strategies also becomes visible when calculating the average partial effect (APE) of becoming higher paid for being on higher pay at $t-1$ and $t=0$ and being on low pay in both time points (this equates the difference of the grey cells of Table 6). The APE becoming higher paid declines by 53.4 percentage points when using the point-in-time marker and declines by 77.3 percentage points when using the mean monthly marker.[18]

Table 7: Predicted transition probabilities (Monthly markers)

	At $t = 0$		
	Higher Pay	*Weak low pay*	*Strong low pay*
$P(\mathit{Higher\ pay}_t \mid \mathit{Higher\ pay}_{t-1})$	0.929	0.798	0.716
	(0.077)	(0.130)	(0.145)
$P(\mathit{Weak\ low\ pay}_t \mid \mathit{Higher\ pay}_{t-1})$	0.068	0.189	0.231
	(0.071)	(0.115)	(0.104)
$P(\mathit{Strong\ low\ pay}_t \mid \mathit{Higher\ pay}_{t-1})$	0.003	0.014	0.053
	(0.008)	(0.021)	(0.054)
$P(\mathit{Higher\ pay}_t \mid \mathit{Weak\ low\ pay}_{t-1})$	0.808	0.545	0.386
	(0.130)	(0.142)	(0.128)
$P(\mathit{Weak\ low\ pay}_t \mid \mathit{Weak\ low\ pay}_{t-1})$	0.170	0.375	0.363
	(0.106)	(0.102)	(0.062)
$P(\mathit{Strong\ low\ pay}_t \mid \mathit{Weak\ low\ pay}_{t-1})$	0.022	0.080	0.251
	(0.033)	(0.057)	(0.103)
$P(\mathit{Higher\ pay}_t \mid \mathit{Strong\ low\ pay}_{t-1})$	0.416	0.138	0.048
	(0.134)	(0.062)	(0.026)
$P(\mathit{Weak\ low\ pay}_t \mid \mathit{Strong\ low\ pay}_{t-1})$	0.343	0.393	0.192
	(0.063)	(0.062)	(0.049)
$P(\mathit{Strong\ low\ pay}_t \mid \mathit{Strong\ low\ pay}_{t-1})$	0.241	0.470	0.760
	(0.104)	(0.102)	(0.069)

Notes: Data sourced from IDI (2018). Authors' calculations. Based on a random subsample of population of interest $N = 144{,}942$. Time period = 2007 to 2013. Numbers in parenthesis refer to standard deviations.

[18] Significantly different at the 1 percent level in both cases.

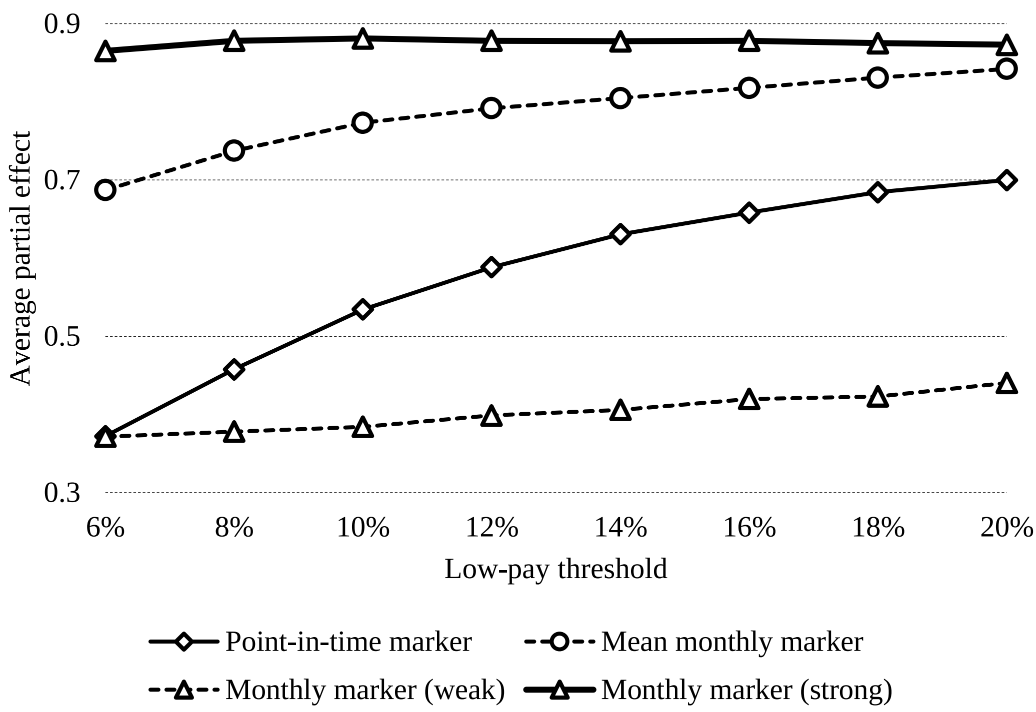
In Table 7, transition probabilities of the monthly marker strategy are provided for three labour market positions (again differentiated according to the labour market position at $t = 0$), which are dependent on previous labour market position. For those on weak low pay at $t = 0$, there is a high level of persistence, accompanied by a higher likelihood of exiting this state and moving up the ladder towards higher pay (2nd column). If the individual experienced weak low pay at $t - 1$, the probability of being weak low pay at time period t is 37.5 percent, while this probability is exceeded by being higher pay of 54.5 percent. Comparable numbers are found when looking at the labour market prospects of the low paid when using the point-in-time marker. The APE becoming higher paid employed between being on higher pay at $t - 1$ and $t = 0$ and being on weak low pay attachment in both time points (difference of grey cells in 1st and 2nd columns in Table 7) is 38.4 percentage points (significantly different at the 1 percent level).

However, the same pattern does not follow when we focus on those with a strong level of low pay attachment (3rd column). Conditioning the transition predictions on strong low pay at $t = 0$, the likelihood of staying strong low pay far exceeds the probability of either of the two other outcomes – weak low pay or higher pay. After experiencing strong low pay at $t - 1$, the probability of being strong low pay at time period t is 76.0 percent, while the probability of exiting towards higher pay is just 4.8 percent. Moreover, the APE becoming higher paid employed between being on higher pay at $t - 1$ and $t = 0$ and being on strong low pay attachment in both time points (difference of grey cells in 1st and 3rd columns in Table 7) is 88.1 percentage points (significantly different at the 1 percent level). Thus, unlike the evidence presented in the existing studies, as well as when we used point-in-time marker information, for individuals whose attachment to the low pay sector is strong, low pay jobs do not operate as stepping stones towards higher pay, but are effectively dead-ends. Thus, they are highly likely to be stuck in a low pay cycle with little chance of climbing up the salary ladder and exiting the low pay sector.

5.3. Variation of the low pay threshold

As a robustness check, we repeated our estimation and use different percentile levels for our low pay threshold (6, 8, 12, 14, 16, 18 and 20 percent). To visualize our findings, we calculate for each threshold the average partial effect of becoming higher paid following the above definition.

Figure 3: Robustness estimation
(Average partial effects for different low pay cut-off points)



Notes: Data sourced from IDI (2018). Authors' calculations. Based on a random subsample of population of interest $N = 144{,}942$. Time period = 2007 to 2013.

There are two noteworthy findings in Figure 3. First, the APE for weak and strong low pay attachment hardly changes for the different threshold cut-off points. For example, the APE for strong low pay attachment is 86.5 percentage points at a threshold of 6 percent and increases to 87.3 percentage points for 20 percentage points. Second, the APE of the point-in-time marker and the mean monthly marker are sensitive to the low pay cut off point. The first one increases from 37.2 percentage points (threshold of 6 percent) to 70.0 percentage points (threshold of 20 percent), and the second from 68.7 percentage points to 84.2 percentage points.

6. Conclusions

Prior studies have estimated the extent to which individuals who were working in the low wage sector at time point $t-1$ are likely to find themselves again in this labour market position in the subsequent period t. While the literature does point to significant levels of persistence in low pay, there is evidence that the probability of transitioning towards higher pay is usually higher (see Uhlendorff 2006, Mosthaf 2014, Cai et al. 2017). These studies therefore signal steppingstone effects from low pay being of greater likelihood relative to low-paid employment being a dead-end. Importantly, these past studies have had to rely on survey data and identification of low pay status based on one time point per year. In our research, we are able to delve into a finer level of data detail by employing monthly administrative wage and salary records for the NZ working population.

Our data permits differentiation of those employed into three groups: those without any low pay experience (higher pay); those spending less than half of their employed months in the low pay sector (weak low pay); and the final group spending at least fifty percent of their employed time in low pay (strong low pay). These three groups signal the intensity of attachment to the low pay sector on an annual basis.

To estimate the likelihood of low pay persistence (i.e. state dependence in low pay), as well as the probability of movement towards higher pay (i.e. stepping stone effect) we conduct two separate empirical analyses. One using the prevailing identification strategy in the literature based on a point-in-time marker for low pay status, and the other utilising information on the intensity of attachment to the low pay sector, derived from the monthly information.

Under the traditional approach of using a point-in-time marker for low pay status, we find similar results to those found in the extant literature. We find that the likelihood of being low-paid in time period t if being initially low-paid and likewise in time period $t-1$ is 55.1 percent, while the likelihood of higher pay in t is 44.9 percent.

After differentiating our analysis according to intensity of attachment to the low pay sector, we find heterogeneous results. For individuals with weak low pay status at time $t=0$, there is a high level of state dependence, accompanied by a higher likelihood of the low pay job being a stepping stone to higher pay (37.5 versus 54.5 percent). These results accord with the pattern found when using point-in-time markers. However, this finding does not repeat for those with initially strong low pay attachment. For these individuals, the probability of staying strong low pay is 76.0 percent, while the probability of moving into higher pay is just 4.8 percent. It is therefore clear that low-paid jobs are not stepping stones for this group of individuals. These findings are further emphasized when we utilise all monthly information to produce a mean monthly marker.

Our findings have direct policy implications with respect to welfare reforms. Thus far, prior empirical evidence has generally been supportive of the 'work-first approach' to workforce participation (e.g. Buddelmeyer et al. 2010[19], Fok et al. 2015, Cai et al. 2017), as well as strategies such as abolishing the high minimum wage level to promote employment, 'even if the jobs created are low-paid' [Cai et al. 2017, p. 30]. These approaches are based on the premise that 'any job is helpful' with respect to climbing up the wage ladder, and future wage and labour market prospects – i.e. that low-paid jobs are more likely to be stepping stones than dead-ends. However, our results indicate that these approaches may not be appropriate for those with a strong attachment to the low pay sector. Our findings for this particular group within the working population align more closely with the hypothesis that not every job contributes to the individuals' human capital level (e.g. Stewart 2007). For those with a strong attachment, these jobs are likely to be dead-ends, with negligible hope of exiting out of this low pay cycle, towards higher pay.

[19] Buddelmeyer et al. (2010) label it 'jobs-first approach'.

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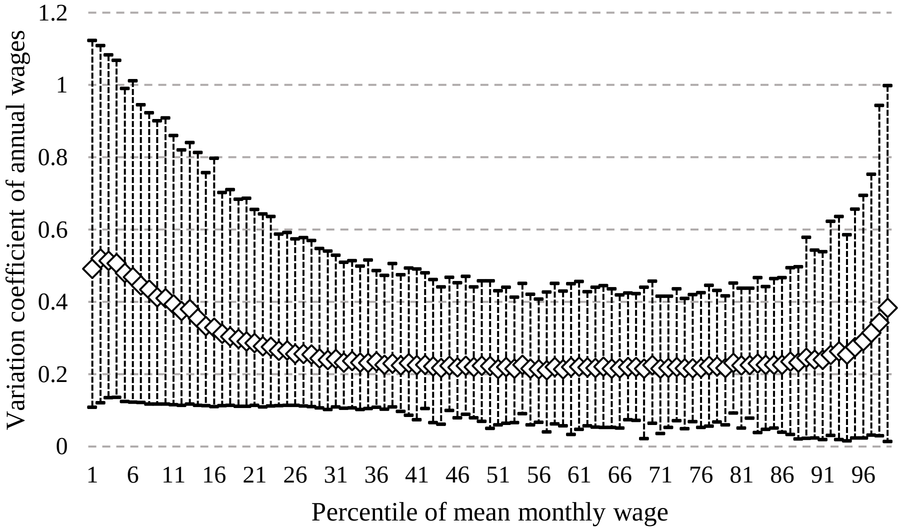
Appendix

A1. Within-year wage variation

To provide descriptive evidence on in-year wage variation, we calculate for each individual the annual variation coefficient $\left(\frac{\mathrm{sd}(\mathrm{wage}_{it})}{\mathrm{mean}(\mathrm{wage}_{it})}\right)$ of wages for the period 2007 to 2013. Figure A 1 shows the mean variation coefficient distribution with respect to the wage distribution. A U-shape distribution can be found, indicating that the mean variation coefficient is especially prominent at the lower and upper tail of the distribution. For example, the mean value is 0.22 for the 50th percentile but 0.48 for the 5th and 0.41 for the 10th. The increase of the mean variation coefficient becomes apparent after the 95th percentile.

Figure A 1: Wage variation coefficient



Notes: IDI (2019) and own calculations, $N = 144{,}942$. The diamond shows the mean variation coefficient across the period 2007 to 2013. The upper (lower) bar shows the 90th (5th) percentile.

A2. Disclaimer

The results in this paper are not official statistics, they have been created for research purposes from the Integrated Data Infrastructure (IDI), managed by Statistics New Zealand. The opinions, findings, recommendations, and conclusions expressed in this paper are those of the authors, not Statistics NZ.

The results are based in part on tax data supplied by Inland Revenue to Statistics NZ under the Tax Administration Act 1994. This tax data must be used only for statistical purposes, and no individual information may be published or disclosed in any other form, or provided to Inland Revenue for administrative or regulatory purposes. Any person who has had access to the unit record data has certified that they have been shown, have read, and have understood section 81 of the Tax Administration Act 1994, which relates to secrecy. Any discussion of data limitations or weaknesses is in the context of using the IDI for statistical purposes, and is not related to the data's ability to support Inland Revenue's core operational requirements.

Access to the anonymised data used in this study was provided by Statistics NZ in accordance with security and confidentiality provisions of the Statistics Act 1975. Only people authorised by the Statistics Act 1975 are allowed to see data about a particular person, household, business, or organisation, and the results in this paper have been confidentialised to protect these groups from identification. Careful consideration has been given to the privacy, security, and confidentiality issues associated with using administrative and survey data in the IDI.

Further detail can be found in the Privacy impact assessment for the Integrated Data Infrastructure available from www.stats.govt.nz.