ECONOMIC RECORD

ECONOMIC RECORD, 2021

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

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*The economic literature considers a low-paid job as a 'stepping-stone' if it improves jobless individuals' future likelihood of transitioning towards higher pay. The majority of empirical studies rely on annual surveys and are unable to differentiate individuals by their degree of attachment to the low-paid sector. Using population-wide administrative data with monthly earnings information, our study first confirms the stepping-stone effect. However, our analysis indicates that annual survey-based evidence on the future likelihood of transitioning to higher-paid jobs is likely overstated when respective groups of low-paid workers and non-employed individuals are identified by binary indicators.*

## I *Introduction*

Recent years have witnessed a surge in public debate on rising economic inequality levels [see, for example, Piketty, 2015; Berg & Ostry, 2017]. Moreover, the ongoing political discussion on the evolution of wage inequality is often fuelled by either an increasing or a stagnating share of low-paid employment. For instance, the average low-pay incidence among the member nations of the Organisation for Economic Co-operation and Development in 2015 was estimated to be as high as 16 per cent, although with remarkable gender and country differences. On this account, there has been a substantial increase in the number of empirical studies analysing the labour market prospects of low-paid workers. These studies' primary focus is to empirically examine the extent to which low-paid employment may operate as a 'stepping-stone' towards improved labour market prospects (characterised by better pay), especially for unemployed workers.

Employment in low-pay sectors can often be perceived as an indicator of worker quality by potential employers. However, despite bearing considerable future employability risks, low-paid employment is usually characterised as a temporary labour market position, operating as 'a trajectory to "decent" jobs' (Fok *et al*., 2015, p. 892) rather than being a dead-end [e.g. Uhlendorff, 2006; Buddelmeyer *et al*., 2010; Cai, 2014; Mosthaf, 2014; Fok *et al*., 2015; Cai *et al*., 2018]. Notably, one of the salient features of the previous literature on testing the stepping-stone effect of low-paid employment is the use of individual-level surveys that allow assessment of changes in labour market conditions only at the annual level. This study aims to provide novel insights into the stepping-stone effect of low-paid employment using population-wide monthly data on employment and earnings that incorporate important individual-level heterogeneities that otherwise remain unaccounted for in annual surveys.

As already highlighted, the stepping-stone effect refers to an increase in unemployed workers' likelihood of transitioning into higher-paid employment following a transitory spell in low-paid jobs. However, the theoretical explanation presented in the extant literature on the impact of a low-paid job on future labour market prospects presents two broadly contradictory arguments. On the one hand, low pay might have a positive effect on the human capital level (Mosthaf, 2014; Cai

JEL classifications: J62, J31, C33, C55
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doi: 10.1111/1475-4932.12609

*et al.*, 2018) and signal the willingness to work (Knabe & Plum, 2013). At the same time, being previously employed in some kind of 'low-quality job' might be perceived as a negative productivity signal (McCormick, 1990; Acemoglu, 2001). In support of this hypothesis, Layard *et al.* (2005; p. 249) find evidence to argue that '[w]hile unemployment is a bad signal, being in a low-quality job may well be a worse one'. Given these opposing views, determining whether low-paid jobs actually operate as a stepping-stone is a crucial empirical question.

The stepping-stone effect of low pay can be identified by estimating the *genuine* impact of *past* labour market status on *future* labour market outcome. To this end, in his seminal paper Stewart (2007) suggests using dynamic nonlinear random-effects models, a standard approach commonly adopted in the relevant research space. It is also worth noting that the majority of the related literature analyses labour market dynamics using individual-level information on earnings and labour market status from longitudinal surveys like the British Household Panel Survey (BHPS), the German Socio-Economic Panel, or the Household Income and Labour Dynamics in Australia (HILDA) Survey. While these surveys provide a rich set of individual and labour market-related information, a major limitation of such data sources is that relevant employment-related data are collected only at a particular time period in the year. Importantly, a few recent studies indicate that the type of time aggregation might affect estimation of the *true* state dependence of a labour market status. For example, Bhuller *et al.* (2017) show in their Norwegian study on welfare benefit receipt dynamics that persistence in benefit receipts increases when switching from a model that uses information at the monthly level to one at the annual level.

On a related note, relying on survey-based evidence, while past studies have shown that the unemployment duration has a significant impact on the magnitude of the stepping-stone effect [e.g. Plum, 2019], not much is known about the employment history of those on low pay. For example, annual surveys may not reveal whether low-paid employment observed at a specific time point relates to workers with a strong prior attachment to the low-pay sector or is just a transitory labour market phase. In the two highlighted cases, we expect different likelihoods of entering higher-paid employment, which eventually determines whether low pay can be perceived as a stepping-stone.

We circumvent the above empirical issue specifically arising from a lack of frequently observed data points by making use of administrative tax records at the monthly level. To the best of our knowledge, this is the first study to consider the intensity with which an individual is observed to be in the low-pay sector within a year. To be specific, we begin our analysis by classifying our sample into several distinct groups based on individuals' monthly labour market status in the 12 months prior to the evaluation period. The reference category incorporates those who were continuously non-employed for all 12 months and we compare the reference group's probability of entering higher pay with those continuously in low-paid employed. We further compare our findings with the more commonly used identification strategy applied to individual-level data drawn from annual surveys. More specifically, in studies using longitudinal surveys, most dynamic empirical models incorporate the labour market position observed only at the time of survey in the preceding year as the lagged indicator of labour market status (e.g. whether or not on low pay) without being able to perform further differentiation of the low-pay intensity.

Our descriptive analysis shows that there are two distinct low-paid groups. One group has a strong attachment to the low-pay sector (either working continuously in low-paid job(s) or moving between non-employment and low pay), while the second group moves between low and higher pay. Looking at the descriptive evidence of the conditional probability of entering higher-paid employment, the differences appear to be stark: 56 per cent of individuals who have both low- and higher-pay periods in the previous 12 months will be on higher pay in the next month, whereas this proportion drops to 4.9 per cent for those who were continuously low-paid in the last 12 months (and the share remains similar for those who had spells of both low pay and non-employment). Not surprisingly, those who are continuously unemployed have the lowest transition rate into higher pay (below 1 per cent).

To determine the *genuine* effect of past labour market status empirically, we estimate a dynamic multinomial logit model with random effects. The findings indicate that workers who worked for 12 months continuously on low pay have, on average, a probability of 28.1 per cent of becoming higher-paid employed in the next month, and this number drops to 1 per cent when being non-employed continuously over the past 12 months. Furthermore, this number increases to 72.8 per cent for those who experience spells of both low pay and higher-paid jobs in the 12 months. Importantly, we also find that when switching to the point-in-time approach where we look at the labour market position 12 months ago, those low-paid and non-employed have, on average, a substantially higher probability of entering higher pay (74.7 per cent and 63.6 per cent, respectively). Overall, our results indicate the following:

1. prior intensity of attachment to the low-pay sector plays a pivotal role in determining the transition probability of entering higher-paid employment;
2. confirmation of a sizeable stepping-stone effect (27 percentage points more likely to move into higher pay if continuously low-paid over the prior 12 months compared to continuously non-employed); and
3. the transition probabilities (towards higher pay) based on the point-in-time approach (as done in annual surveys), for dichotomously identified groups of non-employed and low-paid employed, tend to be overstated.

Our analysis further delves into investigating age-related heterogeneity of our findings. Results reveal that for continuously low-paid employed, the transition probability of entering higher-paid employment declines with age.

The remainder of this paper is structured as follows. Section II provides an overview of the current literature on low-pay dynamics. Section III encompasses an overview of the administrative data and presents key descriptives. Section IV describes the econometric model. Section V presents our results. Section VI concludes.

## *II Literature Review*

The academic discussion about whether low-paid employment is a stepping-stone towards higher-paid jobs is based on comparing the employment and earnings prospects of the unemployed with those on low pay. Therefore, it is crucial to understand how the respective labour market statuses affect future employment and earnings prospects.

### *(i) Employment and Earnings Prospects of the Unemployed*

There exist several theoretical claims explaining why unemployment tends to be strongly persistent, including discussions related to deterioration of human capital (Pissarides, 1992); disincentives caused by unemployment insurance (Gangl, 2006); institutional settings (Cockx & Ghirelli, 2016); decline in search intensity (Vishwanath, 1989; Cockx & Dejemeppe, 2012); rational herding (Oberholzer-Gee, 2008); and stigmatization by employers (Vishwanath, 1989; Lockwood, 1991; Omori, 1997).

To quantify state dependence in unemployment, it is crucial to isolate heterogeneities arising from unobserved structural differences between the employed and unemployed groups. To that end, one of the well-known identification strategies used to estimate the relationship between past and future unemployment is to employ panel data specifications suggested by Arulampalam *et al*. (2000). In particular, to estimate the 'causal link between past unemployment and current unemployment' Arulampalam *et al*. (2000, p. 25), the authors apply a first-order Markov model that includes a one-period lag of the dependent variable on the right-hand side of the equation. Moreover, to control for individual-specific effects, the authors further incorporate a random-effects error term. The study shows that for men of age 25 and over, state dependence accounts for about 40 per cent of the observed persistence in the unemployment probability. This finding has been backed by a number of later studies [e.g. Biewen & Steffes, 2010; Plum & Ayllón, 2015].

A second strand of literature tries to identify duration dependence in unemployment by using field experiments. The underlying concept is to generate fictitious curricula vitae that differ in the length of the unemployment spell and send them to real job postings. Duration dependence in unemployment is measured by the change in the call-back rates depending on the length of unemployment spell reported in the fake curriculum vitae. Kroft *et al*. (2013) find that the longer the spell of unemployment, the smaller is the probability of a job applicant receiving a call-back, which is most likely to come in the first year of unemployment. As for evidence in Europe, Eriksson and Rooth (2014) show that in the case of highly educated Swedish workers unemployment spells do not affect employers' hiring decisions. In contrast, the same adversely affect less-educated workers' employability.

Moreover, the experience of unemployment not only deteriorates the probability future employment, but also leaves scars on future earnings. For example, Addison and Portugal (1989) use CPS data and the authors show a negative relationship between unemployment duration and subsequent earnings. Studies a few later supported this finding (see Jacobson *et al.*, 1993; Krebs, 2007).

*(ii) Stepping-stone Effect of Low Pay*

Overall, substantial empirical evidence demonstrates the detrimental impact of unemployment spells on long-term labour market prospects. To avoid such negative consequences, one potential 'antidote' is to pick up a 'bad job' (Acemoglu, 2001), which might be perceived as a more prudent option concerning future earnings and employability than a prolonged period of unemployment. However, as previously pointed out, such conclusions are not that straightforward. For instance, McCormick (1990) argues that highly productive workers strongly prefer working in skilled professions. As such, if unemployed, such workers may choose to devote their time to looking for their preferred jobs rather than taking up low-paid interim employment or continue on-the-job search for desired positions if already employed. The employer can observe this search strategy, and might use the employment history of an applicant as a screening mechanism to predict workers' productivity levels.

The number of low-pay empirical studies has increased substantially in recent years. Most of these studies have focused on either estimating persistence in low-paid employment [e.g. Clark & Kanellopoulos, 2013] or comparing future unemployment risk of the low-paid relative to those unemployed [e.g. Stewart, 2007; Buddelmeyer *et al.*, 2010]. Alternatively, more recent papers have looked at the probability of transition from low-paid employment to higher pay [e.g. Mosthaf, 2014; Fok *et al.*, 2015; Cai *et al.*, 2018].

Table 1 provides an overview of recently published articles focusing on the stepping-stone effect of low pay. Cai *et al.* (2018) look at the British labour market sector to compare low-paid and unemployed groups' likelihood of transitioning to higher-paid jobs in the subsequent period. Using 18 survey waves of the British Household Panel Study (BHPS) covering years spanning the years 1991–2008, the authors find a 'statistically significant stepping-stone effect of low paid employment' [Cai *et al.*, 2018, p. 293]. To be specific, the difference between the two comparable groups is quantified as 12 percentage points. The authors further repeat their analysis using the Understanding Society data set, a successor of the BHPS. In contrast to the BHPS evidence, the stepping-stone effect seems to be substantially smaller in Understanding Society (as indicated by a mark-up of a statistically insignificant estimate of 4.1 percentage points). The authors believe that the drop in the stepping-stone effect can be explained by the Great Recession overlapping with the Under- standing Society survey. In a subsequent analysis, Plum (2019) extends Cai *et al.* (2018)'s BHPS evidence by differentiating the (un)employed group by the duration spent in the labour market without having a job. Plum (2019) shows that the stepping-stone effect seems to be the strongest for groups experiencing the longest prior unemployment spells.

Mosthaf (2014) uses administrative data from the German Integrated Employment Biographies Sample to investigate labour market transitions between higher pay, low pay and non-employment for 2000–6. Unlike other studies, Mosthaf (2014)'s analysis is differentiated by individuals' qualification level. The key findings indicate that educational attainment plays a crucial role as the stepping-stone effect is especially pronounced for workers with low qualifications. In particular, less qualified individuals on low pay are, on average, 13 per cent more likely to move up to higher pay compared to when being non-employed. The relevance of qualification levels in this literature has been further emphasized by Knabe and Plum (2013). Using data from the German Socio-Economic Panel for the period 2002–7, the authors show that low-paid employment has the largest effect on less qualified workers and those who experience prolonged unemployment. More specifically, for groups characterised by a low education level and prior experience of long unemployment spells, the probability mark-up is, on average, 14.2 percentage points, which is significantly different from zero. That low-paid employment can support the unemployed going through an easier transition into higher-paid jobs is also found by Uhlendorff (2006).

Finally, Cai (2014) uses data from HILDA to look at labour market transitions. The author concludes that, independent of the low-pay threshold used, interim low-paid employment

Table 1
*Transition Probabilities of Different Studies*

| Study | Low-pay cut-off | Survey (period) | Male sample ages | $P(Hp_t \mid Lp_{t-1})$ (1) | $P(Hp_t \mid Ue_{t-1})$ (2) | Difference (1)–(2) |
|---|---|---|---|---|---|---|
| Cai *et al*. (2018, Table 3) | 2/3 × median hourly earnings | British Household Panel Survey (1991–2008) | 18–64 | 0.556 | 0.440 | 0.116*** (0.036) |
| Cai *et al*., (2018, Table 7) | | Understanding Society, UK (2009–15) | | 0.472 | 0.432 | 0.041 (0.041) |
| Plum (2019, Table 3) | 2/3 × median gross hourly wage | British Household Panel Survey (1996–2008) | 20–60 | – | – | 0.129*** (0.040) |
| Mosthaf (2014, Table 6) | 2/3 × median gross wage of full- time employed | Integrated Employment Biographies Sample, Germany (2000–6) | 29 (in 2000) to 59 (in 2006) | 0.695 | 0.563 | [0.130][a] |
| Knabe and Plum (2013, Table 6) | 2/3 × median gross hourly wage | German Socio-Economic Panel (2002–7) | 25–60 | 0.732 | 0.590 | [0.142**] |
| Uhlendorff (2006, Table 8) | 2/3 × median hourly earnings | German Socio-Economic Panel (1998–2003) | 20–54 | 0.888 | 0.842 | [0.046][a] |
| Uhlendorff (2006, Table 8) | First quantile of wage distribution | | | 0.861 | 0.801 | [0.060][a] |
| Cai (2014, Table 2A) | 2/3 × median hourly earnings | Household, Income and Labour Dynamics in Australia | 21–60 | 0.772 | 0.718 | 0.054** (0.024) |
| Cai (2014, Table 2B) | First quantile of wage distribution | | | 0.697 | 0.642 | 0.055** (0.024) |

*Note*: Cai *et al*. (2018) provide estimates based on the BHPS (Table 3) and Understanding Society data (Table 7). Plum (2019) refers to comparing long-term unemployed (more than 360 days) with low-paid who were employed for more than 360 days. Mosthaf (2014) provides a range of estimates based on different qualification groups; shown here is the low qualification level. Knabe and Plum (2013) refer to a job with a ISEI score (an occupational status index) above 30 and the individual has less than a college degree and has long unemployment experience. Due to gender differences in labour market behaviour, the above estimates presented from each study are based on sample of male workers only, although Cai *et al*. (2018) and Knabe and Plum (2013) also focus on female workers. Additionally, while most studies employ multinomial logistic regressions to estimate labour market dynamics using categorical indicators of labour market status as outcome variables, the empirical analysis performed by Knabe and Plum (2013) and Plum (2019) relies on random effects probit models. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively. Numbers in square brackets are own calculations.
[a]No significance level provided.

prompts a ‘stepping-stone effect towards higher pay’ (p. 486).

A predominant feature of the aforementioned empirical studies on estimating the stepping-stone effect is that the empirical evidence primarily relies on point-in-time data (mainly retrieved from surveys). Using empirical specifications that attempt to control for individual-specific observed as well as unobserved heterogeneities, the vast majority of the studies in the relevant space characterise low-paid jobs as a stepping-stone towards higher-paid employment. In other words, compared to the choice of continuing to remain unemployed, taking up a low-paid job is empirically documented to have an incremental effect on the likelihood of entering a better-paid job.

An obvious but less-discussed limitation of the commonly implemented identification strategy is the apparent lack of relevant data related to unobserved periods within two consecutive surveys. For instance, in analyses using survey data, beyond the earnings information for the one specific time point not much is known about the characteristics of the low-paid employment, for example, the duration of the low-paid employment or whether the individual also had higher-paid spells in between the survey interviews. That this aspect might have an impact on the findings has been shown by Stewart (2007), Knabe and Plum (2013) and Plum (2019), who classify the unemployed population by their unemployment duration. Furthermore, Stewart (2007) finds that after excluding individuals with continuing unemployment spells, there is no significant difference between the effects of experience of unemployment and of low-paid employment on the future unemployment risk. Furthermore, Knabe and Plum (2013) and Plum (2019) find that the chances of entering higher pay especially deteriorate for individuals who have experienced long unemployment spells. As such, for that group, the stepping-stone effect (i.e. from low-paid to higher-paid jobs) is likely to be more pronounced. One approach to dealing with this issue is to implement a higher-order Markov process. For example, Stewart (2007) uses second-order dynamic random-effects models and finds significant differences between continuous low-paid employment and when being unemployed at $t-2$ and on low pay at $t-1$. This finding has been confirmed by Buddelmeyer *et al.* (2010). However, the underlying limitation of missing labour market information between consecutive (survey) interview time points still persists. As such, our study provides novel empirical evidence by using administrative tax records on the monthly level that allow us to track the exact duration of a low-pay spell. Consequently, the high-frequency data enable us to separate those individuals with a continuous spell of low-paid employment from individuals who move between low- and higher-paid jobs.

## III Data and Descriptive Statistics

### (i) Data

To empirically analyse the stepping-stone effect of low-paid employment, we use administrative data from Statistics NZ’s Integrated Data Infrastructure (IDI). The IDI contains population-wide longitudinal microdata about individuals, households, and organisations. These data are sourced from government and from non-government agencies, as well as Statistics NZ surveys. The data are confidentialised through assigning a unique identifier to each individual. The monthly earnings and employment-related information are derived from administrative tax records provided by New Zealand’s Inland Revenue (IR). The IR tax data are available from April 1999 for the entirety of the NZ workforce and document monthly information on all income sources. The seven potential income categories are: earnings (measured in terms of wages and salaries); withholding payments; benefits; student allowance; paid parental leave; pensions (superannuation); and claimants compensations. For our analysis, we use gross earnings before tax.

To investigate whether low-paid employment increases the chances of climbing up the pay distribution for unemployed workers, we identify our population of interest using the two most recent consecutive census data sets (of years 2013 and 2018). The respective census years mark the beginning and end of our study period. The census holds a range of information related to individual characteristics and labour market information. Being the only source of population-based individual-level characteristics, the census is used to access information on the nature of employment (paid employee, employer, self-employed, etc.) and the labour force status (e.g. full-time employed, part-time employed, unemployed, not in the labour force). We first trim our sample to men aged between 21 and 60 as of the survey month (March) of the 2013 Census. Next, we restrict the sample to those individuals who are successfully linked with the 2018 Census to ensure we have information on the relevant labour market characteristics at both time limits. Furthermore, we restrict our sample to men who report being in either full-time employment and paid employed or unemployed.[1] Before linking our sample of interest (or the spine) to the IR data, we also exclude men who are observed to be employed on a part-time basis in either of the two census data sets. We impose this restriction as the monthly IR tax data on earnings do not hold information on the hours worked.

It is important to note that an employee registered in the IR records might hold multiple jobs or change existing jobs within a month. As such, there could be more than one entry per month for each individual. Therefore, for measures of monthly earnings, we aggregate all reported income from wages and salaries in each month. Finally, we link our sample to the tertiary education data provided by the Ministry of Education, which documents whether an individual is enrolled in college or tertiary education. We drop those individuals who were enrolled in tertiary education during our period of interest.

To identify individuals' labour market status, we make use of the monthly information on earnings provided by the IR. An individual is considered non-employed if he does not receive any earnings income. Additionally, we classify workers with earnings belonging to the two lowest deciles as being on low pay. It is worth noting that our findings are robust to the other definitions or thresholds of low pay as well (e.g. higher or lower relative cut-off point), including using a threshold of two-thirds of the monthly median earnings. Finally, to optimise computation time, we trim our data set to a 5 per cent random subsample, which results in a sample of 12,807 individuals.

*(ii) Descriptive Profile*

To broadly highlight how data granularity can intuitively support estimation of the stepping-stone effect of low pay, we begin with a transition matrix of past and current labour market status when using the point-in-time approach, which is commonly adopted in the existing literature. In particular, adopting a design resembling a survey, we look at the labour market position in March of each of the years from 2013 to 2018. In what follows, the time identifier $t$ is scaled at the monthly level, thus $t-12$ refers to the same month in the previous year. Table 2 provides the probability of being in a certain labour market position at time $t$ conditional on the labour market position 12 months before ($t-12$). The matrix shows that the conditional probability of moving into higher pay when being on low pay 12 months before (29.5 per cent) is greater than the conditional probability of transitioning directly from non-employment into higher-paid employment (22 per cent). This finding might be interpreted as descriptive evidence of a stepping-stone effect of low pay.

Table 2 also illustrates high persistence in staying in the same labour market position over time. This is evident from the leading diagonal of the table.

As previously discussed, a limitation of a point-in-time transition matrix like Table 2 is that it is unknown whether the individual had a stable labour market position between the observed time points (i.e. March of each year) or whether there were transitions between different statuses. For example, an individual who temporarily transits between higher pay and low pay might have substantially different chances of entering higher pay in the future than someone who was continuously on low pay. The same is potentially the case when looking at non-employed individuals, where it is unclear whether the individual is short-term or long-term non-employed. For this reason, we construct a new categorical variable accounting for different labour market positions an individual was in between $t=-12$ and $t=-1$ (see Table 3).

Table 4 shows the distribution of each labour market status at $t-12$ and the labour market transitions between $t-12$ and $t-1$. First, we can see that almost half (44.8 per cent) of the men who were non-employed at $t-12$ were continuously non-employed for the period until $t-1$. Furthermore, 9.3 per cent had some spells of higher-paid employment and 22 per cent experienced at least one low-paid spell. Focusing on male workers who were on low pay at $t-12$, only a small share (17.5 per cent) stayed on low pay throughout the period until $t-1$ and about 67.8 per cent also had a mix of low- and higher-paid spells. However, we observe an alternative depiction for men who had higher-paid employment at

[1] We exclude those not in the labour force as they react distinctively differently than unemployed groups (Heckman & Borjas, 1980).

TABLE 2
*Transition Matrix (Point-in-time)*

| Status at $t-12$ | Status at $t$ Higher pay | Low pay | Non-employed | Total |
|---|---|---|---|---|
| Higher pay | 0.9046 | 0.0734 | 0.0219 | 0.7605 |
| Low pay | 0.2951 | 0.6444 | 0.0606 | 0.1926 |
| Non-employed | 0.2196 | 0.2415 | 0.5389 | 0.0469 |
| Total | 0.7551 | 0.1913 | 0.0536 | |

*Source*: Authors' calculations using data from the IDI.

TABLE 3
*Employment Status (Categorical)*

| Status from $t-12$ to $t-1$ | No. of months between $t=-12$ and $t=-1$ Higher pay | Low pay | Non-employed |
|---|---|---|---|
| Continuously non-employed | – | – | 12 |
| Continuously higher-paid | 12 | – | – |
| Continuously low-paid | – | 12 | – |
| Higher-paid and low-paid | $\geq 1$ | $\geq 1$ | – |
| Higher-paid and non-employed | $\geq 1$ | – | $\geq 1$ |
| Low-paid and non-employed | – | $\geq 1$ | $\geq 1$ |
| All three labour market statuses | $\geq 1$ | $\geq 1$ | $\geq 1$ |

time point $t-12$. Almost three-quarters (74.1 per cent) were continuously higher-paid employed until $t-1$, while 21 per cent also had some low-paid spells.

For our final descriptive understanding of what further insights monthly administrative data can provide compared to survey information, we update the transition matrix in Table 2 and replace the lagged labour market indicator at $t-12$ by the categorical marker as defined in Table 3. The findings of Table 5 can be summarized as follows.

- For male workers who were continuously in a specific labour market position between $t-12$ and $t-1$, the probability of being at the same status at time $t$ is high (above 90 per cent).
- The continuously non-employed have a smaller probability (1.1 per cent ) of moving directly into higher pay than the continuously low-paid employed (4.9 per cent). In both cases, the respective probability estimates are substantially below those displayed in Table 2.
- Those men who had a mix of both higher- and low-paid spells in the period $t-12$ to $t-1$ have a substantially higher probability (56 per cent) of being observed on higher pay than continuously low-paid men (4.9 per cent).

## IV *Econometric Model*

To identify the stepping-stone effect of low-paid employment using monthly data, we apply a first-order Markov process with an underlying assumption that the lagged dependent variable has a *genuine* impact on the outcome of interest. The first-order Markov model is a standard dynamic empirical approach adopted in several low-pay studies, including analyses performed by Uhlendorff (2006); Mosthaf (2014); Fok *et al*. (2015), and more recently by Cai *et al*. (2018). To take advantage of the data granularity afforded by IR monthly tax records, we consider three labour market positions, indexed by the variable $j$ such that $j$ equals 1 when a worker is in higher-paid employment, 2 when in a low-paid

TABLE 4
*Status Comparison*

| Status from $t-12$ to $t-1$ | Status at $t-12$ Higher pay | Low pay | Non-employed | Total |
|---|---|---|---|---|
| Continuously non-employed | | | 0.4481 | 0.0210 |
| Continuously higher-paid | 0.7408 | | | 0.5633 |
| Continuously low-paid | | 0.1747 | | 0.0336 |
| Higher-paid and low-paid | 0.2088 | 0.6782 | | 0.2894 |
| Higher-paid and non-employed | 0.0196 | | 0.0928 | 0.0193 |
| Low-paid and non-employed | | 0.0598 | 0.2206 | 0.0219 |
| All three labour market statuses | 0.0308 | 0.0873 | 0.2385 | 0.0514 |
| Total | 0.7605 | 0.1926 | 0.0469 | |

*Source*: Authors' calculations using data from the IDI. Variable definitions are provided in Table 3.

TABLE 5
*Transition Matrix (with Categorical Indicator)*

| Status from $t-12$ to $t-1$ | Status at $t$ Higher pay | Low pay | Non-employed | Total |
|---|---|---|---|---|
| Continuously non-employed | 0.0111 | 0.0334 | 0.9555 | 0.0210 |
| Continuously higher-paid | 0.9889 | 0.0084 | 0.0027 | 0.5633 |
| Continuously low-paid | 0.0487 | 0.9373 | 0.0139 | 0.0336 |
| Higher-paid and low-paid | 0.5622 | 0.4264 | 0.0115 | 0.2894 |
| Higher-paid and non-employed | 0.5474 | 0.0389 | 0.4136 | 0.0193 |
| Low-paid and non-employed | 0.0514 | 0.5589 | 0.3897 | 0.0219 |
| All three labour market statuses | 0.4235 | 0.3488 | 0.2277 | 0.0514 |
| Total | 0.7551 | 0.1913 | 0.0536 | |

*Source*: Authors' calculations using data from the IDI.

job and 3 when non-employed. Since we track our sample from the month of March 2013 (the census period), it is essential to note that the dependent variable in our dynamic model represents an individual's labour market status (indicated by $j$) in the month of March for the years 2014 to 2018. This is to ensure that we have a non-missing lagged value in the right-hand side of the estimating equation for each dependent variable.

While our dynamic random effects specification follows a standard approach commonly adopted in the extant literature, the empirical validity of our analysis relies on the assumption that individuals' unobserved traits are uncorrelated with observable characteristics. Concerns related to possible confounding influences of unaccounted individual-level information could be partially addressed by employing a Mundlak–-Chamberlain decomposition (Mundlak, 1978; Chamberlain, 1984). However, given our data structure, we cannot implement such empirical decomposition, as the Census 2013-based individual-level controls are time-invariant. This is also the reason why our data restrict us from following an instrumental variable approach such as the Arellano–Bond estimation strategy (see Arellano & Bond, 1991).

*(i) Survey Model: Point-in-time Estimation*

In standard dynamic models estimated in studies that utilise survey data, the probability that individual $i \in \{1,\ldots,N\}$ is observed, at time point $t \in \{12,24,\ldots,60\}$,[2] to be in labour market state $y_{it}=j$ can be written as

$$P\left(y_{it}=j|y_{i(t-12)},X_i,\kappa_{ij}\right)=\frac{\exp\left(X_i\beta_j+y_{i(t-12)}\gamma_j+\kappa_{ij}\right)}{\sum_{k=1}^{3}\exp\left(X_i\beta_k+y_{i(t-12)}\gamma_k+\kappa_{ik}\right)}. \tag{1}$$

$X_i$ is a vector of individual-specific observable characteristics. These are retrieved from the 2013 Census and include prioritised ethnicity (classified into six categories, namely NZ European, Māori, Pacific Peoples, Asian, Middle Eastern/Latin American/African, and others), highest academic qualification (divided into five categories, namely no qualifications, Level 1–4, Level 5–6, bachelor's degree, and postgraduate degree), age (linear as well as a quadratic term), and smoking behaviour as a health indicator (dummy: 1 if smokes regularly, 0 otherwise). The indicator $y_{i(t-12)}$ is a vector of dummy variables representing individual $i$'s previous year's (12-month lag) labour market position. Equation (1) shows how the intertemporal relationship of labour market status is identified when using point-in-time survey data. Additionally, to control for individual-specific unobserved heterogeneity, we include a time-invariant error term $\kappa_{ij}$.

A key issue in this type of specification is that the labour market position in the initial period (in our case March 2013, denoted by $t=0$) might not be randomly distributed, due to a correlation between the time-invariant error term and the initial conditions (Heckman, 1981). As Skrondal and 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 Wooldridge (2005)'s by applying a conditional random-intercept model where

$$\kappa_{ij}=y_{i(t=0)}\nu_j+X_{i\text{pre}}\theta_j+\alpha_{ij}, \tag{2}$$

with $y_{i(t=0)}$ referring to the labour market status in the initial period, $X_{i\text{pre}}$ indicating the number of months employed between March 2011 and February 2013 (categorical: 0–6 months, 7--12 months, 13–18 months, 19–24 months) and share of low-paid months for the same pre-period (continuous). Inserting Equation (2) into Equation (1) results in

$$P\left(y_{it}=j|y_{i(t-12)},X_i,X_{i\text{pre}},\alpha_{ij}\right)=\frac{\exp\left(X_i\beta_j+y_{i(t-12)}\gamma_j+y_{i(t=0)}\nu_j+X_{i\text{pre}}\theta_j+\alpha_{ij}\right)}{\sum_{k=1}^{3}\exp\left(X_i\beta_k+y_{i(t-12)}\gamma_k+y_{i(t=0)}\nu_k+X_{i\text{pre}}\theta_k+\alpha_{ik}\right)}. \tag{3}$$

The reference category is higher pay (i.e. $k=1$), and therefore coefficient vectors $\beta_1$, $\gamma_1$, $\nu_1$, $\theta_1$ and $\alpha_{i1}$ in Equation (3) are set equal to zero. It is assumed that the random effects are normally distributed $\alpha_{ij}\sim N\left(0,\sigma^2_{\alpha_j}\right)$ and are correlated by $\rho_\alpha$. The likelihood function for individual $i$ takes the form

$$L_i=\int_{-\infty}^{\infty}\prod_{t=12}^{60}\prod_{j=2}^{3}\left\{\frac{\exp\left(X_i\beta_j+y_{i(t-12)}\gamma_j+y_{i(t=0)}\nu_j+X_{i\text{pre}}\theta_j+\alpha_{ij}\right)}{1+\sum_{k=2}^{3}\exp\left(X_i\beta_k+y_{i(t-12)}\gamma_k+y_{i(t=0)}\nu_k+X_{i\text{pre}}\theta_k+\alpha_{ik}\right)}\right\}^{d_{ijt}}f(\alpha)d\alpha \tag{4}$$

Note that $d_{ijt}$ equals 1 if individual $i$ is in state $j$ at time point $t$, and 0 otherwise. To integrate out the random effects, we use maximum simulated likelihood (MSL) estimation. Denoting the total number of draws by $R$, we use random numbers based on Halton draws [see Train, 2009] twice (for each labour market status) to derive $R$ standard uniformly distributed draws transformed by the inverse cumulative standard normal distribution $\Phi^{-1}$. The MSL is given by[3]

$$\text{MSL}=\prod_{i=1}^{N}\frac{1}{R}\sum_{r=1}^{R}\left\{\prod_{t=12}^{60}P_{it}\left(\alpha_1^r,\alpha_2^r\right)\right\}, \tag{5}$$

where $P_{it}\left(\alpha_1^r,\alpha_2^r\right)$ denotes the joint probability of the variables $\alpha_1$ and $\alpha_2$.

### *(ii) Within-year Labour Market Transitions*

As shown in the descriptive estimates in Section III, breaking down past labour market movements by accounting for labour market status during the period spanning between $t-12$ and $t-1$ can reveal further heterogeneity in the likelihood of climbing up the pay

[2] Note that we have a balanced sample, in which each individual is observed in the period from March 2013 to March 2018. $t=12$ refers to March 2014, $t=24$ to March 2015,. . ., $t=60$ to March 2018.

[3] We use 50 draws, but the results remain consistent when we vary the number of draws.

distribution. For this reason, we replace the lagged dependent variable by $y_{ir(t-12)}^{\text{cat}}$ with $r \in \{1,\ldots,7\}$ as indicated by the different labour market statuses defined in Table 3. Note that the time identifier $t-12$ for $y_{ir(t-12)}^{\text{cat}}$ refers to 12 months before $t$. As such, Equation (1) takes the form

$$P\left(y_{it}=j|y_{ir(t-12)}^{\text{cat}},X_i,\kappa_{ij}\right) = \frac{\exp\left(X_i\beta_j+\sum_{r=2}^{7}y_{ir(t-12)}^{\text{cat}}\varepsilon_{rj}+\kappa_{ij}\right)}{\sum_{k=1}^{3}\exp\left(X_i\beta_k+\sum_{r=2}^{7}y_{ir(t-12)}^{\text{cat}}\varepsilon_{rk}+\kappa_{ik}\right)}. \tag{6}$$

Note that the reference category $y_{i1(t-12)}^{\text{cat}}$ is being continuously non-employed between $t=-12$ and $t=-1$. Moreover, based on our new categorical labour market indicator, we accordingly adjust the initial conditions problem:

$$\kappa_{ij}=\sum_{r=2}^{7}y_{ir(t=0)}^{\text{cat}}\mu_{rj}+X_{i\text{pre}}\theta_j+\alpha_{ij}. \tag{7}$$

Inserting Equation (7) into Equation (6) leads to our final equation:

$$P(y_{it}=j|y_{ir(t-12)}^{\text{cat}},y_{ir(t=0)}^{\text{cat}},X_i,X_{i\text{pre}},\alpha_{ij}) = \frac{\exp\left(X_i\beta_j+\sum_{r=2}^{7}y_{ir(t-12)}^{\text{cat}}\varepsilon_{rj}+\sum_{r=2}^{7}y_{ir(t=0)}^{\text{cat}}\mu_{rj}+X_{i\text{pre}}\theta_j+\alpha_{ij}\right)}{\sum_{k=1}^{3}\exp\left(X_i\beta_k+\sum_{r=2}^{7}y_{ir(t-12)}^{\text{cat}}\varepsilon_{kr}+\sum_{r=2}^{7}y_{ir(t=0)}^{\text{cat}}\mu_{kr}+X_{i\text{pre}}\theta_k+\alpha_{ik}\right)}. \tag{8}$$

## V *Results*

Our study's primary aim is to understand whether, for someone who is initially not employed, an interim low-paid employment enables a better transition into higher-paid jobs than the option of remaining without employment. For this reason, we apply a dynamic multinomial logit model with random effects and follow Wooldridge (2005)'s suggestion to address the initial conditions problem. As the models' coefficients cannot be directly interpreted,[4] we begin by calculating the predicted probability estimates for being in a specific labour market position conditional on past labour market status.

In columns (1)–(3) of Table 6, the upper panel (Panel A) shows the respective predictive probabilities when using the point-in-time model where only the status at $t-12$ is accounted for. For example, Panel A shows that the likelihood of being non-employed at $t$ if in the same labour market state at $t-12$ is 15.7 per cent. Cai *et al.* (2018) find a similar figure for British workers, with a probability of remaining without a job being 15.5 per cent. Mosthaf (2014, Table 6) also finds that individuals who are observed to be non-employed a year before have a higher chance of entering paid jobs than remaining non-employed. In terms of the stepping-stone effect, we find that the probability of being on higher pay at $t$ is greater if low-paid at $t-12$ (74.73 per cent) than if non-employed at $t-12$ (63.64 per cent).

Next, we calculate the partial effects (columns (4)–(6) of Table 6), where we consider non-employed 12 months prior as the reference category. The estimates represent the mark-up in percentage points (pp) for higher-paid and low-paid workers at $t-12$ relative to the non-employed group. For example, the likelihood of being on higher pay at $t$ is 11 pp higher if low-paid at $t-12$ relative to the reference group of non-employed at $t-12$.

For estimates presented in Panel B of Table 6, we rerun our model and replace the lagged labour market indicator of Panel A with a categorical variable covering the period from $t-12$ to $t-1$. The Panel B results represent the mean predicted probabilities for the seven different labour market states.

Starting with the continuously non-employed, we find that the risk of being in the same position at $t$ is 96.7 per cent. On the other hand, being continuously low-paid or higher-paid over the preceding year results in a small risk of being non-employed at time $t$ (2.4 per cent and 0.4 per cent, respectively).

In terms of being higher-paid at $t$, the likelihood is just 1.1 per cent if continuously non-employed over the preceding year. This is in comparison to 28.1 per cent if continuously low-paid over the prior 12 months. This indicates a sizeable stepping-stone effect: specifically, 27 pp more likely to move into higher pay if continuously low-paid over the prior 12 months compared to continuously non-employed. It is worth noting that this is larger than the stepping-stone effect found using the point-in-time approach of 11 pp (which is based on dichotomously identified groups of non-employed and low-paid employed).

A further key finding with the results in Panel B is that the probability estimates of entering higher pay are much lower than the results in Panel A when using the point-in-time model. The

[4] Output can be found in Appendix Table A1 for the point-in-time model and Table 10 for the model accounting for within-year labour market transitions.

TABLE 6
*Estimated Labour Market Dynamics*

| | Predicted probabilities | | | Partial effects | | |
|---|---|---|---|---|---|---|
| | Higher pay$_t$ (1) | Low pay$_t$ (2) | Non-employed$_t$ (3) | Higher pay$_t$ (4) | Low pay$_t$ (5) | Non-employed$_t$ (6) |
| Panel A. Status at $t-12$ | | | | | | |
| Higher pay | 0.8399 | 0.1405 | 0.0196 | 0.2035 | −0.0665 | −0.1371 |
| | (0.0021) | (0.0019) | (0.0002) | (0.0189) | (0.0114) | (0.0192) |
| Low pay | 0.7473 | 0.2263 | 0.0264 | 0.1109 | 0.0193 | −0.1303 |
| | (0.0025) | (0.0024) | (0.0003) | (0.0168) | (0.0104) | (0.0184) |
| Non-employed | 0.6364 | 0.2070 | 0.1567 | Reference category | | |
| | (0.0025) | (0.002) | (0.0009) | | | |
| Panel B. Status from $t-12$ to $t-1$ | | | | | | |
| Continuously non-employed | 0.011 | 0.0223 | 0.9667 | Reference category | | |
| | (0.0000) | (0.0001) | (0.0001) | | | |
| Continuously higher-paid | 0.9764 | 0.0196 | 0.0041 | 0.965 | −0.003 | −0.963 |
| | (0.0003) | (0.0003) | (0.0000) | (0.0050) | (0.0050) | (0.0060) |
| Continuously low-paid | 0.2809 | 0.6953 | 0.0238 | 0.270 | 0.673 | −0.943 |
| | (0.0014) | (0.0015) | (0.0001) | (0.0250) | (0.0260) | (0.0080) |
| Higher-paid and low-paid | 0.7276 | 0.2616 | 0.0109 | 0.717 | 0.239 | −0.956 |
| | (0.0019) | (0.0018) | (0.0000) | (0.0140) | (0.0130) | (0.0060) |
| Higher-paid and non-employed | 0.4728 | 0.0552 | 0.472 | 0.462 | 0.033 | −0.495 |
| | (0.0013) | (0.0004) | (0.0009) | (0.0270) | (0.0090) | (0.0280) |
| Low-paid and non-employed | 0.1448 | 0.3636 | 0.4916 | 0.134 | 0.341 | −0.475 |
| | (0.0006) | (0.0013) | (0.0007) | (0.0180) | (0.0250) | (0.0310) |
| All three labour market statuses | 0.5322 | 0.2468 | 0.2211 | 0.521 | 0.224 | −0.746 |
| | (0.0017) | (0.0015) | (0.0003) | (0.0190) | (0.0140) | (0.0180) |

*Source*: Authors' calculations using data from the IDI. Standard errors in parentheses.

probability of being higher-paid in $t$ if low-paid at the time of the survey 12 months prior is 74.7 per cent. In comparison, the probability of being higher-paid in $t$ once we account for the intensity of attachment to the low-pay sector is 28.1 per cent for those continuously low-paid over the preceding 12 months. This indicates that prior literature estimates regarding the probability of entering higher pay (whether from low-paid employment or non-employment) are likely overstated, given they were not able to account for the degree of attachment to the previous labour market state.

Also evident in Table 6 are the heterogeneous effects on the likelihood of being higher-paid at $t$ depending on the mix of labour market statuses experienced in the prior year. For example, we can see from the estimated partial effects that, relative to being continuously non-employed in the prior year, the likelihood of being higher-paid at $t$ is 13.4 pp higher if one has experienced a mix of low pay and non-employment over the last 12 months, 46.2 pp higher if one has had higher pay and non-employment in that time, and 52.1 pp higher if one has experienced all three labour market statuses.

We next delve into the age-related heterogeneity of earnings prospects (shown in Tables 7 and 8). We form four age groups (21–29, 30–39, 40–49, 50–60) and run separate regressions. Once again we focus on two empirical specifications. The first specification emulates the point-in-time model, while the second accounts for labour market status in all the previous 12 months. From the point-in-time model (see Table 7), we can see that the risk of remaining non-employed increases with age if the worker was already non-employed 12 months before (e.g. moving from, on average, 40.7 per cent for the youngest age group to 57.4 per cent for men aged 50–60 in March 2013). However, when it comes to the chance of entering higher pay, it looks like an inverted U-shape pattern for those who were on low pay at $t-12$, with a peak in the 40–49 age group. Accordingly, when moving to the partial effects, we find that, on average, the stepping-stone effect is the largest for this age group.

In Table 8, consistent with our previous findings, we see that workers who were non-employed in the past 12 months have a very low probability of entering higher-paid employment. Moreover, from age 30 onwards, there is a constant drop in the probability of moving from continuous low-paid employment into higher pay: while the predicted probability was, on average, around 34.3 per cent for the 30–39 age group (as at March 2013), it drops to 23.2 per cent for the 50–60 age group. Likewise, the likelihood of remaining on low pay increases with age. In terms of the partial effect, we find that, on average, it drops by 10 pp between the two age groups.

*(i) Robustness Specifications and Initially Non-employed*

So far, our identification strategy is based on splitting the labour market dynamics in the period from $t-12$ to $t-1$ into seven groups. To test the robustness of our findings, we replace our lagged variable with an indicator variable on the relative amount of time spent in the respective labour market positions (Robustness 1; see Table A3). We also interact the three parameters on labour market status with each other (Robustness 2; see Table A4). A summary of these robustness checks is presented in Table A5. Importantly, our main findings are confirmed.

- The likelihood of being non-employed at $t$ is, on average, very large for those who were non-employed in all 12 months (Robustness 1, 92.9 per cent; Robustness 2, 84.7 per cent).
- Being on low pay in the past 12 months is associated with a very low risk of entering non-employment (estimated between 2.3 and 2.9 per cent).
- The probability of entering higher pay is low for those who were non-employed or on low pay throughout the past 12 months, though the chances are somewhat larger for those on low pay (Robustness 1, 7.1 pp; Robustness 2, 10.3 pp),

As a final robustness check, we trim our data set to men who are identified as non-employed in March 2013. Estimation results for the point-in-time approach and when accounting for the status during the period from $t-12$ to $t-1$ can be found in Table A6. Starting with the point-in-time approach (top panel), we can see a shift in the probabilities compared to Table 6. First, the likelihood of remaining non-employed 12 months later moves up to 64.5 per cent (15.7 per cent for the full sample), but also the average risk is higher for those who were on low pay 12 months before (27.2 per cent compared to 2.6 per cent for the full sample). Next, the chances of entering higher pay are much lower, and the difference is apparent for the non-employed at $t-12$: compared to the full sample with an average

TABLE 7
*Estimated Labour Market Dynamics by Age Groups (Point-in-time)*

| | Predicted probabilities | | | Partial effects | | |
|---|---|---|---|---|---|---|
| | Higher pay$_t$ (1) | Low pay$_t$ (2) | Non-employed$_t$ (3) | Higher pay$_t$ (4) | Low pay$_t$ (5) | Non-employed$_t$ (6) |
| Age as at March 2013: 21–29 | | | | | | |
| Non-employed | 0.1147 | 0.4784 | 0.4069 | Reference category | | |
| | (0.0018) | (0.0022) | (0.0016) | | | |
| Low pay | 0.1889 | 0.6958 | 0.1153 | 0.0742 | 0.2174 | −0.2916 |
| | (0.0029) | (0.0029) | (0.0007) | (0.0222) | (0.0449) | (0.0474) |
| Age as at March 2013: 30–39 | | | | | | |
| Non-employed | 0.2572 | 0.3313 | 0.4114 | Reference category | | |
| | (0.0024) | (0.0031) | (0.0017) | | | |
| Low pay | 0.4297 | 0.4870 | 0.0833 | 0.1724 | 0.1557 | −0.3281 |
| | (0.0038) | (0.004) | (0.0006) | (0.0455) | (0.0516) | (0.0641) |
| Age as at March 2013: 40–49 | | | | | | |
| Non-employed | 0.2256 | 0.2256 | 0.5488 | Reference category | | |
| | (0.0017) | (0.003) | (0.0018) | | | |
| Low pay | 0.5893 | 0.2913 | 0.1194 | 0.3638 | 0.0657 | −0.4294 |
| | (0.0038) | (0.004) | (0.0007) | (0.044) | (0.0344) | (0.0507) |
| Age as at March 2013: 50–60 | | | | | | |
| Non-employed | 0.0914 | 0.3341 | 0.5744 | Reference category | | |
| | (0.0008) | (0.0025) | (0.002) | | | |
| Low pay | 0.2226 | 0.6429 | 0.1345 | 0.1312 | 0.3088 | −0.4400 |
| | (0.0022) | (0.0029) | (0.001) | (0.0435) | (0.0648) | (0.0552) |

*Source*: Authors' calculations using data from the IDI. Standard errors in parentheses.

probability of 63.6 per cent dropping to 12.9 per cent. Additionally, the mark-up in the probability of entering higher pay between non-employed and low-paid employed moves up from 11.1 pp (full sample) to 16.5 pp.

When replacing the variable referring to the labour market position at $t-12$ with the categorical variable which differentiates seven different labour market positions based on the transitions in the 12 months before $t$, the differences between the full and trimmed sample are less striking. In both samples, we find that being continuously non-employed leads to a very high risk of remaining in that position. Also, in a similar fashion to Table 6, we again find that those who were continuously higher-paid or low-paid face almost no risk of being non-employed at $t$. Table A6 shows some evidence of a decline in upward mobility when analysis is limited to this trimmed sample of initially non-employed. For example, in the full sample, the probability of moving to higher-paid employment if continuously low-paid was 28.1 per cent. This falls to 9.9 per cent in the trimmed sample.

## *VI Conclusions*

Prior studies have estimated the extent to which low-paid employment operates as a stepping-stone towards higher-paid jobs in the sense that for someone unemployed, the prospects of climbing up the salary ladder are significantly improved when picking up a low-paid job. While the literature does point to significant levels of persistence in unemployment and low pay, there is evidence that the probability of transitioning towards higher pay is larger when being on low pay than when unemployed [e.g. Uhlendorff, 2006; Mosthaf, 2014; Cai *et al*., 2018].

Importantly, these past studies have had to rely on survey data and identification of low pay status based on one time point per year. Though not much discussed in the literature, this identification strategy has some limitations as the degree to which an individual is attached to low pay is unclear: someone might be working continuously in the low-pay sector, or might receive a salary that makes them hover around the low-pay threshold. In this study, we are able to delve into a finer level of data detail by employing monthly

TABLE 8

*Estimated Labour Market Dynamics by Age Groups (Within-year Labour Market Transitions)*

| | Predicted probabilities | | | Partial effects | | |
|---|---|---|---|---|---|---|
| | Higher pay$_t$ (1) | Low pay$_t$ (2) | Non-employed$_t$ (3) | Higher pay$_t$ (4) | Low pay$_t$ (5) | Non-employed$_t$ (6) |
| Age as at March 2013: 21–29 | | | | | | |
| Continuously non-employed | 0.0123 | 0.0462 | 0.9415 | Reference category | | |
| | (0.0002) | (0.0004) | (0.0004) | | | |
| Continuously low-paid | 0.1649 | 0.7978 | 0.0373 | 0.1526 | 0.7516 | −0.9042 |
| | (0.0032) | (0.0035) | (0.0004) | (0.0308) | (0.0349) | (0.0188) |
| Age as at March 2013: 30–39 | | | | | | |
| Continuously non-employed | 0.0089 | 0.0235 | 0.9676 | Reference category | | |
| | (0.0001) | (0.0004) | (0.0003) | | | |
| Continuously low-paid | 0.3426 | 0.6456 | 0.0118 | 0.3338 | 0.6221 | −0.9559 |
| | (0.0031) | (0.0032) | (0.0001) | (0.0551) | (0.0562) | (0.0155) |
| Age as at March 2013: 40–49 | | | | | | |
| Continuously non-employed | 0.0132 | 0.0123 | 0.9745 | Reference category | | |
| | (0.0001) | (0.0002) | (0.0001) | | | |
| Continuously low-paid | 0.2926 | 0.6828 | 0.0246 | 0.2793 | 0.6706 | −0.9499 |
| | (0.0027) | (0.0028) | (0.0001) | (0.0548) | (0.0551) | (0.0147) |
| Age as at March 2013: 50–60 | | | | | | |
| Continuously non-employed | 0.0044 | 0.0226 | 0.9730 | Reference category | | |
| | (0.0000) | (0.0002) | (0.0002) | | | |
| Continuously low-paid | 0.2322 | 0.7575 | 0.0103 | 0.2278 | 0.7349 | −0.9627 |
| | (0.002) | (0.0021) | (0.0001) | (0.0505) | (0.052) | (0.0121) |

*Source*: Authors' calculations using data from the IDI. Standard errors in parentheses.

recorded administrative earnings for the working population of New Zealand. This enables us to identify those individuals who were continuously non-employed within a 12-month spell (reference group) and those on low pay throughout the same period.

The empirical identification strategy follows the established approach in the literature. We use a dynamic multinomial logit model with random effects. As the outcome in the initial period is potentially correlated with the individual-specific time-invariant error term, we follow the suggestion of Wooldridge (2005) to control for the initial conditions problem. To estimate the probability of movement towards higher pay we conduct two separate empirical analyses. The first uses the prevailing identification strategy in the literature based on a point-in-time marker for labour status, and the second utilises information on the intensity of attachment to the low-pay sector, derived from 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: the likelihood of being higher-paid in time period $t$ if low-paid 12 months before ($t-12$) is, on average, 74.7 per cent, while the likelihood for those who were non-employed at $t-12$ is, on average, 63.6 per cent. Thus, picking up low-paid employment improves the chances of entering higher pay by 11 percentage points, indicating that low pay operates as a stepping-stone towards higher pay.

However, when looking at the descriptives, we can see that out of those individuals who were on low pay at $t-12$ about 17.5 per cent were continuously on low pay until $t-1$ and 67.8 per cent also had higher-paid spells. Of those who were non-employed, we find that almost half (44.8 per cent) were without a job in the 12 months before $t$. Once we account for the intensity of the relevant labour market state over the year we see a major shift in findings via the point-in-time model. For those who were continuously non-employed, the probability of moving into higher pay after 12 months of no earnings is very small (on average, around 1.1 per cent). This compares to the estimated probability of 63.6 per cent of being on higher pay at $t$ if non-employed at $t-12$. Furthermore, for those who were continuously on low pay over the previous 12 months, the probability of moving into higher pay is 28.9 per cent. This is also a substantial drop relative to the 74.7 per cent found when using the point-in-time model and the dichotomous low-pay indicator.

We therefore conclude that the prior literature that relied on point-in-time data from annual surveys likely overstates the transition probabilities of moving towards higher pay (whether from low pay or non-employment). Our analysis highlights the importance of accounting for the intensity of prior low-pay attachment to the labour market. As such, a range of policies need to be considered, given the heterogeneous nature of low-pay employment.

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## *Appendix*

Table A1
*Regression Results (Point-in-time Model)*

| | Low pay$_t$ | | Non-employed$_t$ | |
|---|---|---|---|---|
| | Coeff. | Std err. | Coeff. | Std err. |
| Status at $t-12$ | | | | |
| Non-employed | Reference category | | | |
| Higher-paid | −1.333 | 0.084 | −2.834 | 0.098 |
| Low-paid | −0.278 | 0.085 | −2.138 | 0.097 |
| Status in March 2013 | | | | |
| Non-employed | Reference category | | | |
| Higher-paid | −2.484 | 0.16 | −2.7 | 0.195 |
| Low-paid | −1.303 | 0.157 | −2.024 | 0.188 |
| Ethnicity | | | | |
| NZ European | Reference category | | | |
| Māori | 0.06 | 0.071 | 0.314 | 0.092 |
| Pacific Peoples | 0.291 | 0.089 | 0.183 | 0.125 |
| Asian | 0.412 | 0.07 | 0.171 | 0.093 |
| Middle Eastern/Latin American/African | 0.057 | 0.206 | 0.297 | 0.254 |
| Others | 0.188 | 0.146 | −0.157 | 0.218 |
| Smoking regularly | 0.254 | 0.054 | 0.291 | 0.073 |
| Qualification level | | | | |
| No qualifications | Reference category | | | |
| Level 1–4 | −0.389 | 0.058 | −0.313 | 0.08 |
| Level 5–6 | −0.767 | 0.114 | −0.393 | 0.152 |
| Bachelor's degree | −1.046 | 0.129 | −0.502 | 0.165 |
| Postgraduate degree | −1.499 | 0.082 | −0.575 | 0.103 |
| Age | −0.011 | 0.016 | −0.039 | 0.021 |
| Age squared | 0.000 | 0.000 | 0.001 | 0.000 |
| Months employed between March 2011 and February 2013 | | | | |
| 0–6 months | Reference category | | | |
| 7–12 months | −0.616 | 0.144 | 0.098 | 0.169 |
| 13–18 months | −0.387 | 0.131 | −0.019 | 0.158 |
| 19–24 months | −0.133 | 0.108 | −0.597 | 0.132 |
| Low-paid months (03/2011–02/2013, %) | 3.671 | 0.098 | 2.036 | 0.135 |
| Log-likelihood | −27,426.669 | | | |
| *N* | 64,035 | | | |

*Source*: Authors' calculations using data from the IDI. Estimation is based on multinomial logit model with correlated random effects. The model also includes constants, the variances of the random effects and their correlation parameter (not shown here).

TABLE A2
*Regression Results (Within-year Labour Market Transitions)*

| | Low pay$_t$ | | Non-employed$_t$ | |
|---|---|---|---|---|
| | Coeff. | Std err. | Coeff. | Std err. |
| Status between $t-12$ and $tt$ | | | | |
| Continuously non-employed | Reference category | | | |
| Continuously higher-paid | −5.288 | 0.350 | −10.294 | 0.324 |
| Continuously low-paid | 0.473 | 0.361 | −6.856 | 0.381 |
| Higher-paid and low-paid | −1.937 | 0.345 | −8.79 | 0.316 |
| Higher-paid and non-employed | −3.066 | 0.377 | −4.578 | 0.313 |
| Low-paid and non-employed | 0.360 | 0.366 | −3.206 | 0.333 |
| All three labour market statuses | −1.575 | 0.346 | −5.413 | 0.31 |
| Status: March 2013 to February 2014 | | | | |
| Continuously non-employed | Reference category | | | |
| Continuously higher-paid | −1.639 | 0.191 | −0.529 | 0.211 |
| Continuously low-paid | −0.18 | 0.208 | 0.166 | 0.242 |
| Higher-paid and low-paid | −0.767 | 0.186 | −0.401 | 0.204 |
| Higher-paid and non-employed | −1.364 | 0.262 | −0.61 | 0.24 |
| Low-paid and non-employed | −0.06 | 0.21 | 0.2 | 0.222 |
| All three labour market statuses | −0.96 | 0.193 | −0.506 | 0.208 |
| Ethnicity | | | | |
| NZ European | Reference category | | | |
| Māori | −0.023 | 0.06 | 0.128 | 0.084 |
| Pacific Peoples | 0.099 | 0.074 | 0.251 | 0.114 |
| Asian | 0.086 | 0.06 | 0.039 | 0.087 |
| Middle Eastern/Latin American/African | −0.14 | 0.18 | −0.044 | 0.225 |
| Others | 0.122 | 0.132 | −0.024 | 0.202 |
| Smoking regularly | 0.092 | 0.045 | 0.132 | 0.066 |
| Qualification level | | | | |
| No qualifications | Reference category | | | |
| Level 1–4 | −0.117 | 0.048 | −0.077 | 0.072 |
| Level 5–6 | −0.124 | 0.103 | −0.038 | 0.144 |
| Bachelor's degree | −0.258 | 0.121 | −0.096 | 0.164 |
| Postgraduate degree | −0.593 | 0.074 | −0.258 | 0.098 |
| Age | 0.007 | 0.014 | −0.024 | 0.02 |
| Age squared | 0.000 | 0.000 | 0.000 | 0.000 |
| Months employed between March 2011 and February 2013 | | | | |
| 0–6 months | Reference category | | | |
| 7–12 months | −0.535 | 0.119 | −0.105 | 0.144 |
| 13–18 months | −0.475 | 0.108 | −0.223 | 0.133 |
| 19–24 months | −0.155 | 0.09 | −0.114 | 0.113 |
| Low-paid months (03/2011–02/2013, %) | 2.078 | 0.072 | 1.325 | 0.107 |
| Log-likelihood | −20,918.377 | | | |
| *N* | 64,035 | | | |

*Source*: Authors' calculations using data from the IDI. Estimation is based on multinomial logit model with correlated random-effects. The model also includes constants, the variances of the random-effects and their correlation parameter (not shown here).

Table A3
*Regression Results (Share of Months)*

| | Low pay$_t$ | | Non-employed$_t$ | |
|---|---|---|---|---|
| | Coeff. | Std err. | Coeff. | Std err. |
| Status between $t-12$ and $t$ (share) | | | | |
| Non-employed | Reference category | | | |
| Higher-paid | −4.433 | 0.121 | −8.436 | 0.124 |
| Low-paid | 1.524 | 0.129 | −5.113 | 0.150 |
| Status: March 2013 to February 2014 (share) | | | | |
| Non-employed | Reference category | | | |
| Higher-paid | −0.479 | 0.128 | 0.050 | 0.161 |
| Low-paid | −0.066 | 0.133 | 0.018 | 0.177 |
| Ethnicity | | | | |
| NZ European | Reference category | | | |
| Māori | −0.055 | 0.053 | 0.074 | 0.084 |
| Pacific Peoples | 0.124 | 0.064 | 0.115 | 0.111 |
| Asian | 0.14 | 0.052 | 0.140 | 0.086 |
| Middle Eastern/Latin American/African | −0.032 | 0.16 | −0.105 | 0.24 |
| Others | 0.045 | 0.110 | −0.258 | 0.209 |
| Smoking regularly | 0.090 | 0.039 | 0.109 | 0.066 |
| Qualification level | | | | |
| No qualifications | Reference category | | | |
| Level 1–4 | −0.149 | 0.042 | −0.147 | 0.072 |
| Level 5–6 | −0.370 | 0.087 | −0.280 | 0.145 |
| Bachelor’s degree | −0.421 | 0.102 | −0.222 | 0.160 |
| Postgraduate degree | −0.725 | 0.062 | −0.309 | 0.096 |
| Age | −0.011 | 0.012 | −0.042 | 0.019 |
| Age squared | 0.000 | 0.000 | 0.001 | 0.000 |
| Months employed between March 2011 and February 2013 | | | | |
| 0–6 months | Reference category | | | |
| 7–12 months | −0.265 | 0.106 | 0.223 | 0.149 |
| 13–18 months | −0.130 | 0.097 | 0.334 | 0.138 |
| 19–24 months | −0.033 | 0.081 | 0.087 | 0.119 |
| Low-paid months (03/2011–02/2013, %) | 0.506 | 0.075 | 0.456 | 0.119 |
| Log-likelihood | −19,945.374 | | | |
| *N* | 64,035 | | | |

*Source*: Authors’ calculations using data from the IDI. Estimation is based on multinomial logit model with correlated random effects. The model also includes constants, the variances of the random effects and their correlation parameter (not shown here).

TABLE A4
*Regression Results (Share of Months, Interacted)*

| | Low pay$_t$ | | Non-employed$_t$ | |
|---|---|---|---|---|
| | Coeff. | Std err. | Coeff. | Std err. |
| Status between $t-12$ and $t$ (share) | | | | |
| Non-employed | Reference category | | | |
| Higher-paid | −4.085 | 0.139 | −7.337 | 0.126 |
| Low-paid | 1.459 | 0.142 | −4.255 | 0.159 |
| Higher-paid × low-paid | 4.386 | 0.222 | −0.110 | 0.479 |
| Higher-paid × non-employed | 1.318 | 0.571 | 8.409 | 0.437 |
| Low-paid × non-employed | 2.339 | 0.520 | 2.271 | 0.562 |
| Status: March 2013 to February 2014 (share) | | | | |
| Non-employed | Reference category | | | |
| Higher-paid | −0.625 | 0.145 | −0.142 | 0.171 |
| Low-paid | −0.304 | 0.147 | 0.055 | 0.187 |
| Higher-paid × low-paid | 0.057 | 0.223 | −0.917 | 0.422 |
| Higher-paid × non-employed | −1.498 | 0.679 | −0.177 | 0.687 |
| Low-paid × non-employed | −0.067 | 0.549 | 0.053 | 0.686 |
| Ethnicity | | | | |
| NZ European | Reference category | | | |
| Māori | −0.063 | 0.051 | 0.080 | 0.083 |
| Pacific Peoples | 0.059 | 0.062 | 0.165 | 0.111 |
| Asian | 0.088 | 0.05 | 0.211 | 0.085 |
| Middle Eastern/Latin American/African | −0.082 | 0.155 | −0.071 | 0.23 |
| Others | 0.008 | 0.108 | −0.304 | 0.211 |
| Smoking regularly | 0.062 | 0.038 | 0.104 | 0.066 |
| Qualification level | | | | |
| No qualifications | Reference category | | | |
| Level 1–4 | −0.119 | 0.041 | −0.140 | 0.072 |
| Level 5–6 | −0.281 | 0.085 | −0.254 | 0.144 |
| Bachelor's degree | −0.28 | 0.101 | −0.204 | 0.159 |
| Postgraduate degree | −0.579 | 0.061 | −0.412 | 0.096 |
| Age | −0.004 | 0.011 | −0.044 | 0.019 |
| Age squared | 0.000 | 0.000 | 0.001 | 0.000 |
| Months employed between March 2011 and February 2013 | | | | |
| 0–6 months | Reference category | | | |
| 7–12 months | −0.273 | 0.101 | 0.031 | 0.143 |
| 13–18 months | −0.189 | 0.093 | 0.111 | 0.133 |
| 19–24 months | −0.073 | 0.078 | −0.015 | 0.114 |
| Low-paid months (03/2011–02/2013, %) | 0.451 | 0.071 | 0.532 | 0.116 |
| Log-likelihood | −19,432.508 | | | |
| *N* | 64,035 | | | |

*Source*: Authors' calculations using data from the IDI. Estimation is based on multinomial logit model with correlated random effects. The model also includes constants, the variances of the random-effects and their correlation parameter (not shown here).

Table A5
*Estimated Labour Market Dynamics (Robustness)*

| | Predicted probabilities | | | Partial effects | | |
|---|---|---|---|---|---|---|
| | Higher pay$_t$ (1) | Low pay$_t$ (2) | Non-employed$_t$ (3) | Higher pay$_t$ (4) | Low pay$_t$ (5) | Non-employed$_t$ (6) |
| Robustness 1: Sum of months from $t-12$ to $t-1$ | | | | | | |
| Higher pay | 0.9625 | 0.0281 | 0.0094 | 0.9406 | −0.0211 | −0.9195 |
| | (0.0001) | (0.0001) | (0.0000) | (0.0035) | (0.0063) | (0.0078) |
| Low pay | 0.0925 | 0.8842 | 0.0233 | 0.0706 | 0.8350 | −0.9056 |
| | (0.0003) | (0.0004) | (0.0000) | (0.0075) | (0.0092) | (0.0071) |
| Non-employed | 0.0219 | 0.0492 | 0.9289 | Reference category | | |
| | (0.0000) | (0.0001) | (0.0001) | | | |
| Robustness 2: Sum of months from $t-12$ to $t-1$ (interacted) | | | | | | |
| Higher pay | 0.9733 | 0.0188 | 0.0079 | 0.8986 | −0.0597 | −0.8389 |
| | (0.0001) | (0.0001) | (0.0000) | (0.0094) | (0.0101) | (0.0163) |
| Low pay | 0.1781 | 0.7929 | 0.0290 | 0.1034 | 0.7144 | −0.8178 |
| | (0.0005) | (0.0005) | (0.0000) | (0.0148) | (0.0148) | (0.0148) |
| Non-employed | 0.0747 | 0.0785 | 0.8468 | Reference category | | |
| | (0.0002) | (0.0001) | (0.0002) | | | |

*Source*: Authors' calculations using data from the IDI. Standard errors in parentheses.

Table A6
*Estimated Labour Market Dynamics (Initially Non-employed)*

| | Predicted probabilities | | | Partial effects | | |
|---|---|---|---|---|---|---|
| | Higher pay$_t$ (1) | Low pay$_t$ (2) | Non-employed$_t$ (3) | Higher pay$_t$ (4) | Low pay$_t$ (5) | Non-employed$_t$ (6) |
| Status at $t-12$ | | | | | | |
| Higher-paid | 0.5296 | 0.2474 | 0.0824 | 0.4472 | 0.0692 | −0.5164 |
| | (0.0024) | (0.0019) | (0.0009) | (0.0212) | (0.0189) | (0.0135) |
| Low-paid | 0.3416 | 0.5639 | 0.2724 | 0.1650 | 0.2915 | −0.4565 |
| | (0.0017) | (0.0015) | (0.0008) | (0.0126) | (0.0136) | (0.0095) |
| Non-employed | 0.1288 | 0.1887 | 0.6452 | Reference category | | |
| | (0.0008) | (0.0007) | (0.001) | | | |
| Status from $t-12$ to $t-1$ | | | | | | |
| Continuously non-employed | 0.0054 | 0.0387 | 0.9559 | Reference category | | |
| | (0.0000) | (0.0002) | (0.0002) | | | |
| Continuously higher-paid | 0.9329 | 0.0588 | 0.0083 | 0.9275 | 0.0201 | −0.9476 |
| | (0.0008) | (0.0007) | (0.0001) | (0.0107) | (0.0119) | (0.0083) |
| Continuously low-paid | 0.0987 | 0.8848 | 0.0164 | 0.0933 | 0.8461 | −0.9395 |
| | (0.0011) | (0.0012) | (0.0001) | (0.0154) | (0.0181) | (0.0083) |
| Higher-paid and low-paid | 0.4651 | 0.5211 | 0.0138 | 0.4597 | 0.4824 | −0.9421 |
| | (0.0027) | (0.0027) | (0.0000) | (0.0341) | (0.0335) | (0.0077) |
| Higher-paid and non-employed | 0.296 | 0.1124 | 0.5916 | 0.2905 | 0.0738 | −0.3643 |
| | (0.0017) | (0.0007) | (0.0012) | (0.0382) | (0.0191) | (0.0434) |
| Low-paid and non-employed | 0.0603 | 0.5348 | 0.4049 | 0.0549 | 0.4961 | −0.551 |
| | (0.0006) | (0.0015) | (0.001) | (0.0105) | (0.0362) | (0.0372) |
| All three labour market statuses | 0.3008 | 0.4519 | 0.2473 | 0.2954 | 0.4132 | −0.7086 |
| | (0.0021) | (0.002) | (0.0005) | (0.0301) | (0.0304) | (0.0283) |

*Source*: Authors' calculations using data from the IDI. Standard errors in parentheses.

*Disclaimer*

The results in this paper are not official statistics, but 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.

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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 details can be found in the privacy impact assessment for the Integrated Data Infrastructure available from www.stats.govt.nz.