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Michael Leith Cowling
Mark Wooden

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Michael Leith Cowling
Melbourne Institute: Applied Economic & Social Research,
The University of Melbourne

Mark Wooden
Melbourne Institute: Applied Economic & Social Research
The University of Melbourne

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Melbourne Institute: Applied Economic & Social Research
The University of Melbourne
Victoria 3010 Australia
***Telephone* +61 3 8344 2100**
***Fax* +61 3 8344 2111**
***Email* melb-inst@unimelb.edu.au**
***Website* melbourneinstitute.unimelb.edu.au**

Abstract

This paper examines the extent to which solo self-employment serves as a vehicle for job creation. Using panel data from the Household, Income and Labour Dynamics in Australia (HILDA) Survey, a dynamic multinomial logit model of transitions between labour market states is estimated. The empirical strategy closely follows that used in a previous study employing household data from Germany by Lechmann and Wunder (2017). Estimates of true cross-state dependence between solo self-employment and employership are obtained that are relatively small. Further, our results imply that the probability of a male remaining an employer just two years after transitioning out of solo self-employment is only 2% (and among women, it is virtually zero). The extent of both true cross-state dependence and true state dependence in employership is, however, much greater among individuals who have demonstrated a preference for self-employment in the past. This implies that pro-entrepreneurial policies that target more 'entrepreneurial' individuals will have more pronounced and long-term effects in stimulating job creation.

JEL classification: L26

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1. Introduction

Governments in many Western countries devote tax-payer funded resources to supporting self-employed entrepreneurs on the grounds that new start-up businesses are critical for the creation of new jobs. Yet most self-employed workers do not hire anyone. Data available from the International Labour Organization (ILO) website (ilostat.ilo.org/data), for example, indicate that, among developed nations, the percentage of self-employed workers who employ others ranged, in 2018, from just 14% in the UK to 44% in Germany, with the multi-country average being around 31%.[1] Policies that incentivize transitions out of unemployment into self-employment, while obviously reducing unemployment in the short-run, may thus have little additional job creation impacts. Indeed, and as noted by Congregado, Golpe and Carmona (2010), such measures, by attracting persons who are not well suited to self-employment, may have employment effects that are only temporary.

For entrepreneurship policies to be successful, in the sense of creating firms that generate new jobs, requires targeting those entrepreneurs who are most likely to transition from working alone (i.e., the solo self-employed, often also referred to as own-account workers) to employing others (i.e., employers). Somewhat surprisingly, however, especially given the many studies seeking to unpack the mechanisms that encourage individuals to enter self-employment (for reviews see Parker, 2009; Simoes et al., 2016; van Praag and Versloot, 2007), there has been relatively little research on the factors influencing transitions out of solo self-employment into employer status.[2]

Notable exceptions here are a series of studies involving analysis of data from the European Community Household Panel (ECHP) by Millán and colleagues (Congregado, Millán and Román, 2010; Millán et al., 2013, 2014, 2015) – though only one (Millán et al., 2014) provides a direct test of whether solo self-employment has any effect on the probability of becoming an employer in the future – and analyses of household panel data from both the

[1] Derived from a list of 22 countries, with the only notable exclusions being the Republic of Korea and the USA, with the ILO site not distinguishing employers from other self-employed in these two cases.

[2] There is a related, but still relatively small, literature on the determinants of job creation by the self-employed. Leading examples here are Burke et al. (2002), Cowling et al. (2004), Henley (2005), Mathur (2010) and van Praag and Cramer (2001).

German Socio-Economic Panel (SOEP) (Lechmann and Wunder, 2017) and the UK Household Longitudinal Study (Henley, 2019).

Millán et al. (2014) estimate discrete-time models of the hazard of exit out of both solo self-employment and employership within a competing risks framework. Prior experience is represented by a simple dummy variable indicating whether the respondent reported ever previously working as an own-account worker (i.e., solo self-employed worker), an employer or a paid employee. To the authors' surprise, prior experience as a solo self-employed worker is not found to influence the probability of transitioning from solo self-employment to employership. At the same time, the estimated probability of switching from solo self-employed to employer is found to be markedly higher than the probability of exiting to other states, which the authors take as a "sign of success" and so conclude that the results are consistent with the notion that there is persistence in entrepreneurship and hence provide support for public investments in new start-ups. We suggest such a conclusion is not warranted. First, it is inconsistent with their finding that previous experience in self-employment is irrelevant, and second, their estimation method does not allow the "true" effect of solo self-employment on employership in the future (true state dependence) to be isolated from the effects of other factors that influence both solo self-employment in the past and employership in the future (spurious state dependence).

Henley (2019) too estimates a discrete-time model of the hazard of exiting solo self-employment into employership, but with the sample restricted to those observed in self-employment.[3] Furthermore, he includes a person-specific random error component as a way of controlling for unobserved heterogeneity. In addition, prior self-employment experience is captured with a cumulative measure of years of experience rather than a dummy. In contrast to Millán et al. (2014), a positive relationship between transition into employer status and elapsed duration in self-employment is found, providing arguably stronger evidence for the hypothesis that prior experiences of self-employment have a causal effect on the probability of employing workers in the future. Nevertheless, the methods applied are still problematic. Like Millán et al (2014), the data are censored for cases where the self-employed are never observed becoming employers over the (6-year) data period, and the use of random effects

[3] He also estimates a logit model of the likelihood being an employer relative to being solo self-employed and an ordered logit model of the scale of employment.

imposes the unlikely assumption that the explanatory variables are uncorrelated with the unobserved error component.

Far more convincing is the estimation strategy employed by Lechmann and Wunder (2017). They employ a very broad sample, which is not just restricted to persons observed entering self-employment, and estimate a dynamic multinomial logit model that controls for both the previous observed employment state and initial conditions as well as unobserved heterogeneity, but this time using correlated random effects. They find that the "genuine effect" of experiencing solo self-employment (relative to wage employment or non-employment) on future employership is both small (about a 5 percentage point increase for men and a little over just 2 percentage points for women) and not long-lasting. As such, these results are discouraging for proponents of subsidies and policy measures designed to encourage individuals to enter self-employment. Of course, this is only one study utilising one data from one country, and thus replication both in Germany and in other institutional settings is required before it can be confidently concluded that such measures will typically have little lasting effect on employment.

Providing such a replication is the aim of this study. More specifically, we utilise a similar household panel survey data set to that used by both Lechmann and Wunder (2017) and Henley (2019), but from Australia (a country where self-employment rates have tended to be higher than the average across other industrial nations, and certainly much higher than in Germany), and apply the same estimation strategy used by Lechmann and Wunder. We obtain estimates of true cross-state dependence that are strikingly similar in size to those found in the German study.

2 Empirical Strategy

Following Lechmann and Wunder (2017), we estimate a dynamic logit model of the determinants of transitions between four different labour market states: solo self-employment; employership; wage and salary employment (i.e., employees); and non-employment. The simplest version of this model takes the form:

$$Prob\left(y_{it} = \mathrm{j} \mid x_{it}, y_{i,t-1}, \alpha_{ij}\right) = \frac{exp\left(\beta_j' x_{it} + \gamma_j' y_{i,t-1} + \alpha_{ij}\right)}{\sum_{k=1}^{4} exp\left(\beta_k' x_{it} + \gamma_k' y_{i,t-1} + \alpha_{ik}\right)} \tag{1}$$

where y_{it} represents the individual's employment state *j* at time *t*, $y_{i,t-1}$ is a vector of variables indicating the individual's employment state at the previous period, x_{it} is a vector of observed individual characteristics, and α_{ij} is a random error component intended to capture individual-specific unobserved heterogeneity.

Inclusion of a lagged dependent variable, however, is problematic. The dynamic structure of the model implies that employment status at time *t* is dependent on employment status at all previous periods, but we only observe labour market outcomes over the period covered by the data, and for most individuals this will not cover their entire employment history. As a result, the initially observed employment state is likely to be correlated with the random error term, causing the level of state dependence to be overstated. Further, random effects estimation requires the unrealistic assumption that α_{ij} is uncorrelated with any of the individual's observables, and thus likely introducing further inconsistency to our estimates.

To deal with these two problems, and again following Lechmann and Wunder (2017), who in turn adopted an approach suggested by Wooldridge (2005), we model the unobserved heterogeneity α_{ij} as a function of the initial observed state y_{i0} (to deal with the initial conditions problem), a vector of individual-specific time averages of the exogenous characteristics $\bar{x}_i$ (thus allowing for a correlation between α_{ij} and the observed individual characteristics) and a new random error term v_{ij} that is assumed to be uncorrelated with both the initial labour market state and the observed characteristics of the individual. That is:

$$\alpha_{ij} = \delta'_{yj} y_{i0} + \delta'_{xj} \bar{x}_i + v_{ij} \qquad (2)$$

Combining (1) and (2) gives us our final estimation equation:

$$Prob\left(y_{it} = \mathrm{j} \mid x_{it}, y_{i,t-1}, y_{i0}, v_{ij}\right) = \frac{exp\left(\beta'_j x_{it} + \gamma'_j y_{i,t-1} + \delta'_{yj} y_{i0} + \delta'_{xj} \bar{x}_i + v_{ij}\right)}{\sum_{k=1}^{4} exp\left(\beta'_k x_{it} + \gamma'_k y_{i,t-1} + \delta'_{yk} y_{i0} + \delta'_{xk} \bar{x}_i + v_{ik}\right)} \qquad (3)$$

The standard multinomial logit model imposes the IIA (independence of irrelevant alternatives) assumption. This essentially requires that each of the employment states is equally substitutable, which obviously is not the case here – employership, for example, will be a closer substitute for solo self-employment than either wage and salary employment or non-employment. As proposed by Skrondal and Rabe-Hesketh (2003), we relax this assumption by allowing the random effects to be correlated across the different employment states.

Estimation is carried out in STATA 15 using the 'gsem' command and applied to a two-level multinomial logistic model with separate but correlated random effects. Average predicted probabilities are obtained with the post-estimation command 'margins', which are then used to calculate estimates of state dependence.[4]

3 Data and Descriptive Statistics

We use data from the first 16 waves of the Household, Income and Labour Dynamics in Australia (HILDA) Survey, a longitudinal study that commenced in 2001 with the collection of data (both by interview and via a self-administered paper form) from all adult members (persons aged 15 years or older) of a nationally representative sample of Australian households. Further interviews are then sought every subsequent year with these respondents together with any children turning 15 years of age and any other persons residing in a household with an original sample member.[5]

The sample for this analysis is restricted to persons aged between 21 and 64 years, a group that might be loosely described as the working-age population. Any observations where the respondent was unable, or unwilling, to report their employment status were excluded (n=9). We also omitted any observations where the respondent reported study (or an intent to return to study) was a reason for not looking for work (n=1287). After these exclusions, we were left with an initial working sample comprising 30,496 persons contributing 169,974 observations.[6]

[4] For further details about the estimation procedures, including the numerical integration method used to obtain coefficient estimates, see StataCorp (2019). For a simple explanation of how estimates of state dependence are calculated, see Lechmann and Wunder (2017).

[5] For further details about the HILDA Survey and its sample, see Watson and Wooden (2012) and / or Summerfield et al. (2018).

[6] While we have described our study as a replication of Lechmann and Wunder (2017), the sample used here differs in a number of ways from the sample used by Lechmann and Wunder. First, the age range for our sample is slightly narrower – 21 to 64 years compared with 20 to 65 years. Second, Lechmann and Wunder excluded all persons in education whereas we only exclude students if they are not working and report study as the reason for not looking for work. Third, Lechmann and Wunder excluded all self-employed farmers, whereas we make no such exclusion. Fourth, Lechmann and Wunder excluded all pensioners, whereas we again make no such exclusion. (For men, this last-mentioned exclusion will have little impact given eligibility for the Age Pension in Australia over our observation period was 65 years, though war veterans were eligible for the Service Pension at age 60. For women, however, eligibility for the Age Pension has been progressively increased from age 60 in the late 1990s, only reaching parity with men in 2013.)

As previously noted, the outcome variable distinguishes between four mutually-exclusive labour market states or outcomes. These outcomes are derived from responses to survey questions that closely mirror questions included in the monthly Labour Force Survey (LFS) conducted by the Australian Bureau of Statistics (ABS), which in turn follow standards and guidelines set out by the ILO. Respondents are first identified as employed if they undertook any paid employment during the 7 days prior to interview (or were away from work because of holidays, sickness or some other reason).[7] All other respondents are classified as not employed. Among the employed, we distinguish between employees (persons who work for a wage or salary) and the self-employed.[8] We differ from the ABS, however, in how we treat owner-managers of incorporated businesses. We treat all owner-managers, regardless of the legal status of their businesses, as self-employed, whereas the ABS traditionally classified owner-managers of incorporated businesses as employees (of their own business). We argue that while the legal status of a business has implications for who is held responsible in the event of insolvency, it has no bearing on the employment relationship – the owner of a firm is fundamentally different to other persons employed in that firm, not least because of the power the owner has over hiring and firing decisions and the allocation of tasks among workers.[9] Finally, among the self-employed we distinguish between those that have employees working in their businesses (employers) and those that do not (the solo-self-employed).

As evidence of the quality and representativeness of our sample, in Table 1 we show how population-weighted estimates of labour force status from the HILDA Survey (covering the entire population aged 15 years or older) compare with those from the monthly LFS for the

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[7] All persons away from work for less than 4 weeks are classified as employed. Persons away from work for 4 weeks or more are only classified as employed if they were: (i) paid for any part of the last 4 weeks; or (ii) on workers compensation and expect to return to their current employer; or (iii) absent from work because of industrial action.

[8] Additionally, there is third but very small group of workers – contributing family workers – who do not fit easily into either category. In our regression analyses we have included them within the much larger employee group.

[9] This is consistent with current ILO guidelines, which, as revised in 2013, specifically identify owner-managers of incorporated enterprises as a group that may be classified either as employees or as self-employed, but then suggested that classification as self-employed will generally be best for labour market analyses (ILO, 2013, p. 18). We also think it is likely to be consistent with the way respondents classified themselves in the GSOEP, which makes no reference to whether the business owned is incorporated or not, and simply identifies the self-employed by whether someone indicated they were a: (i) self-employed farmer; (ii) freelance professional or self-employed academic; or (iii) other self-employed (though as previously noted, Lechmann and Wunder [2017] exclude self-employed farmers from their analyses of these data).

first and last years of our data period. Differences in survey methodology mean that we do expect differences – the initial HILDA Survey sample, for example, excluded persons living in non-private dwellings (though respondents are followed into such dwellings when they move) and persons living in very remote parts of Australia. The HILDA Survey also has the problem that it has no mechanism for automatically recruiting new immigrants who enter Australia after the original sample was drawn (though a refreshment sample was added in 2011 to partly address this problem). These differences in sample and survey methodology help explain some of the differences reported in Table 1, especially the lower rate of non-employment in the HILDA Survey. Nevertheless, Table 1 suggests that the HILDA Survey data may systematically understate the incidence of self-employment in Australia, and more specifically the share of employment accounted for by solo self-employment. This difference in estimated self-employment rates has previously been noted by Laß and Wooden (forthcoming), who point to relatively high rates of non-response among the self-employed in the HILDA Survey that may not have been adequately corrected for by the weighting procedure as one possible explanation. Nevertheless, they also identify potential classification errors in the LFS stemming from interviewing one responsible adult in the household rather than every adult household member (as is the practice in the HILDA Survey) as another potential explanation. It is thus not entirely clear how much of the difference is due to understatement in the HILDA Survey or overstatement in the LFS.

Despite these differences in the estimated levels of self-employment, the trends in the self-employment share in the two data sources are, as shown in Figure 1, very similar. According to both data sources, the shares of both solo self-employed workers and employers have exhibited steady decline over the period covered by our analysis, a trend that Australia shares with many other high-income countries (Naude, 2019).

Returning to the sample used in this analysis, Table 2 presents figures on both the number of annual transitions between the four different labour market states and the number of non-transitions (i.e., where the observed labour market state was unchanged from the previous year). As would be expected, most people do not change their labour market state from one year to the next. Nevertheless, we still observe 9796 men changing states across any two consecutive survey waves (14.1% of the total male sample) and 11495 women (15.0%). Of these transitions, 15% (among men) and 5% (among women) involve shifts between solo self-employment and employership, 31% and 18% involve shifts between either type of self-employment and a paid employee job, while a further 9% and 10% involve shifts between self-employment and non-employment. This table also shows that of those who transition into employership, many, but far from all, will come from solo self-employment (58.8% of men transitioning into employership and 39% of women).

Next, we show, in Figures 2 and 3, how the distribution of our sample across the four labour market states, conditional on being in a specific state in the initial period, varies over time. As found by Lechmann and Wunder (2017) for Germany, employees exhibit by far the greatest degree of persistence. Nevertheless, the degree of persistence in wage and salary employment is less in the Australian data. For example, Lechmann and Wunder (2017) reported that 95% of male employees in Germany were still employees one year later and 85% in that same state five years on. The comparable figures in the HILDA Survey are 86% and 82% (see Figure 2, Panel C). The levels of initial (i.e., one year) persistence in both solo self-employment and employership in these raw data are also less in the Australian data, but among the solo self-employed this situation reverses over longer periods. After nine years, 39% of the male solo self-employed and 24% of the female solo self-employed were still in solo self-employment (Figures 2, Panel A and Figure 3, Panel A). The comparable figures in Germany were only around 20% (for both men and women). Of most relevance to this study are the rates of transition out of solo self-employment into employership. Among men (Figure 2, Panel A), about 13% of the solo self-employed are employers one year later, and, perhaps surprisingly (but mirroring what Lechmann and Wunder found in their German data), while this level does rise over time, the increase is very modest. Among women (Figure, Panel A) the initial rate of transition into employership is even lower – 9% – and in contrast to men, remains at or around this level for virtually the entire observation period.

Turning to the covariates included in our multivariate model, these are listed in Appendix Tables A1 and A2. Selection of these covariates began with the list of variables used by Lechmann and Wunder (2017) but with the final list differing in numerous ways. Notably, we include measures of the presence of a restrictive long-term health condition, impairment or disability[10], whether resident in an urban or rural location, years of accumulated prior work experience, home ownership, and the ABS monthly regional unemployment rate (which is

[10] The underlying question requires respondents to only report conditions that restrict everyday activities and that have lasted, or are expected to last, for 6 months or more.

measured at Statistical Area Level 4 in the Australian Statistical Geography Standard and divides Australia into 87 regions, and comes from ABS, 2019, Table 16[11]). Comparable measures are not included in the specification employed by Lechmann and Wunder. The inclusion of a measure of work experience we believe is particularly important given the extensive evidence on the importance of experience as a factor positively influencing entry into self-employment (for a review, see Simoes et al., 2016). At the same time, however, the range and value of alternative labour market options increase with experience (Millán et al., 2012), and hence a priori it is unclear in what direction prior experience will influence transitions in and out of different employment states. Nevertheless, we suggest (and find) that a quadratic relationship will provide the best fit. We also include measures of marital status, immigrant status and education that differ markedly from the comparable variables included by Lechmann and Wunder (2017). We treat de facto partnerships as equivalent to marriages, our immigrant variables provide for three categories of respondents (rather than just two) with a distinction made between immigrants born in one of the main English-speaking countries and those born in other countries[12], and education is represented by a series of dummy variables identifying highest level of education rather than a single measure of years of education. Our household income variable is also likely constructed differently. Most obviously, we use net annual household income (from the previous financial year, and then lagged one period) whereas Lechmann and Wunder use net average monthly household income (as recorded at the previous interview).[13] Additionally, there are three variables included in the Lechmann and Wunder (2017) specification that we did not include. These were measures of whether the father was self-employed (which is not collected in the HILDA Survey), attitudes towards risk (with the only available measure in the HILDA Survey coming from its self-administered questionnaire, which is associated with additional non-response, and not available in all survey waves), and household size (which we thought close to redundant in the presence of measures of marital status and the number of dependent

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[11] Monthly unemployment rates for each year have been matched to the month of interview for each respondent.

[12] Following ABS practice, the main English-speaking countries are the UK, the Republic of Ireland, New Zealand, Canada, the USA and South Africa.

[13] The income variable used, which is provided in the HILDA Survey data release file, is created by summing different income components within individuals, and then summing incomes across individual household members. Missing values on any component or for any individual household member are imputed, and thus no cases are lost as a result of either unit or item non-response. For details about the imputation methods used, see Summerfield et al. (2018, pp. 74-81).

children). Finally, like Lechmann and Wunder, we also include respondent age (also specified as a quadratic), year dummies (which are potentially important given the marked downward trend in the incidence of self-employment over the period), and major region dummies (which identify the eight States and Territories of Australia, and within the five largest States, between the capital city and the remainder of the State.)

4 Results

Table 3 reports the main results of interest from the separate estimation of the dynamic multinomial logit model for males and for females. Consistent with the descriptive data, the estimates suggest a strong degree of state dependence from one year to the next, with all the estimates of own state dependence being large and positive. More importantly for this analysis, the estimated parameters of cross-state dependence suggest that solo self-employment serves as an entry point into employership. Indeed, the point estimates (3.27 for men and 2.91 for women) we obtain in HILDA Survey data are larger than found by Lechmann and Wunder in German data (2.67 and 2.27 respectively). However, when these estimates are converted into predicted transition probabilities, reported in Table 4, we find estimates that are strikingly similar to those reported for Germany. The average predicted annual probability of transition from solo self-employment to employership is 9.2% among men and just 4.0% for women. The comparable probabilities reported by Lechmann and Wunder (2017) were 9.0% and 3.0%. Also as found by Lechmann and Wunder, these predicted probabilities are noticeably smaller than the observed probabilities (reported in Figures 2 and 3), thus highlighting the important role played by individual characteristics (both observed and unobserved) in explaining labour force transitions. Indeed, about 29% of the transitions from solo self-employment to employership observed in the raw data for men, and about 64% of the persistence observed in the raw data for women, can be accounted for by individual characteristics.

Again following Lechmann and Wunder (2017), we next use these predicted probabilities to derive estimates of true state, and true cross-state, dependence. These are reported in Table 5. For comparative purposes, we also report the comparable estimates for Germany. Based on these estimates, Lechmann and Wunder (2017) conclude that the levels of both true state and true cross-state dependence in Germany are small. And in the case of cross-state dependence, our estimates from the HILDA Survey data suggest an identical conclusion. Our estimates indicate that, for men, solo self-employment in one year raises the probability of being an employer in the next year by 6.0 to 6.2 percentage points relative to transitioning to an alternative state (i.e., either wage employment or non-employment). The comparable figures for Germany are 4.9 to 5.1 percentage points. For women, the effects are even smaller – just a 2.3 to 2.4 percentage point relative increase, very similar to what was found for Germany (2.1 to 2.4 percentage points).

While not our focus, Lechman and Wunder (2017) also emphasise the magnitudes of their estimates of true state dependence, arguing that these too are quite small – 9.6 or 13.3 percentage points for male solo-self-employment, and 9.7 or 9.2 percentage points for women. Our HILDA Survey estimates, however, are much larger – 15.3 or 19.5 percentage points for men, and 14.2 or 15.4 percentage points for women. There is thus greater true persistence in solo self-employment in Australia than in Germany. Similarly, we also observe among men (but not women) that the level of true state dependence in employership is much greater in the Australian data (18.1 to 18.3 percentage points) than in the German data (8.3 to 8.6 percentage points). Together these contribute to levels of true state dependence in total self-employment in Australia which, at 26.7% for men and 16.9% for women (when calculated relative to wage employment), are considerably larger than that reported by Lechmann and Wunder (2017). While it is possible such differences may reflect differences in specification, they nevertheless are entirely consistent with the markedly higher rate of self-employment in the Australian data (average annual sample means of 17.3% and 8.2% for men and women respectively) than in the German data (means of 10.8% and 4.7%).[14]

One potential problem that seems to have been ignored by previous studies of self-employment dynamics is that of bias resulting from non-random attrition. As both a simple test of, and control for, the selectivity bias that might result, we follow Verbeek and Nijman (1992) and include an additional regressor identifying whether the sample member is a non-respondent at the next wave (which in turn results in the observations from wave 16 – n=11237 – not being used in this estimation). The estimated coefficients on this attrition

[14] Our estimates, however, are smaller than what has been found in one previous Australian study, with Fitzpatrick (2017) reporting estimates of state dependence in self-employment ranging from 26% to 29%. While utilising the same data set as employed here (but over the shorter period 2001 to 2011), the approach adopted by Fitzpatrick is quite different. Specifically, he only models the choice between self-employment and wage employment, and hence both ignores the distinction between solo self-employment and employership and excludes all non-employed observations.

variable (not reported here) are jointly significant (at least among men), with attrition being much more likely among the non-employed, but with differences between the different classes of workers being relatively small.[15] But much more importantly, the inclusion of this variable had, as shown in Table 6, very little impact on the estimated coefficients on our lagged employment status variables, suggesting that our key results are not affected by selective attrition.

We also checked whether the results were being driven by the agriculture sector given the decision by Lechmann and Wunder (2017) to exclude self-employed farmers from their sample. We suspect this exclusion was motivated by concerns that the agriculture sector, with its very high rates of self-employment (in our sample 52.8% of all workers in the agriculture, forestry and fishing industries are classified as self-employed), may not be representative of other industries. Omitting all workers reporting employment in businesses in the agriculture, forestry and industries (n=4222), however, resulted in no qualitative differences in our estimates (see Table 6), and hence again our conclusions are unaffected.

We also checked whether our results were affected by the inclusion of students in our sample. As noted above, Lechmann and Wunder (2017) excluded all persons in education from their sample, whereas we only excluded students if they were not working and not looking for work and reported that study was a reason for not looking for work. Our analytical sample thus includes 18,784 observations (comprising 1,228 individuals) cases where, at the time of the interview, the respondent is studying for a qualification. Omitting these cases only has a modest effect on our results, with estimates of true cross-state dependence becoming slightly larger (see Table 6).

Finally, and again taking our lead from Lechmann and Wunder (2017), we examine how sensitive our results are to initial endowments and preferences by recalculating our state dependence estimates after setting the initial labour market condition to first self-employment (which required re-estimating our model after combining the initial conditions for solo self-employment and employership into the one variable) and then employership. The results are reported in Table 7 and show that extent of true cross-state dependence and true state

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[15] We used a Wald chi-squared test (with 3 degrees of freedom) to test the joint significance of the attrition variables across three equations. For men, with a test statistic of 8.95, we reject the null hypothesis that the attrition variables are jointly insignificant at the 5% significance level. For women the t-statistics is 5.84, meaning we fail to reject the null hypothesis.

dependence in employership is much greater among individuals who have demonstrated a preference for self-employment in the past (and much greater again if they have previously employed workers). This implies that pro-entrepreneurial policies targeting more 'entrepreneurial' individuals will have more pronounced and long-term effects in stimulating job creation.

5 Conclusion

This paper examined the transitional dynamics between solo self-employment and employership in the Australian labour market. Because of information asymmetries between new firms and employees, and the first employee hiring threshold, many self-employed will be reluctant to hire employees at the time of start-up. Hiring employees is further complicated by the uncertainty many of the newly self-employed will have about their own entrepreneurial ability. This partly explains both why a clear majority of self-employed workers are solo self-employed, and why the transition rate into employership is highest from solo self-employment. It is therefore expected that individuals enter solo self-employment, at least in part, to experiment and learn about their entrepreneurial ability, and to minimise information asymmetries between themselves and future workers. If this is true, then there should be cross-state dependence in employership – solo self-employment should increase an individual's probability of becoming an employer in the future. Further, there should also be state dependence in employership – being an employer at one point in time should increase the individual's probability of being an employer at the next point.

Using individual-level panel data from the HILDA Survey, we estimated a dynamic multinomial logit model with correlated random effects to show how being observed in solo self-employment or employership in one year affects the individual's decision to be an employer in the subsequent year. We find evidence consistent with the hypothesis that individuals enter self-employment as a solo self-employed worker to learn more about their true entrepreneurial ability – that is, there is evidence of both true cross-state dependence and true state dependence in employership within the Australian labour market. However, the magnitudes of these estimates of state dependence in employership are relatively small when compared to the observed rates of transition into employership and persistence within employership. This reflects the importance of heterogeneity, both observed and unobserved, in shaping labour market outcomes.

Our preferred estimates of true cross-state dependence are also very similar in magnitude to those reported by Lechmann and Wunder (2017, p. 104) for Germany, who, based on their findings, drew the conclusion that self-employment incentives, unless targeted on individuals with higher than average tastes for self-employment, are likely to have "predominantly short-run effects". We are compelled to reach a similar conclusion. While our estimates of persistence in employership are higher than those reported by Lechman and Wunder (2017), the predicted probability of a solo-self-employed worker moving into and then remaining an employer over even a modest length of time are simply too low to conclude otherwise. For example, our results imply that the probability of a male remaining an employer just two years after transitioning out of solo self-employment is only 2% (and among women, it is virtually zero). For pro-entrepreneurial policies to be cost-effective really requires targeting individuals who have pro-entrepreneurial endowments, something however that is not easily observed for those with little prior work experience.

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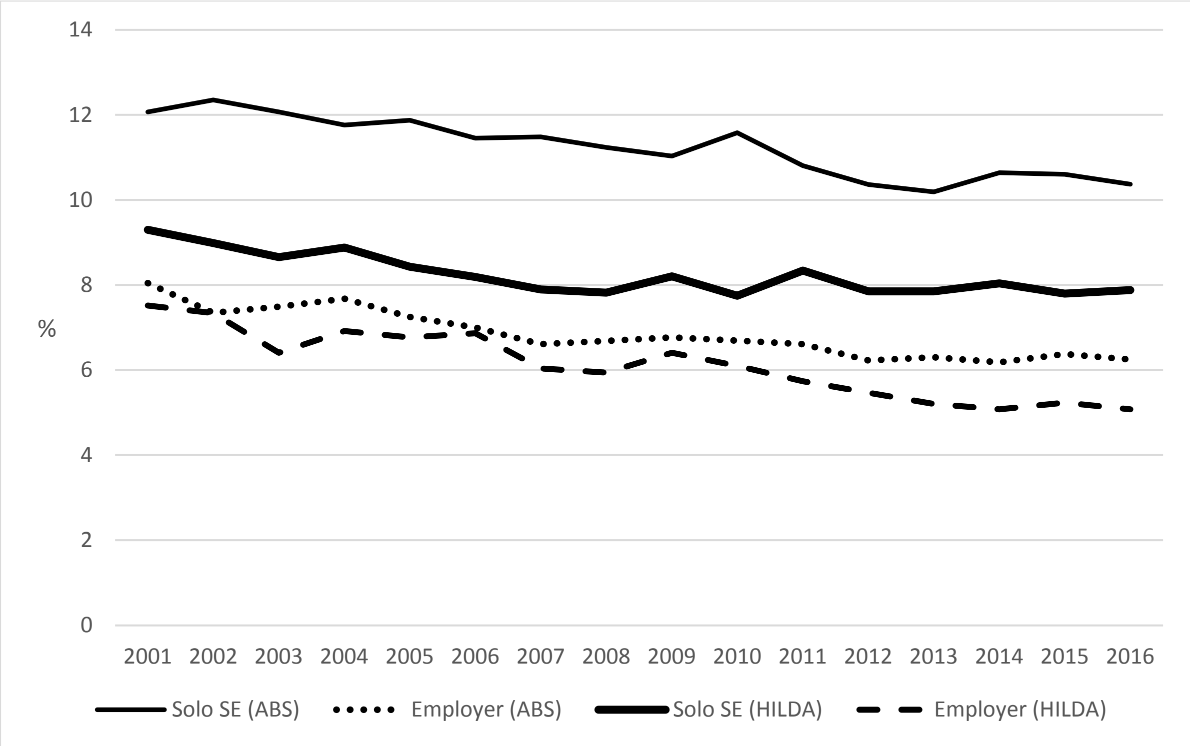
Figure 1

Trends in self-employment (% of employed persons), 2001-2016: HILDA Survey and Labour Force Survey (LFS) population estimates compared



Note: LFS estimates relate to the month of October, which lies roughly at the mid-point of the HILDA Survey fieldwork period.

Sources: ABS, *Labour Force, Australia*, *Detailed - Electronic Delivery* (cat. no. 6291.0.55.001), Time series spreadsheets, Table 08 (Employed persons by status in employment of main job and sex); HILDA Survey General Release 16, confidentialised unit record data file (Department of Social Services / Melbourne Institute, 2017).

Figure 2

Distribution of labour market states conditional on labour market state *t* years earlier: males

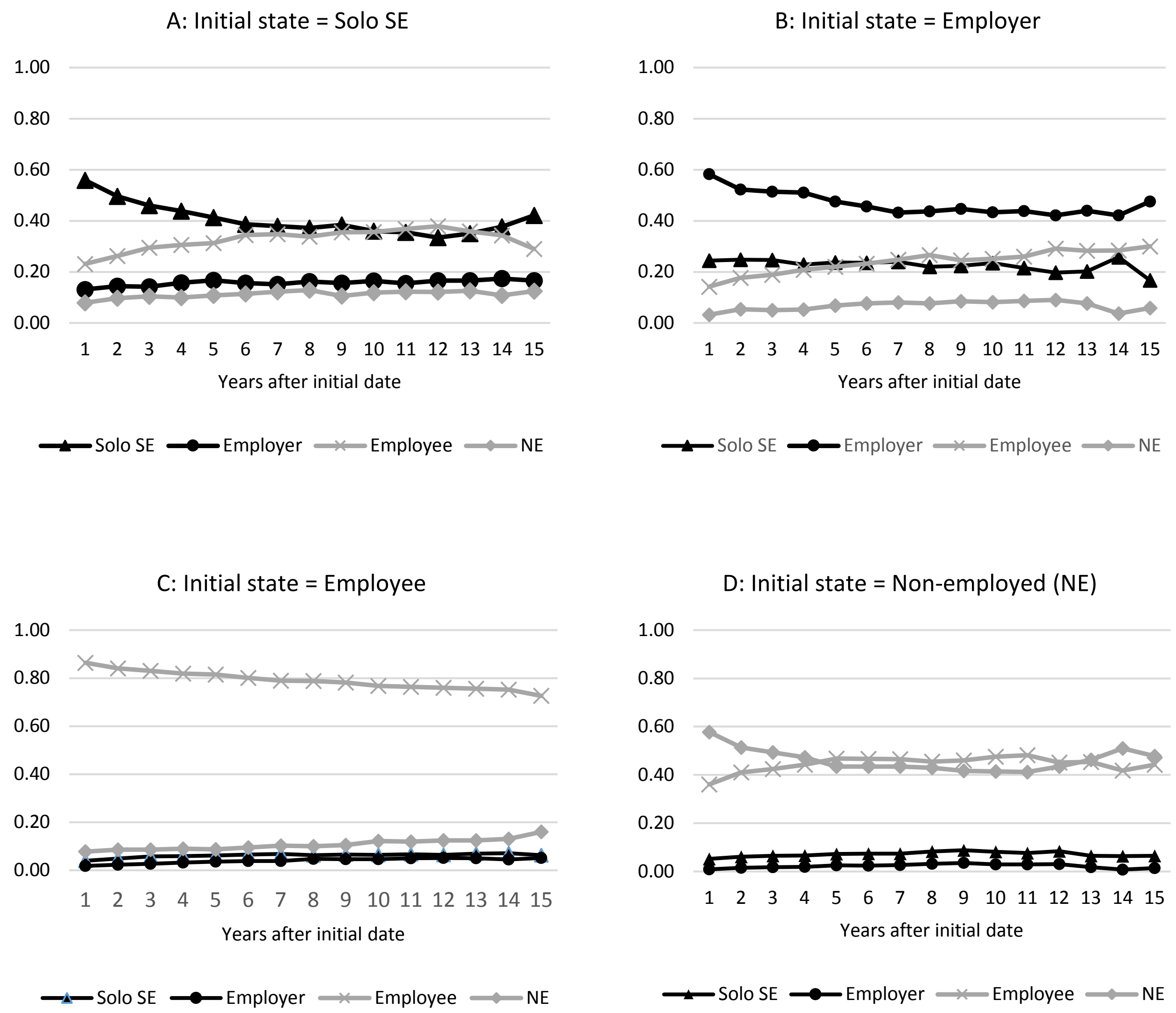


Figure 3

Distribution of labour market states conditional on labour market state *t* years earlier: females

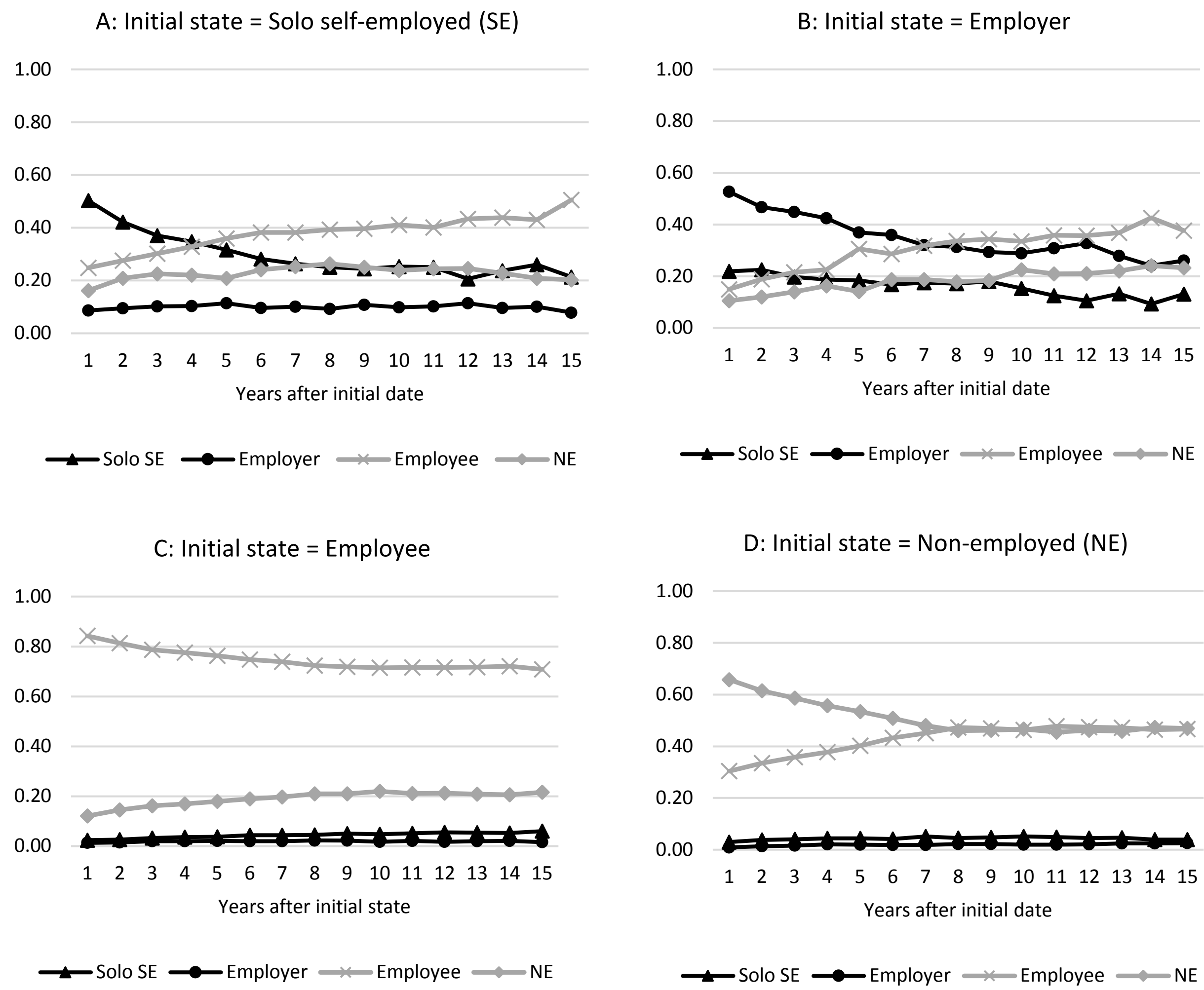


Table 1

Labour force status (% of population aged 15+): HILDA Survey and Labour Force Survey (LFS) population estimates compared

Labour force state	2001		2016	
	LFS	HILDA	LFS	HILDA
A. Males				
Solo self-employed	10.0	8.4	8.3	7.0
Employer	6.4	6.4	5.3	4.8
Employee	50.3	53.2	52.7	55.7
Non-employed	33.1	32.0	33.7	32.6
A. Females				
Solo self-employed	4.4	3.6	4.5	3.8
Employer	3.2	2.9	2.4	1.9
Employee	43.7	46.9	48.8	51.3
Non-employed	48.5	46.7	44.2	42.9

Notes: LFS estimates relate to the month of October, which lies roughly at the mid-point of the HILDA Survey fieldwork period. Columns may not sum to 100 due to a small number of contributing family workers not included in any of our four labour force categories.

Sources: ABS, *Labour Force, Australia, Detailed - Electronic Delivery* (cat. no. 6291.0.55.001), Time series spreadsheets, Table 02 (Labour force status by state, territory, greater capital city, rest of state (ASGS) and sex) and Table 08 (Employed persons by status in employment of main job and sex); HILDA Survey General Release 16, confidentialised unit record data file (Department of Social Services / Melbourne Institute, 2017).

Table 2

Employment states and (annual) transitions by gender

State at time *t-1*	State at time *t*			
	Solo SE	Employer	Employee	Non-employed
A. Males				
Solo SE	4761 (69.1)	761 (11.1)	963 (14.0)	404 (5.9)
Employer	737 (14.3)	3910 (75.6)	415 (8.0)	107 (2.1)
Employee	1138 (2.4)	480 (1.0)	43167 (91.6)	2346 (5.0)
Non-employed	343 (3.4)	54 (0.5)	2048 (20.1)	7737 (76.0)
B. Females				
Solo SE	2501 (64.4)	295 (7.6)	661 (17.1)	424 (10.9)
Employer	302 (12.3)	1697 (69.1)	282 (11.5)	174 (7.1)
Employee	730 (1.5)	342 (0.7)	42792 (89.4)	3996 (8.4)
Non-employed	449 (2.0)	128 (0.6)	3712 (16.5)	18269 (81.0)

Note: Figures in parentheses are percentages and sum to 100 across rows.

Table 3

Multinomial logit estimation: Summary of key results

	Male			Female		
Variable	Solo SE	Employer	Employee	Solo SE	Employer	Employee
Employment state at *t*-1						
Solo SE	2.911**	3.275**	0.948**	3.365**	2.913**	1.348**
	(0.156)	(0.225)	(0.111)	(0.145)	(0.193)	(0.101)
Employer	2.550**	4.738**	1.056**	2.511**	4.096**	1.314**
	(0.194)	(0.277)	(0.166)	(0.184)	(0.230)	(0.140)
Employee	0.815**	1.494**	2.269**	1.148**	1.733**	2.601**
	(0.114)	(0.203)	(0.072)	(0.104)	(0.160)	(0.050)
Initial employment (*t*=0)						
Solo SE	3.410**	2.844**	0.318*	3.079**	2.753**	0.184
	(0.234)	(0.283)	(0.146)	(0.211)	(0.292)	(0.131)
Employer	2.558**	4.436**	0.170	2.051**	4.350**	-0.057
	(0.265)	(0.335)	(0.189)	(0.262)	(0.357)	(0.177)
Employee	0.409**	0.381	0.863**	0.224	0.032	0.730**
	(0.147)	(0.205)	(0.094)	(0.124)	(0.192)	(0.061)
$\mathrm{Cov}(a_{i,Solo}, a_{i,j})$	3.712**	3.123**	0.882**	3.247**	2.559**	0.431**
	(0.320)	(0.327)	(0.129)	(0.304)	(0.308)	(0.097)
$\mathrm{Cov}(a_{i,Employer}, a_{i,j})$		4.806**	1.004**		4.813**	0.405**
		(0.463)	(0.172)		(0.488)	(0.140)
$\mathrm{Cov}(a_{i,Employee}, a_{i,j})$			1.563**			1.188**
			(0.116)			(0.070)
Log likelihood	-26,396.2			-30,980.8		
N (person years)	65,751			73,183		
N (individuals)	9,217			9,770		

Notes: Dynamic multinomial logit model with correlated random effects. Figures in parentheses are robust standard errors. The reference category for the dependent variable is non-employment. Also included, but not reported, are controls for age (specified as a quadratic), marital status, number of dependent children, presence of a long-term health condition, country / region of birth, educational attainment, cumulative years of work experience (specified as a quadratic), home ownership, net annual household income at *t*-1 (logged), location (urban vs rural), the regional unemployment rate, year, region fixed effects, and individual-specific time averages of the exogenous characteristics. Significance: * p<0.05, ** p<0.01.

Table 4

Average predicted probabilities of labour market transitions

State at time *t*-1	State at time *t*							
	Solo SE		Employer		Employee		Non-employed	
	Mean	SE	Mean	SE	Mean	SE	Mean	SE
A. Males								
Solo SE	0.247	0.011	0.092	0.005	0.503	0.012	0.158	0.007
Employer	0.156	0.009	0.213	0.014	0.483	0.018	0.148	0.011
Employee	0.053	0.002	0.030	0.002	0.801	0.004	0.116	0.003
Non-employed	0.094	0.006	0.032	0.004	0.578	0.009	0.296	0.008
B. Females								
Solo SE	0.180	0.011	0.040	0.003	0.508	0.014	0.272	0.012
Employer	0.097	0.009	0.099	0.009	0.519	0.019	0.285	0.016
Employee	0.026	0.001	0.017	0.001	0.766	0.004	0.190	0.004
Non-employed	0.038	0.003	0.016	0.002	0.424	0.007	0.522	0.007

Notes: Calculations are based on the results presented in Table 3. Standard errors are calculated using the Delta method.

Table 5

Estimates of true-state dependence (TSD) and cross-state dependence (CSD) in solo employment and employership: HILDA Survey and GSOEP compared

	CSD in employership relative to:		TSD in employership relative to:		TSD in solo SE relative to:	
	Employee	NE	Employee	NE	Employee	NE
A. Males						
HILDA Survey	0.062	0.060	0.183	0.181	0.195	0.153
GSOEP	0.051	0.049	0.086	0.083	0.133	0.096
B. Females						
HILDA Survey	0.023	0.024	0.081	0.083	0.154	0.142
GSOEP	0.024	0.021	0.118	0.115	0.092	0.079

Sources: HILDA Survey estimates are based on results presented in Table 4. GSOEP estimates are taken or derived from Lechmann and Wunder (2017, Tables 5 and 6).

Table 6

Estimates of true-state dependence (TSD) and cross-state dependence (CSD) in solo employment and employership: Robustness checks

	CSD in employership relative to:		TSD in employership relative to:		TSD in solo SE relative to:	
	Employee	NE	Employee	NE	Employee	NE
A. Males						
Preferred	0.062 (0.006)	0.060 (0.007)	0.183 (0.015)	0.181 (0.015)	0.195 (0.012)	0.153 (0.013)
Including controls for attrition	0.066 (0.007)	0.063 (0.008)	0.191 (0.017)	0.189 (0.017)	0.191 (0.013)	0.151 (0.013)
Omitting workers in Agriculture	0.068 (0.008)	0.066 (0.008)	0.199 (0.019)	0.197 (0.019)	0.201 (0.015)	0.165 (0.015)
Omitting students	0.073 (0.008)	0.070 (0.009)	0.211 (0.021)	0.208 (0.021)	0.205 (0.015)	0.157 (0.016)
B. Females						
Preferred	0.023 (0.004)	0.024 (0.004)	0.081 (0.010)	0.083 (0.010)	0.154 (0.011)	0.142 (0.012)
Including controls for attrition	0.021 (0.004)	0.023 (0.004)	0.077 (0.010)	0.080 (0.010)	0.149 (0.012)	0.137 (0.012)
Omitting workers in Agriculture	0.024 (0.005)	0.027 (0.005)	0.089 (0.013)	0.092 (0.013)	0.161 (0.014)	0.152 (0.014)
Omitting students	0.022 (0.005)	0.025 (0.005)	0.087 (0.013)	0.091 (0.013)	0.151 (0.014)	0.138 (0.014)

Note: Standard errors are calculated using the Delta method and are reported in parentheses.

Table 7

Estimates of true-state dependence (TSD) and cross-state dependence (CSD) in solo employment and employership when the initial condition is set to self-employment

	CSD in employership relative to:		TSD in employership relative to:		TSD in solo SE relative to:	
Initial condition	Employee	NE	Employee	NE	Employee	NE
A. Males						
Self-employed	0.101	0.103	0.411	0.413	0.346	0.239
	(0.013)	(0.016)	(0.021)	(0.024)	(0.016)	(0.021)
Employer	0.200	0.198	0.457	0.455	0.225	0.147
	(0.019)	(.026)	(0.022)	(0.028)	(0.016)	(0.019)
B. Females						
Self-employed	0.041	0.055	0.284	0.299	0.356	0.317
	(0.013)	(0.013)	(0.025)	(0.025)	(0.018)	(0.020)
Employer	0.115	0.137	0.338	0.361	0.234	0.210
	(0.021)	(0.023)	(0.023)	(0.026)	(0.022)	(0.021)

Note: Standard errors are calculated using the Delta method and are reported in parentheses.

Table A1

Covariate descriptive statistics by labour market state: Males

	Solo self-employment		Employer		Employee		Non-employment	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Age	46.15	10.93	46.08	9.71	40.37	11.37	48.35	13.25
Married / De facto (0/1)	0.77	0.42	0.88	0.33	0.74	0.44	0.59	0.49
Dependent children (no. <15 yrs)	0.67	1.06	0.95	1.18	0.69	1.02	0.39	0.94
Long-term health condition (0/1)	0.22	0.42	0.17	0.37	0.16	0.36	0.59	0.49
Country / region of birth								
Australia	0.75	0.43	0.75	0.43	0.80	0.40	0.77	0.42
Main English-speaking country (1/0)	0.14	0.35	0.13	0.33	0.10	0.30	0.10	0.30
Other (1/0)	0.11	0.31	0.12	0.33	0.11	0.31	0.13	0.34
Education attainment								
Year 11 or less (0/1)	0.23	0.42	0.17	0.38	0.18	0.39	0.38	0.49
Year 12 (0/1)	0.10	0.30	0.12	0.33	0.14	0.35	0.12	0.32
Certificate	0.37	0.48	0.32	0.46	0.30	0.46	0.28	0.45
Diploma	0.10	0.30	0.10	0.31	0.10	0.29	0.08	0.28
Degree or higher	0.20	0.40	0.29	0.45	0.28	0.45	0.15	0.35
Urban location (0/1)	0.74	0.44	0.78	0.41	0.90	0.31	0.84	0.37
Work experience (years)	27.57	11.58	27.73	10.28	21.48	11.84	23.53	14.18
Home ownership								
Own home outright (0/1)	0.36	0.48	0.39	0.49	0.22	0.41	0.39	0.49
Own home with mortgage (0/1)	0.39	0.49	0.46	0.50	0.47	0.50	0.19	0.39
Rent (0/1)	0.22	0.41	0.13	0.34	0.30	0.46	0.38	0.49
Other (0/1)	0.03	0.16	0.02	0.13	0.02	0.15	0.03	0.18
Net annual (financial year) household income at *t*-1 ($000; 2016 prices)	96.4	79.3	143.6	129.4	109.0	69.6	72.7	74.9
Regional unemployment rate (%)	5.31	1.99	5.21	1.96	5.35	1.98	5.75	2.05
Initial conditions (at *t*=0)								
Solo-self-employment (0/1)	0.49	0.50	0.18	0.38	0.03	0.18	0.05	0.22
Employer (0/1)	0.13	0.34	0.53	0.50	0.02	0.14	0.03	0.16
Employee (0/1)	0.32	0.47	0.27	0.44	0.88	0.33	0.39	0.49
Non-employment (0/1)	0.06	0.23	0.02	0.16	0.07	0.26	0.53	0.50
No. of person-year observations	6308		4825		44741		9877	

Note: Not reported here, but nevertheless included in the multivariate models, are 15 year dummies and 12 region dummies.

Table A2

Covariate descriptive statistics by labour market state: Females

	Solo self-employment		Employer		Employee		Non-employment	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Age	45.07	10.56	45.58	9.56	41.00	11.32	45.15	12.94
Married / De facto (0/1)	0.79	0.41	0.90	0.30	0.70	0.46	0.71	0.45
Dependent children (no. <15 yrs)	0.77	1.07	0.93	1.16	0.63	0.95	0.91	1.22
Long-term health condition (0/1)	0.21	0.41	0.16	0.36	0.17	0.37	0.40	0.49
Country / region of birth								
Australia	0.77	0.42	0.79	0.41	0.80	0.40	0.76	0.43
Main English-speaking country (1/0)	0.12	0.32	0.09	0.28	0.09	0.28	0.09	0.28
Other (1/0)	0.11	0.32	0.12	0.33	0.11	0.32	0.16	0.37
Education attainment								
Year 11 or less (0/1)	0.23	0.42	0.28	0.45	0.21	0.40	0.44	0.50
Year 12 (0/1)	0.10	0.30	0.17	0.37	0.14	0.35	0.15	0.36
Certificate	0.20	0.40	0.14	0.35	0.17	0.38	0.16	0.37
Diploma	0.14	0.35	0.13	0.33	0.11	0.32	0.08	0.28
Degree or higher	0.33	0.47	0.29	0.45	0.37	0.48	0.17	0.37
Urban location (1/0)	0.76	0.43	0.74	0.44	0.89	0.31	0.86	0.35
Work experience (years)	21.92	10.41	23.30	9.70	19.06	10.71	14.74	11.57
Home ownership								
Own home outright (0/1)	0.35	0.48	0.43	0.50	0.24	0.43	0.35	0.48
Own home with mortgage (0/1)	0.43	0.50	0.43	0.50	0.47	0.50	0.27	0.45
Rent (0/1)	0.19	0.39	0.12	0.33	0.27	0.44	0.35	0.48
Other (0/1)	0.03	0.17	0.02	0.12	0.02	0.14	0.03	0.17
Net annual (financial year) household income at *t*-1 ($000; 2016 prices)	104.8	100.7	138.2	115.0	109.4	73.18	81.6	79.49
Regional unemployment rate (%)	5.15	1.95	5.34	2.05	5.34	1.98	5.59	2.05
Initial conditions (at *t*=0)								
Solo-self-employment (0/1)	0.34	0.47	0.15	0.36	0.02	0.15	0.02	0.16
Employer (0/1)	0.08	0.27	0.46	0.50	0.01	0.10	0.02	0.13
Employee (0/1)	0.40	0.49	0.27	0.45	0.81	0.39	0.34	0.47
Non-employment (0/1)	0.17	0.38	0.12	0.32	0.15	0.36	0.62	0.49
No. of person-year observations	3597		2252		45669		21653	

Note: Not reported here, but nevertheless included in the multivariate models, are 15 year dummies and 12 region dummies.

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