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Persistence of Individual Unemployment in Indonesia: Dynamic Probit Analysis from Panel SUSENAS 2008-2010

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ABSTRACT

This paper presents a dynamic probit analysis of individual unemployment incidence using a panel survey on the national socio-economy (SUSENAS), 2008-2010. It compares a variety of dynamic random effects estimators, particularly focusing on the Heckman's (1981) and Wooldridge's (2005) approaches. The main result shows a strong evidence of persistence or state dependence of individual unemployment in Indonesia and therefore consistent with the theory of scar unemployment. This means that a person's unemployment experience has an implication to his his/her future of labour market experience.

Keywords: Persistent Unemployment, State Dependence, Heckman's Estimator, Wooldridge's Estimator
JEL Classifications: J64, J65, J68

1. INTRODUCTION

In microeconomic literature, individual persistent unemployment or state dependence in unemployment could be defined as a causal effect between past and current unemployment (Heckman and Borgas, 1980). This is also consistent with the theory of scar unemployment which postulates that, in fairly general conditions, the probability of being unemployed is higher for individuals that have experienced long periods of unemployment than for those who have had no or limited unemployment duration (Vishwanath, 1986).

This topic is widely studied in industrial countries such as the United States of America (USA), the United Kingdom (UK) and Germany because of availability of individual panel data. In the USA, Heckman and Borgas (1980) used data from the National Longitudinal Survey 1969-1971 for young males and Corcoran and Hill (1985) focused on men aged 35-64 and both studies had found no evidence of state dependence in unemployment duration. However, Narendranathan and Elias (1993) and Gregg (2001) found strong evidence of state dependence in unemployment status using the National child development study from the UK. Arulampalam et al. (2000) also found strong evidence of unemployment persistence, especially for men older than 25 using the British Household Panel Survey. Strong evidence of individual unemployment was also found in the case of Germany, such as the studies by Flaig et al. (1993), Muhleisen and Zimmermann (1994) and Biewen and Steffes (2010).

Related to individual unemployment persistence, there was strong evidence showing that unemployment benefits or insurance caused disincentive effects to unemployment duration, particular in the USA and European countries (Atkinson and Micklerweight, 1991; Holmlund, 1998; and Meyer, 2002). The availability of these benefits for long time periods might discourage unemployed person from searching for a job and cause them to prolong their unemployment duration in the labour market. Another effect of these benefits, was that they could damage individual employability through productivity deterioration (Pissarides, 1992). Similar effects of a transfer cash program for individual unemployment were found in the case of Argentina (Iturriza et al., 2011). However, for those countries that do not have unemployment benefits or government support systems, South Africa for example, the financial support from family and household formation may prolong unemployment (Klasen and Woolard, 2009).

Compared to those empirical works in the developed countries, individual unemployment persistence in developing countries, including Indonesian has not or rarely been investigated using individual dynamic panel data. Most of unemployment studies in Indonesia however, use regional panel data at provincial or district level (Soekarni, et al., 2009; Dhanani, et al., 2009; Comola and de Mello, 2011; Suryadarma et al., 2013). This might be because not enough individual panel data are available. The Indonesia's National Workforces Surveys (Sakernas) are based on individual data but cannot be used as panel data because they use a different random sample for each survey. Thus, an empirical analysis based on these data would be suitable for national or regional (provincial-district) panel analysis. Meanwhile Indonesia's Panel National Social-Economic Surveys (Panel SUSENAS) are recorded in limited 3 year periods, the latest one having took place from 2008 to 2010.

Therefore, this paper tries to analyse individual unemployment persistence in the case of Indonesia using SUSENAS Panel, 2008-2010. The method focuses the dynamic probit panel data model based on Wooldridge (2005) as an alternative to Heckman (1981). These methods are comparable, especially using short-time periods of panel data (Arulampalam and Stewart, 2009). For the empirical approach, this paper also investigates the effects of internal and external factors that affect employment prospects of an unemployed person. On internal side, it includes person's education, age, gender, marital status. On the external side, it also consists of internal and external household support. The models also include household formation. Again, for developing countries, especially for the Indonesian case, this kind of empirical research is relatively rare.

The next section describes the dataset of the SUSENAS panel and the methods on which the empirical analysis is based. Section 3 shows the evidences on the persistence of individual unemployment in Indonesia and relative importance of family support and external support from government and other institution as well household formation to the probability of being unemployed. The last section concludes.

2. METHODOLOGY

2.1. Data

The data contains a sample of households from the Panel National Survey on Socio-Economy (SUSENAS) who have a family member between the age 18 and 64 in March 2008 and who participated in all three waves of the survey from 2008 to 2010. There are 21,686 observations on the surveys that meet these criteria. The definition of unemployment is based on the standard International Labour Organisation's definition: A person is unemployed if he or she does not have a job, and is actively looking for work. This is also the narrow version of the official definition for unemployment from the Indonesian Central body of statistics (CBS). Thus, the unemployment rates in this paper are relatively low compared to those reported by CBS. The study restricts the observations to only those are in the labour force in all 3 years of period.

The dependent variable or unemployment status consists of employed and not employed. The explanatory variables include lag of unemployment for representing state dependence or persistent unemployment, number of employed adults in household and household's income, indicating family support to the unemployed. These variables are expected to be positively related to the probability of being unemployed. Household formation is represented by the number of children below 6 years of age, children in school, and elders in household and are all expected to have negative effects on the probability of unemployment. Support from outside the household comes from the number of received social safety net programs from the government and how much financial support via financial credit from bank, non-bank and informal parties they received. These variables should have positive effects on the probability of being unemployed.

The individual's education in years, sex, age, age squares, marital status, urban and year dummies are placed as control variables to account for observed heterogeneities. For the advanced modelling of the Heckman's and Wooldridge's models, we include additional time-invariant variables to solve unobserved heterogeneity and initial conditions problems. These variables will be explained later in the section of methodology.

Table 1 shows the state transitions of employed and unemployed individuals during the periods of 2008-2010. From 21,686 total individuals in 2008, there were 21,020 individuals or 96.93% that never fell into unemployment during the other periods. Meanwhile, there were 550 individuals that experienced unemployment in one period. Of these, 251 had an unemployment status in 2008 but became employed in 2009-2010. There are 132 individuals who finally got a job in 2010 and 167 people who fell into unemployment in 2009 only. From 89 individuals that had two periods of unemployment, 45 of them finally got job in 2010 after trying to get jobs in 2008-2009, while 28 and 16 individuals had a job only in 2008 and 2009, respectively. Lastly, there were only 27 people that had very persistent unemployment or never got jobs during the 3 years of period.

2.2. Modelling Persistence of Individual Unemployment

The observed dependent variable, referring to the other studies, is binary and takes the value of one if the observation is unemployed and zero otherwise, named individual unemployment *un*. Then, we may specify the dynamic model of the unemployment status for individual *i* at the interview date at time *t* as follows:

Table 1: State transitions of individual unemployment in 2008-2010

State transitions	Frequency (%)
Never unemployed	21,020 (96.93)
One period of unemployed:	
U2008, E2009, E2010	251 (1.16)
E2008, U2009, E2010	167 (0.77)
E2008, E2009, U2010	132 (0.61)
Two period of unemployed:	
U2008, U2009, E2010	45 (0.21)
U2008, E2009, U2010	16 (0.07)
E2008, U2009, U2010	28 (0.13)
Never employed	27 (0.12)
Total individuals	21,686 (100.00)

U: Unemployed, E: Employed

$$un_{it}^{*} = f\left(un_{it-1}, fs_{it}, hf_{it}, es_{it}\right) \tag{1}$$

Where *un** enotes the unobservable individual propensity to be unemployed as a function of lagged observed unemployment status (un_{it-1}), family support (*fs*), household formation (*hf*), and external support from outside the household (*es*), such as government supports via social safety net programs, financial credit from the bank or loans from informal financial sources. The lagged unemployment status would increase the propensity being unemployed. Furthermore, the internal support from other family members and external support from outside the household would also increase that propensity. Meanwhile, the household formation with dependent children and elders would reduce it.

The general model of dynamic random effects probit for individual unemployment in equation (1) can be rewritten as (see also Arulampalam et al., 2000):

$$un_{it}^{*} = \gamma un_{it-1} + x_{it}^{'}\beta + v_{it} \tag{2}$$

$$un_{it} = 1(un_{it}^{*} > 0) \tag{3}$$

Where: $i = 1, 2,\ldots, N$, $t = 2,\ldots, T$; x is a vector of explanatory variables affecting un_{it}, β is the vector of coefficients associated with explanatory variables x, and v is the unobservable error term. In equation (3), a person is observed to be unemployed when his/her propensity to be unemployed crosses zero, that is, $un_{it} = 1$ if $un_{it}^{*} > 0$ and zero otherwise. However, in equation (2), un_{it}^{*} is a function of the observed status of an unemployed person in the previous period or un_{t-1}. The inclusion of lagged unemployment on the right side of the equation allows us to test the persistence of the individual unemployment. The positive and significant effect of this variable is also consistent with the testing for state dependence in unemployment or so-called the scar unemployment (Arulampalam et al., 2000).

2.3. Heckman's Estimator

Heckman and Borjas (1980) pointed out a potential problem arising in equation (2) is that it could produce a spurious coefficient of lagged unemployment by including inappropriate control variables or by not including unobserved heterogeneity which might have a significant effect on the propensity of unemployment. They suggested controlling for all potential observable and unobservable individual characteristics. Hence, it assumes that the unobservable individual-specific heterogeneity is time-invariant and decomposes the error $v_{it}=c_i+e_{it}$, then equation (2) could be modified as,

$$un_{it}^{*} = \gamma un_{it-1} + x_{it}^{'}\beta + c_i + e_{it} \tag{4}$$

Where c_i is assumed to be independent for x all i and which is called the uncorrelated random effect model.

Furthermore, there is another problem in equation (4) when the initial observation of unemployed, un_{i1} has a significant correlation with the unobservable heterogeneity c_i (Heckman, 1981). This problem emerges because the start of observation period, year of 2008 in this case, does not coincide with the stochastic process generating individual's unemployment experiences. Heckman suggested approximating the density function of the initial period using the same parametric form as conditional density for the rest of observations (Arulampalam and Stewart, 2009). Then equation (4) can be rewritten as,

$$un_{it}^{*} = \gamma un_{it-1} + x_{it}^{'}\beta + \theta_t c_i + e_{it} \tag{5}$$

With $\theta_T = 1$ for identification of σ_c^2, and the equation for the initial observation as,

$$un_{i1}^{*} = \lambda' z_i + \theta_1 c_i + e_{i1} \tag{6}$$

Where z is a vector of exogenous covariates that is expected to include instrument variables such as pre-sample variables and c_i denotes the full set of time-varying explanatory variables. The standard assumption of the e_{it} and c_i are both normally distributed with variance 1 and σ_c^2, respectively.

In his paper, Heckman (1981) allowed the error in the equation of the initial condition ($\theta_1 c_i + e_{i1}$) to be freely correlated with the error in the equation for the other periods ($\theta_t c_i + e_{it}$). In addition, he also relaxed the standard assumption of equi-correlated errors in period $t = 2,\ldots,T$. Hence, the $cov\,(c_i + e_{it}, c_i + e_{is})$ is also equal to σ_c^2 for $t, s = 2,\ldots,T$ where $t \neq s$. Therefore, the correlation between the two periods is given by $\rho = \sigma_c^2 / (\sigma_c^2 - 1)$ (Arulampalam and Stewart, 2009). Then, we could specify equation (5) as the same model as in equation (4),

$$un_{it}^{*} = \gamma un_{it-1} + x_{it}^{'}\beta + c_i + e_{it} \tag{7}$$

And equation (6) as:

$$un_{i1}^{*} = \lambda' z_i + \theta c_i + e_{i1} \tag{8}$$

These two equations are jointly estimated by maximum likelihood and we could test for the exogeneity of the initial conditions on θ. It is noted that Heckman estimators approximate the joint probability of the full observed *un* sequences ($un_{i1}, un_{i2}, \ldots, un_{iT}$).

2.4. Wooldridge's Estimator

An alternative to the Heckman approach is a simplified model proposed by Wooldridge (2005). Based on his approach, the initial conditions problem is solved by modelling un_{it} at period $t = 2., T$ conditional on the initial period (un_{i1}) and exogenous variables (x_{it}). Recall equation (4),

$$un_{it}^{*} = \gamma un_{it-1} + x_{it}^{'}\beta + c_i + e_{it} \tag{9}$$

Then specify an approximation for density of c_i conditional on un_{i1} and the period-specific versions of time-varying explanatory variables starting from the second period of observations as:

$$c_i = \alpha_0 + \alpha_1 un_{i1} + x_i^{+'}\alpha_2 + \varepsilon_i \tag{10}$$

Where $x_i^{+} = \left(x_{i2}^{'}, \ldots, x_{iT}^{'}\right)'$ and ε_i is the normal distribution with mean 0 and variance σ_ε^2. Substituting equation (10) into equation (9) gives,

$$un_{it}^{*} = \alpha_0 + x_{it}'\beta + \gamma un_{it-1} + \alpha_1 un_{i1} + x_i^{+'}\alpha_2 + e_{it}, \qquad (11)$$

This equation can be estimated by the standard random effects probit model. It notices that Wooldridge estimators starting *un* sequence from the second period of observation compared to the full observations in the Heckman estimators.

2.5. Correlated Random Effects of Dynamic Panel Model

The standard uncorrelated random effects probit model assumes that c_i is uncorrelated with x_{it}. If this is not the case then the maximum likelihood of the estimates will be inconsistent. To avoid this problem, it could relax the assumption by following Mundlak (1978) and adding within-means of explanatory variables into the main equation in the Heckman estimators. Instead of using means of the full period of the observations, we use within-means of time-varying variables at *T-1* of the observations. Then, the Heckman models would be re-specified as:

$$un_{it}^{*} = \gamma un_{it-1} + x_{it}'\beta + \bar{x}_i' + a_1 + c_i + e_{it} \qquad (12)$$

$$un_{i1}^{*} = \lambda' z_i + \theta c_i + e_{i1} \qquad (13)$$

Where $\bar{x}_i^{+} = \frac{1}{T-1}\sum_{t=2}^{T} x_{it}$

It would be relatively different in the case of Wooldridge estimators. The popular version of the correlated random effect models for the Wooldridge approach is to replace x_i^{+} with the means of time-varying explanatory variables of all time periods (Stewart, 2007; Biewen and Steffes, 2010; Akay, 2012). Then the equation (11) is rewritten as follows:

$$un_{it}^{*} = \gamma un_{it-1} + x_{it}'\beta + \alpha_1 un_{i1} + \bar{x}_i'\alpha_2 + e_{it} \qquad (14)$$

Nevertheless, the equation (14) can be severely biased in the short periods of panel data, particularly in 3-5 time periods (Akay, 2012; Rabe-Hesketh and Skrondal, 2013). As an alternative, we follow the suggestion by Rabe-Hesketh and Skrondal (2013) and use the following equation[1]:

$$un_{it}^{*} = \gamma un_{it-1} + x_{it}'\beta + \alpha_1 un_{i1} + \bar{x}\,?_i^{+'}\, a_2 + e_{it}, \qquad (15)$$

Where $\bar{x}_i^{+} = \frac{1}{T-1}\sum_{t=2}^{T} x_{it}$

The original and constraint models of Wooldridge estimators in the equation (11) and (15) would perform well as Heckman estimators especially for short-period of panel data (Arulampalam and Stewart, 2009; Rabe-Hesketh and Skrondal, 2013).

3. EMPIRICAL EVIDENCES

The results from pooled and random-effects probit estimators for a probability model of unemployment are given in Table 2. Column [2] and [4] give the standard model of state dependence with explanatory variables. The difference is due to the choices in family support variables between the number of employed in household and the household's income or expenditure. The number of employed person in a household has negative effect to the probability of unemployed meanwhile household's income has positive effect. It seems that household's income is seen as financial support to the unemployed in the family, thereby increasing the probability of being unemployed. Meanwhile, instead of being a kind of family support to the unemployed member, the employed persons in the household put a physiological pressure on unemployed in the family to find a job and reduce his/her probability of being unemployed. In column [3] and [5], the estimates include the lag of family support, either lagged household's income or the lag of the number of employed in the household. In those estimates, the lagged family support has positive and significant impacts to the probability of being unemployed.

Increases in the number of children below the age of six and the number of children in school reduce the probability of being unemployed, while the number of elders is insignificant except for the estimates in column [3]. Furthermore, the external support from outside the household, i.e.: The number of received social safety net programs and the other financial support from bank and non-bank institution have an insignificant effect on the probability of being unemployed, except for that estimate where the household's income is included as presented in column [4]. Being unemployed in *t-1* strongly increases the probability of being unemployed at *t* based on a very significant variable of lagged unemployment status in all estimates.

The second part of Table 2 gives the equivalent standard random effect probit estimates, treating lagged unemployment and initial conditions as exogenous variables (Arulampalam and Stewart, 2009). When we introduce control variables into the models, the family support remains significant, except for the estimate in column [8]. However, all variables in the household formation become insignificant. The number of received social safety net program remains positive and significant for all estimates as well as the lagged unemployment. Being married decreases the probability of being unemployed while living in urban area increases that probability. In some estimates, being male also increases the probability of unemployment. Surprisingly, education has no effect on the probability of being unemployed.

The random effects estimates would be similar to pooled probit estimates (all control variables included) if they produce ρ close to zero or zero. Except for the estimates in column [6] which it produces non zero $\rho = 0.199$, all estimates give ρ equal to zero. The coefficient of lagged unemployment at 1.081 is smaller than the pooled probit estimates at 1.680. The other estimated coefficients in the random effects estimated are also smaller to their comparable estimated coefficients on the pooled probit estimates. However, the random effects probit and pooled probit models involve different normalizations (Arulampalam, et al., 2000). To compare coefficients, those from the random effects estimator need to be multiplied by the estimates of $(\sqrt{1-\rho})$, where ρ is a constant cross-period error correlation. Thus, for example, the

1 Rabe-Hesketh and Skrondal (2013) also suggested including all the initial-periods of the explanatory variables in the equation (14) which they admitted was unrealistic even though it would perform well. Such equation would be: $un_{it}^{*} = x_{it}'\beta + \gamma un_{it-1} + \alpha_1 un_{i1} + \bar{x}_i' a_2 + x_{i1}' x a_3 + e_{it}$.

Table 2: Pooled and random-effects probit estimates

Variables	Pooled pobit				Random effects probit			
[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]
Unemployment (t-1)	1.680***	2.151***	1.549***	1.555***	1.081***	1.619***	1.107***	1.120***
	(0.065)	(0.073)	(0.061)	(0.062)	(0.088)	(0.081)	(0.066)	(0.067)
Family supports								
Number of employed	−0.430***	−0.769***			−0.653***	−0.899***		
In HH	(0.026)	(0.032)			(0.058)	(0.036)		
Number of employed		0.471***				0.457***		
in HH (t-1)		(0.022)				(0.025)		
Log of HH's income			0.100***	−0.090*			−0.055	−0.179***
			(0.029)	(0.047)			(0.038)	(0.054)
Log of HH's				0.245***				0.174***
income (t-1)				(0.047)				(0.053)
Household formation								
Number of children	−0.184***	−0.129***	−0.131***	−0.127***	−0.058	−0.016	−0.036	−0.036
below 6	(0.035)	(0.036)	(0.033)	(0.033)	(0.046)	(0.042)	(0.037)	(0.037)
Number of children	−0.156***	−0.132***	−0.129***	−0.131***	−0.009	−0.012	−0.027	−0.03
in school	(0.026)	(0.027)	(0.025)	(0.025)	(0.032)	(0.030)	(0.026)	(0.026)
Number of elders	0.095*	0.036	0.025	0.023	−0.003	−0.048	−0.038	−0.04
	(0.053)	(0.056)	(0.050)	(0.050)	(0.068)	(0.063)	(0.054)	(0.054)
External supports								
Number of safety net	0.026	0.027	0.046*	0.064**	0.099***	0.093***	0.065**	0.075**
programs	(0.028)	(0.029)	(0.028)	(0.028)	(0.036)	(0.034)	(0.030)	(0.030)
Number of other	−0.044	−0.046	−0.145*	−0.135	0.095	0.100	−0.058	−0.051
supports	(0.089)	(0.094)	(0.086)	(0.086)	(0.111)	(0.103)	(0.092)	(0.092)
Control variables								
Education in years					0.006	0.004	0.009	0.007
					(0.006)	(0.006)	(0.006)	(0.006)
Males					0.087	0.071	0.119***	0.119***
					(0.057)	(0.052)	(0.044)	(0.044)
Age					−0.113***	−0.072***	−0.045***	−0.045***
					(0.020)	(0.017)	(0.015)	(0.015)
Age squares divided					0.110***	0.061***	0.036*	0.035*
by 100					(0.025)	(0.022)	(0.019)	(0.019)
Married					−0.830***	−0.680***	−0.512***	−0.504***
					(0.090)	(0.066)	(0.058)	(0.059)
Urban					0.382***	0.340***	0.366***	0.348***
					(0.063)	(0.052)	(0.047)	(0.047)
Year 2009					1.296***	0.134	−0.462	−1.126*
					(0.358)	(0.308)	(0.585)	(0.618)
Year 2010					1.140***	−0.021	−0.552	−1.221*
					(0.352)	(0.311)	(0.591)	(0.625)
_cons	−1.452***	−1.940***	−3.723***	−4.495***				
	(0.056)	(0.063)	(0.427)	(0.453)				
rho (ρ)					0.199	0.000	0.000	0.000
Log likelihood	−2110	−1902	−2279	−2266	−1777	−1619	−2039	−2034
N	43372	43372	43372	43372	43372	43372	43372	43372

scaled coefficient of lagged unemployment in column [6] will be 0.968 instead of 1.081. This estimated coefficient remains strongly significant as well as the other estimated coefficients in column [7] to [9].

Tables 3 and 4 present the random effects probit estimates based on the Heckman's and Wooldridge's approaches. All estimates are modelled with the Mundlak specifications. In the Heckman estimates on Table 3, we include one pre-sampling exogenous instrument, Cohort 1990 (labour force that was born in 1990 then had first experience on the labour market in 2008) on the initial period estimations. The estimations produce positive and significant of the lagged unemployment for all specifications which these support the evidences of the existence of persistent individual unemployment in the case of Indonesia. The coefficients are ranging from 0.663 to 0.713.

Compared to the random-effects estimators in Table 2 that treat the initial condition as exogenous, the estimated coefficients of the lagged unemployment in the Heckman estimations are relatively lower in all cases and the coefficients of ρ are more than twice as high, especially for the first case, 0.520 and 0.199, respectively. In terms of the scaled coefficient estimates, $\gamma(1-\rho)^{0.5}$, the standard random-effects probit with initial conditions being treated as exogenous produces 0.97 while the Heckman estimator gives 0.46 for the standard models.

Moreover, the current number of employed decreases the probability of being unemployed meanwhile its lag is not significant (column [2] and [3]). The result also gives the negative and significant coefficient of the current household's

Table 3: Heckman estimates

Variables	Heckman			
[1]	[2]	[3]	[4]	[5]
Unemployment (t-1)	0.663*** (0.162)	0.713*** (0.171)	0.676*** (0.171)	0.696*** (0.170)
Family supports				
Number of employed in HH	−1.814*** (0.149)	−1.769*** (0.156)		
Num. of employed in HH (t-1)		0.052 (0.064)		
Log of HH's income			−0.336*** (0.097)	−0.287*** (0.107)
Log of HH's income (t-1)				0.105 (0.102)
Household formation				
Number of children below 6	0.109 (0.134)	0.115 (0.133)	−0.037 (0.097)	−0.037 (0.096)
Number of children in school	−0.024 (0.116)	−0.021 (0.115)	−0.045 (0.082)	−0.045 (0.082)
Number of elders	−0.074 (0.209)	−0.071 (0.207)	−0.021 (0.149)	−0.023 (0.148)
External supports				
Number of safety net programs	0.064 (0.076)	0.063 (0.075)	0.052 (0.054)	0.051 (0.054)
Number of other supports	0.227 (0.200)	0.228 (0.198)	0.145 (0.141)	0.143 (0.141)
Control variables				
Education in years	−0.029 (0.029)	−0.028 (0.028)	−0.029 (0.021)	−0.029 (0.021)
Males	0.064 (0.077)	0.064 (0.076)	0.133*** (0.051)	0.132*** (0.051)
Age	0.235 (0.214)	0.230 (0.221)	0.032 (0.158)	0.032 (0.146)
Age squares divided by 100	−0.447 (0.311)	−0.436 (0.321)	−0.158 (0.225)	−0.158 (0.210)
Married	−0.391 (0.291)	−0.389 (0.289)	−0.456** (0.219)	−0.454** (0.218)
Urban	0.550*** (0.096)	0.540*** (0.095)	0.408*** (0.066)	0.403*** (0.065)
Year 2009	1.926 (30.920)	−0.063 (39.302)	−0.136 (42.163)	0.061 (0.064)
Year 2010	1.669 (30.920)	−0.315 (39.302)	−0.180 (42.163)	
Exogenous test on initial condition				
Theta (θ)	1.053*** (0.283)	1.067*** (0.294)	1.126** (0.457)	1.161** (0.495)
rho (ρ)	0.520	0.506	0.212	0.202
Log likelihood	−2763	−2763	−3416	−3415
N	65058	65058	65058	65058

*** P<0.01, ** P<0.05, * P<0.1. Values in parentheses are standard errors

Table 4: Wooldridge estimates

Variables	Wooldridge			
[1]	[2]	[3]	[4]	[5]
Unemployment (t-1)	0.578*** (0.196)	1.174*** (0.161)	0.559*** (0.176)	0.607*** (0.172)
Family supports				
Number of employed in HH	−1.858*** (0.168)	−1.338*** (0.124)		
Num. of employed in HH (t-1)		0.397*** (0.046)		
Log of HH's income			−0.248** (0.113)	−0.170 (0.115)
Log of HH's income (t-1)				0.215*** (0.077)
Household formation				
Number of children below 6	0.255 (0.163)	0.296** (0.134)	−0.040 (0.118)	−0.040 (0.117)
Number of children in school	0.048 (0.141)	0.061 (0.119)	0.014 (0.101)	0.011 (0.099)
Number of elders	−0.021 (0.255)	0.041 (0.212)	0.017 (0.178)	0.01 (0.177)
External supports				
Number of safety net programs	0.091 (0.089)	0.069 (0.075)	0.035 (0.063)	0.034 (0.062)
Number of other supports	0.233 (0.238)	0.208 (0.195)	0.141 (0.165)	0.137 (0.163)
Control variables				
Education in years	−0.033 (0.035)	−0.034 (0.029)	−0.041 (0.025)	−0.039 (0.025)
Males	0.097 (0.083)	0.083 (0.065)	0.139*** (0.053)	0.136*** (0.052)
Age	0.125 (0.255)	0.099 (0.217)	−0.101 (0.178)	−0.104 (0.176)
Age squares divided by 100	−0.436 (0.361)	−0.348 (0.305)	−0.094 (0.248)	−0.089 (0.245)
Married	−0.620* (0.328)	−0.516* (0.273)	−0.666*** (0.237)	−0.655*** (0.235)
Urban	0.523*** (0.097)	0.403*** (0.073)	0.410*** (0.063)	0.388*** (0.061)
Year 2009	0.569 (0.500)	0.055 (0.394)	−0.957 (0.758)	−1.270* (0.753)
Year 2010	0.413 (0.498)	−0.105 (0.393)	−0.954 (0.759)	−1.296* (0.756)
Initial conditions				
Unemployment 2008	1.083*** (0.284)	0.627*** (0.220)	0.679*** (0.202)	0.645*** (0.196)
rho (ρ)	0.574	0.312	0.253	0.228
Log likelihood	−1635.6	−1595.9	−2024.9	−2021.1
N	43372	43372	43372	43372

*** P<0.01, ** P<0.05, * P<0.1. Values in parentheses are standard errors income but not its lag. All variables in household formation are not significant as well as the variables in external support from outside households. Being male and living in urban areas increase the probability of being unemployed meanwhile being married decreases that probability. The estimations of θ in all estimates are significantly >0, thus rejecting the exogeneity of the equation in the first observation.

In the Wooldridge estimates on Table 4, the effect of the current number of employed is consistently significant and negative while the previous number of employed is positively significant to the current status of unemployment. The similar results are also found for the household's income, except for the estimate in column [9] where household's income is insignificant. The variables of household formation are mostly insignificant except for the number of children younger than 6 years old. The variables of external support from the government and the others are also insignificant. The lagged unemployment remains significant for all estimates and their coefficients are ranging between 0.578 and 1.174.

These coefficients are relatively lower than those found in the other empirical studies. Arulampalam et al. (2000) for example produced the coefficients ranging between 1.051 and 1.412. Arulampalam and Stewart (2009) provided the estimated coefficient from Wooldridge's method at 1.062 in the case of the UK. Biewen and Steffes (2010) presented the empirical coefficients ranging between 1.387 and 1.612 in the case of Germany.

The control variables of married and urban dummies are consistently significant for all estimates while the male dummy is only significant for some estimates. Education remains insignificant for all estimates. This is probably because the majority of the labour force in Indonesia has low skill or an average of 8 years of education (Appendix Table 1). Age and age squares are also insignificant for all estimates as well as time dummies with an exception in the last estimate (column [5]). Lastly, the initial condition of unemployment status in the year of 2008 is significant in all estimates.

4. CONCLUSION

In this paper, we have proved that there is strong evidence of a person's previous unemployment experience having implications on his/her future labour market experience, which is consistent with the state dependence or the theory of scar unemployment. This strong conclusion come from all estimates presented in this paper, namely: Pooled probit, random-effects probit, Wooldridge and Heckman estimates. In addition, the consequences of including control variables or observable heterogeneity, unobservable heterogeneity, and initial conditions in the models, the effects of the variables in the household formation and external supports become weaker or insignificant. Meanwhile the variables in the family supports play a significant role in the current unemployment status. The probability of being unemployment increases if the persons are males and live in urban area. It will decrease if they are married. However, the level of education and external household support, especially receiving social safety net programs play no role to the probability of being unemployed.

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APPENDIX

Table 1: Descriptive statistics

Variables	Mean			
	Obs.	2008	2009	2010
Unemployment	21686	0.016	0.012	0.009
Number of adult employment in HH	21686	2.219	2.236	2.219
Log of HH expenditure	21686	14.133	14.250	14.393
Number of children below 6 years	21686	0.502	0.480	0.445
Number of children in school	21686	0.808	0.810	0.808
Number of elder in HH	21686	0.117	0.117	0.117
Number of received social safety net programs	21686	0.604	0.538	0.702
Number of other supports	21686	0.061	0.056	0.079
Education	21686	7.996	8.074	8.115
Males	21686	0.665	0.665	0.665
Age	21686	38.533	39.193	39.868
Married	21686	0.841	0.842	0.846
Urban	21686	0.435	0.435	0.435