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How Important Are Non-Cognitive Personality and Personal Background to the Unemployment Persistence in Korea?*

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This paper examines the causes of unemployment persistence among Korean individuals aged 19-60. We used a random effects dynamic probit model, controlling for unobserved heterogeneity and the initial condition problem, for the panel data of waves 1 to 15 (1998-2012) of the Korean Labor and Income Panel Study (KLIPS). The results show that non-cognitive personality and household background have a predictive power on unemployment persistence, as well as the presence of strong state dependence effects. Interestingly, a wealthy family background, high satisfaction with leisure, and job-hunting efforts with personal connections reduce the probability of unemployment persistence. Our results have important implications for separate unemployment policy among individuals with different unobserved personalities. It is also important to appropriately aid young people in their transitions between school and employment, in order for unemployment to be their first experience in the labor market. In addition, unemployment policies that target individuals with poor family backgrounds should help reduce the role of the difference of non-cognitive personalities and their determination during childhood and early adulthood.

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1. INTRODUCTION

At the end of the 1990s, the unemployment rate in Korea was between 5% and 6%, but fell to 3.5% in 2014. Despite the overall low rate of unemployment, if unemployment persists, it is important to find out whether the same individuals experience unemployment year after year, which would imply highly persistent unemployment among a group of individuals. That is, better understanding of the causes of unemployment persistence could be very useful for the implementation of appropriate policies against unemployment. So, clarifying two questions is a matter of common interest: firstly, is unemployment persistence due to differences across workers in their potential productivity? And, secondly, is there a causal link between previous unemployment and current unemployment?

Human capital theory and segmented market theory are well-known theories of unemployment. The causes of unemployment persistence could be primarily related to macroeconomic fundamentals. However, if we focus on the supply side of labor market, it is required to focus on the individual characteristics as a cause of unemployment from the microeconomic perspective. There is growing evidence on the relationships between personality and the individual's propensity to work in regard to their cognitive abilities. In connection with non-cognitive ability in the labor market, previous studies such as Judge *et al*. (1999), Heckman *et al*. (2006), Mueller and Plug (2006), Caliendo *et al*. (2010), Heineck and Anger (2010), Mohanty (2010), etc. have shown that an individual's ability significantly affects their work state, including occupational choices, job search strategies, employment, and earnings.

Moreover, state dependence — that is, whether being in a certain state in the last period affects the probability of being in that state in this period — has been highlighted by previous studies such as Heckman and Borjas (1980), Corcoran and Hill (1985), Pissarides (1992), Narendranathan and Elias (1993), Arulampalam *et al*. (2000), Knights *et al*. (2002), Stewart (2007), etc. on the individuals' labor market transitions. In particular, these studies connected with unemployment state dependence mainly stressed the related issues as its causes of disincentive effects of unemployment insurance, reduced search effort because of discouragement, decay of human capital, and stigma effects. In the case of Korea, Phang and Kim (2001), Sung and Kim (2003), Cho (2004), Cho (2008), Yeo (2008), Choi and Yi (2010), Eskesen (2010), and Keum and Yi (2013) reported the effects of socioeconomic factors on labor market transitions. Sung and Kim (2003) found that as the education level and income level of parents rise, so does the probability of employment, and also the likelihood of having better jobs. Choi and Yi (2010) suggested that educational and age mismatches were more serious in the Korean labor market, thus job creation through mismatch reduction may have important meaning for unemployment policy.

While the individual specific determinants of unemployment are an unknown but important issue, previous studies in the case of Korea have paid relatively less attention to the role of non-cognitive abilities than to cognitive abilities, which are mainly used as a proxy of human capital. That is, the influence of personality on unemployment persistence is still a long way from being perfectly understood, especially after due consideration of the effects of growth background. Thus it is necessary to pay attention to the questions of the positive correlation between inequality in personality and in household background for the persistence of unemployment in the Korean labor market.

The objective of this study is to examine the effects of personality on unemployment persistence, focusing on the supply side. Specifically, we intend to explore whether and to what extent non-cognitive ability and household background of those in their teens have a predictive power on unemployment persistency. We also add to this debate by examining whether state dependence is enhanced or mitigated by specific personality. For empirical estimation, we use a model based on dynamic panel data of unemployment persistence, in order to control state dependence and unobserved individual heterogeneity. In this paper, the observed dependent variable is binary, taking the value of one if the individual is unemployed at the time of the survey, and zero otherwise. This variable is observed at most in fifteen separate survey years. So the estimation methodology is a random effects dynamic probit model with panel data. It incorporates a correction for unobserved heterogeneity, as well as for the initial condition problem.[1)]

The results show that non-cognitive ability and household background have a predictive power on unemployment persistence, as well as the presence of strong state dependence. Interestingly, all of the household background variables and individual job hunting efforts through personal connections are found to have a significant effect on unemployment probability, but one’s education level, which proxies for cognitive ability, and age do not play a significant role. The results suggest that it is important to consider individual characteristics for a more efficient unemployment policy.

The remainder of the paper is organized as follows. In section 2, we will introduce crucial definition and measurement of cognitive and non-cognitive ability and explain the variables used in our estimation following this categorization about personal trait. Section 3 deals with an empirical modeling of unemployment, and introduces the sources and nature of the data used in the empirical analysis. Section 4 discusses the random effects dynamic probit model allowing for the introduction of state dependence and the initial condition problem. Section 5 reveals the estimation results of unemployment persistence, followed by a summary and concluding remark in the final section.

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1) Heineck (2011) use a similar dynamic setting to investigate how cognitive abilities affect unemployment entry and exit rates.

2. 'COGNITIVE' AND 'NON-COGNITIVE' ABILITIES

There has been much research in economics that investigates the sources and mechanisms of individual differences in labor market productivity. With regard to this, many economists have focused on the abilities and skills of workers. As usually defined, 'achievement related skills' can be divided into two categories: cognitive and non-cognitive abilities. Cognitive abilities, which in itself have multifaceted aspects, are usually identified with intelligence and the ability to solve the abstract problems. And these can be measured objectively with a general survey for the individuals, such as an IQ score or educational attainment. For several decades, these measures of cognitive ability have been used for approximation of individual differences in the labor market productivity.

As another source of individual differences in achievements, the concept of 'non-cognitive abilities' is noteworthy. This was originally introduced in psychology and elaborated by Bowles and Gintis (1976, 2002) and Goldsmith *et al*. (1997) to focus on factors other than those measured by cognitive aspects. Although these determinants have been implicitly addressed in human capital theory, empirical economists have just started to take these findings into account in explaining economic outcomes. This concept, although it is complicated and contested, focuses on the personal traits (e.g., perseverance, motivation, emotional stability, and social skills), rather than academic skills, as determinants of labor market success.

Table 1 shows the definitions of the variables and notation. Since we use the KLIPS (Korea Labor and Income Panel Study) data, which surveys the labor market and income activities of households and individual constituents, we had to choose optimal proxy variables that can measure one's cognitive and non-cognitive abilities. Furthermore, in order to control for other factors that influence unemployment probabilities, we categorize explanatory variables into four groups: basic demographics or characteristics, household background, cognitive personalities, and non-cognitive personalities. Among them, in particular, cognitive and non-cognitive personalities are important.

Table 1 Definitions of Variables

Variable Name	Symbol	Definition
Dependent Variable	U_t	Unemployed at wave t=1, otherwise=0
Lagged Dependent Variable	U_{t-1}	Unemployed at wave t–1=1, otherwise=0
Initial Condition	U_1	Unemployed at wave 2=1, otherwise=0
Basic Demographics or Characteristics		
Gender	GEN	Male=1, Female=0
Age	$\ln AGE$	Log of age
Marital Status 1	S_m	Single=1, otherwise=0
Marital Status 2	D_m	Divorced or widowed=1, otherwise=0
Household Background		
Growth Region	GR_{14}	Metropolis in their teens=1, otherwise=0
Parents' Work Condition	JT_P	Wage worker=1, otherwise=0
Family Wealth	HW_{14}	Family circumstances (scale of 1-5)
Father's Education	$\ln EDY_F$	Log of father's years of schooling
Cognitive Personalities		
Educational Level	$\ln EDY$	Log of years of schooling
Non-cognitive Personalities		
<Propensity for Current Living>		(scale of 1-5)
Satisfaction with Family Income	S_{FI}	Feeling with family income
Leisure Satisfaction	S_{LE}	Feeling with leisure
Residential Environment	S_{RE}	Feeling with residential environment
Family Relations	S_{FR}	Feeling with family relations
Near Relatives	S_{NR}	Feeling with near relatives
Social Familiarity	S_{SF}	Feeling with social familiarity
<Attitude of Workers>		
Job Hunting Effort	JH_P	Use personal connections=1, otherwise=0

The general observed cognitive heterogeneity of the individual is education level. Years of education accumulates one's human capital and increases cognitive ability. Thus, increasing educational preferences raises the individual's occupational outcome and subsequent economic status.[2)] That is, the education level may work as a marker for achieving better jobs.

On the other hand, non-cognitive abilities, as mentioned earlier, focus on factors other than those measured by cognitive aspects. The problem is that non-cognitive abilities are hard to observe, which has limited the empirical analysis of this area. In our model, as proxy variables for individual's non-cognitive abilities, we include the following seven variables: satisfaction with family income, attitude to leisure, residential environment, family relations, relationship with near relatives, social familiarity, and job hunting effort. These selected variables are closely related with aforementioned non-cognitive abilities, such as perseverance (job hunting effort), motivation (attitude toward leisure), emotional stability (satisfaction with family income, residential environment, family relations), and social skills (social familiarity, relationship with near relatives), rather than academic skills, as determinants of labor market success. This reflects the following reasons.

In general, a person who continues to look for job opportunities would be more persistent and sincere than a person who does not. Furthermore, we can regard one's job hunting effort as a proxy representing one's social networking ability in the sense that job search activities require one to exploit personal networks and various channels for employment. Furthermore, the higher the satisfaction with the family income, family relationship, and residential environment, the greater would be the degree of emotional stability. In addition, a person, with a higher level of social familiarity and keeping closer relationships with near relatives, would have higher social skills.

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2) Most studies, such as theoretical analyses, tend to report that income and educational inequality are positively correlated by the productivity differences (see, Jacobs, 1985; Glomm and Ravikumar, 1992; Galor and Tsiddon, 1997; Chakraborty and Das, 2005, etc.).

3. MODELING UNEMPLOYMENT FUNCTION AND DATA DESCRIPTION

3.1. Modeling Unemployment Function

In this paper, our investigation of unemployment persistence at the individual level yields some stylized facts, which we relate to current characteristic cognitive and non-cognitive factors of the individual. We also investigate whether the relationship between previous and current unemployment differs from individual to individual. Thus the unemployment function includes individual heterogeneity and state dependence. First, we can explain state dependence on unemployment by the fact that individuals who have been unemployed for long periods are likely to remain unemployed.[3] This means that past unemployment affects current and future unemployment rates. So we add the one year lagged dependent variable as an explanatory variable.

Second, as mentioned earlier, we categorize the explanatory variables into four broad groups: basic demographics or characteristics, household background, cognitive personalities, and non-cognitive personalities. Basic demographics include those variables such as gender, age, and marital condition while household background includes growth region, parents' work condition, family wealth, and father's education level. And the variables of these two groups are introduced as control variables. The suitability of household background as a relevant instrument is supported by previous studies (Stewart, 2007; Cappellari and Jenkins, 2008) on low income and unemployment dynamics.

Of the personal traits, which have substantial impacts on unemployment persistence, we use one's own years of schooling (educational level) to measure cognitive ability. Some previous studies used family wealth and parental education to instrument for cognitive abilities (Ganzach, 2000).

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[3] In this regard, when the effects of shocks are permanent, we have a phenomenon called hysteresis (see, Blanchard and Summers, 1986).

However, in this study, we do not use these variables as proxies for cognitive abilities not only because the estimates of correlation of these two variables with one's education level were low,[4] but also because, more importantly, these two variables are not related to personal traits, but rather are related to one's household background.

On the other hand, non-cognitive ability must also be an important factor on unemployment persistence.[5] In our model, non-cognitive personalities include variables such as satisfaction with family income, attitude to leisure, residential environment, family relations, relationship with near relatives, social familiarity, and job-hunting effort. In general, an individual's personality, which is formed by a household background in their teens is associated not only with work-related preferences and postures that could affect job search intensity, but also with their potential ability to work. So, the individual's personality may affect their probability of maintaining a job, or unemployment persistence. From the above discussion, our unemployment function in general form is given by the following equation (1).[6]

$$U_{i,t} = f(U_{i,t-1}, CS_{i,t}, NS_{i,t}, BD_i, HB_i), \qquad (1)$$

where dependent variable, $U_{i,t}$, indicates the individual *i*'*s* unemployment state at time *t*, *CS* (resp. *NS*) shows cognitive (resp. non-cognitive) abilities, *BD* stands for basic demographics, and *HB* is household background.

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4) The estimated correlation coefficient of one's own education level with family wealth is 0.247 and that with parental education is 0.251.

5) Hassler and Mora (2000), for example, support the hypothesis that individuals with a higher level of innate cognitive ability can deal better with less knowledge than others do. They state that talented individuals are also more productive and choose a high rate of technological growth.

6) In this study, we do not consider regional variation of the current living region of an individual, as it showed no significant effects on the unemployment probability in pretest.

3.2. Data Description

The raw data is taken from the Korean Labor and Income Panel Study (KLIPS) survey data for waves 1 to 15 (1998-2012), a wide ranging representative survey that contains a large set of personal and labor market characteristics of household members. The panel also includes some questions aimed at capturing the household structure, background in their teens, and current satisfaction with the individual's living environment. In this study, the sample used for estimation corresponds to fifteen waves of the database that includes men and women aged between 19 and 60 years, except for the individuals who are students and temporarily stay out of school in each survey year.

Of the demographic variables (gender, age, and marital status), gender and marital status are measured using dummy variables, whereas age is expressed in log years. Of the household background variables (growth region, parents' work condition, family wealth, and father's education level), growth region and parents' work condition are measured using dummy variables; the father's education level is expressed in log of father's years of schooling; and family wealth is measured by scores ranging from 1 to 5.

We use the log value of individual's years of schooling as cognitive personal ability. In spite of the potential role of non-cognitive ability, this has not yet been explored concretely in the raw data. Here, we consider the individual's propensity to a current living environment as well as one's job-hunting effort as variables representing their non-cognitive personalities. The questions indicating current satisfaction with their living environment are family income, leisure, residential environment, family relations, near relatives, and social familiarity. The score in each item ranges from 1 to 5.

Table 2 shows the distribution of unemployment incidences and persistence across waves for all individuals, and the transition probabilities of the unemployment state. The data shows the presence of a very high percentage of unemployed people in the KLIPS sample. In 1998 (wave 1), 61.6% of the initial sample of 5,755 individuals were unemployed. In wave 2

Table 2 Unemployment Incidence and Persistence

	1998	1999	2000	2001	2002	2003	2004	2005
Percent Unemployed	61.64	66.00	66.46	67.19	69.63	68.61	68.86	68.25
Conditional Prob.								
$\text{Prob}(U_t=1 \mid U_{t-1}=1)$		89.04	90.16	91.10	92.27	90.42	91.51	91.51
$\text{Prob}(U_t=1 \mid U_{t-1}=0)$		29.85	20.47	21.67	23.14	20.78	19.36	18.60
Unemployed Sample	5,755	5,508	5,145	5,098	5,234	5,422	5,495	5,428
Total Sample	9,336	8,345	7,742	7,588	7,517	7,903	7,980	7,953
	2006	2007	2008	2009	2010	2011	2012	Total
Percent Unemployed	69.02	69.26	70.13	69.09	71.44	72.27	72.64	68.71
Conditional Prob.								
$\text{Prob}(U_t=1 \mid U_{t-1}=1)$	92.53	92.79	93.05	92.37	93.00	93.45	94.07	91.51
$\text{Prob}(U_t=1 \mid U_{t-1}=0)$	18.02	17.68	17.86	16.78	23.18	18.77	17.69	21.84
Unemployed Sample	5,532	5,552	5,508	6,497	6,520	6,437	6,524	85,655
Total Sample	8,015	8,016	7,854	9,403	9,127	8,907	8,981	124,667

Note: U_t=1 if the individual is unemployed at *t*, and zero otherwise.

and 3, the unemployment sample increased to 66.0% and 66.5%, respectively. Moreover, during the last three waves 13, 14, and 15, the percentage of unemployment state continuously increased to 71.4%, 72.3%, and 72.6%, respectively. Finally, the total unemployed rate is 68.7% of the sample. Some of this rise would have been due to the business cycle as a consequence of the global crisis and downward trend in growth.

In connection with transition probabilities, the first row of conditional probabilities shows the probability of being unemployed at time *t*, conditional on being unemployed at *t*–1, while the second row presents the probability of being unemployed at *t*, conditional on being employed at *t*–1. From the last column, the data also shows that the unemployment persistence in the KLIPS sample is very high. We can see that, on average, about 91.5% of individuals who experienced unemployment in the previous year are also unemployed in the following year.[7)] For individuals who were employed in year $t-1$, the probability of being unemployed in year *t* is 21.8%. This high unemployment persistence could partly be explained by the presence of state dependence.

More specifically the probability of being unemployed in wave 2 (1999) conditional on unemployment at wave 1 (1998) is 89.0%. In subsequent waves, this conditional probability shows an increasing trend that reaches a maximum of 94.1% in wave 15 (2012). Meanwhile the transition probability of being unemployed at *t*, conditional on being employed at *t*–1, is on average about 21.8%. The highest conditional unemployment probability is 29.9% in wave 2, after which it falls by 9 percentage points by wave 3. Then it rises again through 23.1% and 23.2% in wave 5 and wave 13, respectively. Hence, table 2 suggests that, based on the sample, there is considerable persistence in the state of unemployment. Finally, those transition probabilities imply that Korean individuals are doubly exposed to unemployment risks of not only unemployment persistence, but also of becoming a newly unemployed person.

Table 3 shows the summary statistics of unemployment state and independent variables of the panel data measurements during all the sample periods. The mean age of the sample is 40.4, and their years of schooling are 12.2. The mean years of father’s schooling is about 8.7, and the mean of household wealth in their teens is about 2.6, which is often below normal.

[7)] The high conditional probabilities of the unemployment can be explained in two ways. First, as indicated in our paper, unemployment has high state dependence, i.e., that is, there exists strong unemployment persistence in the Korean labor market. Second, as one of reviewers indicated, it might reflect the sample characteristics. The KLIPS data, which are adopted in our empirical analysis, have been constructed by the Korea Labor Institute in the manner of longitudinal surveys about randomly selected sample of approximately 5,000 households and individual constituents residing in urban areas. However, it must be noted that since the sample also includes voluntary inactive youth, the unemployment rate measured using the KLIPS sample is much higher than the registered unemployment rate and that is also true for the conditional probabilities of the unemployment for the KLIPS sample.

Table 3 Summary Statistics

Category	Individual Characteristics	Mean	S.D.	Min	Max
Basic Demographics or Characteristics	Unemployed State at t	0.687	0.464	0	1
	Gender				
	Male	0.488	0.500	0	1
	Female	0.512	0.500	0	1
	Age	40.416	10.435	19	60
	Marital Status				
	Single	0.197	0.398	0	1
	Married	0.743	0.437	0	1
	Divorced or Widowed	0.060	0.238	0	1
Household Background	Growth Region	0.310	0.463	0	1
	Household Wealth	2.648	0.897	1	5
	Parents' Job Type	0.249	0.432	0	1
	Father's Education Level	8.653	3.802	0	20
Cognitive Personalities	Years of Schooling	12.192	3.160	0	22
Non-cognitive Personalities	<Propensity for Current Living>				
	Satisfaction to Family Income	2.730	0.791	1	5
	Leisure	2.929	0.786	1	5
	Residential Environment	3.254	0.743	1	5
	Family Relations	3.651	0.643	1	5
	Near Relatives	3.463	0.616	1	5
	Social Familiarity	3.441	0.601	1	5
	<Attitude of Workers>				
	Job Hunting Effort	0.075	0.263	0	1

4. ESTIMATION METHODOLOGY

The model used is a random effects dynamic probit model with panel data controlling for unobserved heterogeneity, state dependence, and the initial condition problem.[8] The general dynamic probit model is given by

[8] We use the random effects model because of the following reasons. First, the methodology used in this paper is the estimation of dynamic panel data models, where the lagged dependent variable and initial condition of state are included as explanatory variables.

equation (2), which assumes there is one lag of a dependent variable, and the other explanatory variables are strictly exogenous. By assuming that the unemployment function in equation (1) takes the Cobb-Douglas form, we obtain a final specification of equation (2) that is linear in the parameters. In equation (2), the individual's unemployment state $(U_{i,t})$ is a function of the observed unemployment status of the individual in the previous period $(U_{i,t-1})$; it is the actual experience of unemployment that affects the current incidence of unemployment. The inclusion of the lagged dependent variable on the right hand side of equation (2) allows us to test for the presence of state dependence, or the so-called scarring effect.

$$U_{i,t} = \beta X'_{i,t} + \delta Z'_i + \rho U_{i,t-1} + \varepsilon_{i,t}, \ \ i = 1, \ 2, \ \cdots, \ N \text{ and } t = 1, \ 2, \ \cdots, \ T. \quad (2)$$

In equation (2), $U_{i,t}$ is a binary dummy variable that takes value 1 if individual i is unemployed at t, zero otherwise; ρ measures the unemployment state dependence; X is a vector of time-variant observable characteristics that affect unemployment probabilities; β is the vector of exogenous and coefficients associated with X, which includes cognitive and non-cognitive variables that proxy for the individual's potential productivity; Z is the time-invariant variables; and $\varepsilon_{i,t}$ is a normally distributed error term.

Secondly, in order to avoid biased estimation of the genuine state dependence arising from spurious correlation, it is necessary to model

Second, our model contains time invariant variables (i.e., gender) and the time span (T) is relatively small. So applying the fixed effects model can yield biased estimators. As is well known, the Hausman test is only valid under homoscedasticity and cannot include time fixed effects. For instance, ignoring such heterogeneity could lead to inconsistent or meaningless estimates of interesting parameters (Hsiao, 2003), the Hausman test to solve the problem of heterogeneity bias is neither necessary nor sufficient (Clark and Linzer, 2012). Also the usual standard errors of the fixed effects estimator are drastically understated in the presence of serial correlation, as well as in the case where T is smaller than recommended 30 and over (see, Mundlak, 1978; Nickell, 1981; Chamberlain, 1984: Wooldridge, 2002; Hsiao, 2003; Bertrand *et al*., 2004; Greene, 2012; Baltagi, 2013). Basically, random effects appear to be attractive if the individual dimension N is large relative to the time dimension T, such that individual effects can be viewed as random (Hsiao, 2003; Baltagi, 2013).

unobserved heterogeneity.[9] Assuming the unobservable individual-specific heterogeneity is time-invariant, we can decompose the error term into two components as $v_i + \varepsilon_{i,t}$, where v_i denotes the individual-specific unobservable time-invariant effect (random effect heterogeneity), and $\varepsilon_{i,t}$ is a random error. We treat v_i as random, and use the random effects probit models that we estimate under the common assumption that $\varepsilon_{i,t} \sim IN(0, \sigma_\varepsilon^2)$ and the $\varepsilon_{i,t}$ are independent of the $X_{i,t}$ or all *i* and *t*. Following Chamberlain (1984), we can model the dependence between v and X by assuming that the regression function of v_i is linear in the mean value of all the time-varying covariates. Therefore we can write this as $v_i = \alpha_0 + \lambda \bar{X}_i + \alpha_i$, where we also assume that $\varepsilon_{i,t} \sim IN(0, \sigma_\alpha^2)$ and is independent of $X_{i,t}$ and $\varepsilon_{i,t}$ for all i and t, α_0 is the intercept, and $\bar{X}_i$, which is known as the Chamberlain-Mundlak term, refers to the vector of means of the time-varying covariates for individual i over time.[10]

In addition, our analysis is based on the KLIPS, which began in 1998, and these individuals were already at risk of unemployment before the survey began. Thus we also need to control for the initial condition, i.e., whether someone was unemployed or not in the first survey time, rather than assuming this was exogenously given. The initial observation $U_{i,1}$ and the initial condition problem that occurs if $U_{i,1}$ correlates with the unobservable α_i. This problem arises because the start of the observation period does not coincide with the start of the stochastic process generating the individual's unemployment experiences.[11] To account for this problem, we follow Wooldridge (2005),[12] thus combining the individual heterogeneity

[9] Unobserved personalities are termed unobserved heterogeneity, and could partly explain the observation of unemployment persistence. This could be taken into account by decomposing the error term.

[10] The coefficients in λ corresponding to the time-invariant variables are set equal to zero.

[11] A large proportion of people in our sample entered the labor market prior to the first survey time, and these people were already at risk of unemployment before the survey period began. Thus an individual observed in the state of unemployment at the first survey time may be there because of an earlier history of unemployment, or some observed and unobserved characteristics affecting their unemployment persistence.

[12] In order to solve the initial problem, Wooldridge (2005) proposed a methodology that models the distribution of the unobserved effect on this initial observation value.

and initial condition problem in equation (2) becomes a random effects dynamic probit model with panel data, as in the following equation (3):

$$U_{i,t} = \beta X'_{i,t} + Z_{i'} + \rho U_{i,t-1} + \gamma U_{i,1} + \lambda \bar{X}_i + \varepsilon_{i,t}, \tag{3}$$

where the explanatory variables in time t are $(1, X_{i,t}, Z_i, U_{i,t-1}, \bar{X}_i)$ and $\alpha_i = \nu_i - \alpha_0 - \gamma U_{i,1} - \lambda \bar{X}_i$.[13] We have absorbed the intercept α_0 into the δ. Year fixed-effects are also included in the model, in order to take into account changing macroeconomic conditions.

Finally, this allows us to assess state dependence and unobserved heterogeneity. Thus the random effects dynamic probit model to get the average partial probability effects with an unobserved heterogeneity (ν_i) and initial condition $(U_{i,1})$ is as follows:

$$\begin{aligned} &P(U_{i,t} = 1 | X_{i,t}, \mathrm{Z}_i, U_{i,t-1}, U_{i,1}, \alpha_i) \\ &\quad = \Psi(\beta X'_{i,t} + \delta Z'_t + U_{i,t-1} + \gamma U_{i,1} + \lambda \bar{X}_i + \alpha_i). \end{aligned} \tag{4}$$

5. ESTIMATION RESULTS

5.1. Average Probability Effects

Table 4 summarizes the estimated coefficients of equation (3), for three variants of the model. The coefficients measure the impact of the explanatory variables on the probability of being unemployed. For comparison, the first column reports pooled dynamic probit estimates that ignore the effects of individual heterogeneity and the initial condition problem. Thus, this model is likely to overestimate the coefficient on the lagged unemployment variable.

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[13] In connection with further specification of methodology refer to Mundlak (1978), Nayor and Smith (1982), Chamberlain (1984), and Wooldridge (2005).

Table 4 Coefficient Estimates for Each Specification

Variant / Variable	Pooled Dynamic Probit		Random Effects Dynamic Probit: Without Initial Condition (I)		With Initial Condition (II)		With Initial Condition and Interactions (III)	
U_{t-1}	1.990***	(0.020)	1.570***	(0.021)	1.469***	(0.021)	0.481***	(0.115)
U_1					0.580***	(0.032)	0.562***	(0.031)
GEN	0.618***	(0.018)	0.938***	(0.030)	0.832***	(0.030)	0.813***	(0.030)
lnAGE	–0.734***	(0.209)	0.110	(0.265)	0.306	(0.271)	0.242	(0.271)
S_m	0.086***	(0.027)	0.227***	(0.035)	0.275***	(0.035)	0.266***	(0.035)
D_m	0.161***	(0.040)	0.231***	(0.048)	0.236***	(0.049)	0.232***	(0.049)
HW_{14}	–0.030***	(0.010)	–0.048***	(0.015)	–0.045***	(0.016)	–0.044***	(0.016)
lnEDY_F	–0.036**	(0.015)	–0.057**	(0.024)	–0.058**	(0.025)	–0.059**	(0.025)
GR_{14}	–0.038**	(0.018)	–0.057**	(0.028)	–0.063**	(0.029)	–0.063**	(0.029)
JT_P	–0.067***	(0.019)	–0.096***	(0.029)	–0.093***	(0.029)	–0.093***	(0.029)
lnEDY	–0.177	(0.235)	–0.253	(0.271)	–0.244	(0.274)	–0.244	(0.274)
S_{FI}	0.231***	(0.013)	0.281***	(0.014)	0.281***	(0.014)	0.182***	(0.014)
S_{LE}	–0.187***	(0.013)	–0.203***	(0.014)	–0.201***	(0.014)	–0.228***	(0.014)
S_{RE}	–0.019	(0.013)	–0.015	(0.015)	–0.015	(0.015)	–0.061	(0.015)
S_{FR}	0.021	(0.018)	0.016	(0.019)	0.016	(0.019)	0.031	(0.019)
S_{NR}	–0.044**	(0.020)	–0.037	(0.022)	–0.038	(0.022)	–0.090	(0.022)
S_{SF}	0.149***	(0.018)	0.153***	(0.021)	0.150***	(0.021)	0.163***	(0.021)
JH_p	–0.193***	(0.033)	–0.451***	(0.038)	–0.273***	(0.039)	–0.266***	(0.039)
$S_{FI}\ U_{t-1}$							0.172***	(0.027)
$S_{LE}\ U_{t-1}$							0.053*	(0.028)
$S_{RE}\ U_{t-1}$							0.076***	(0.029)
$S_{FR}\ U_{t-1}$							–0.025	(0.036)
$S_{NR}\ U_{t-1}$							0.088**	(0.043)
$S_{SF}\ U_{t-1}$							–0.020	(0.041)
Constant	–1.493***	(0.251)	–2.165***	(0.348)	–2.110***	(0.357)	–1.536***	(0.358)
Wald $\chi^2(32)$	14,311.41***							
Pseudo R^2	0.447							
Log of Variance $(\ln\sigma_\nu^2)$			–0.728	(0.057)	–0.663	(0.054)	–0.718	(0.055)
Standard Deviation (σ_ν)			0.695	(0.013)	0.718	(0.019)	0.698	(0.019)
$\rho(=\sigma_\nu^2/(\sigma_\nu^2+1))$			0.326***	(0.013)	0.340***	(0.012)	0.328***	(0.012)
LR Test of $\rho=0,\ \chi^2(1)$			1,002.88***		1,199.13***		1,101.21***	
Wald $\chi^2(32)$			10,515.37***		11,053.93***		11,281.73***	
Log-likelihood			–18,346.37		–18,154.88		–18,082.42	

Notes: 1) The number of observations is 56,411, coefficients show average probability effect, z-statistics are in parentheses, and the log-likelihood is obtained by adapting Gauss-Hermite quadrature. 2) ***, **, and * denote significance at the 1%, 5% and 10% level, respectively. 3) All models contain year dummies and the Mundlak term, which contains the time-averaged value of two variables: age and year of schooling. These estimation results are not reported but are available upon request.

The second column reports the traditional random effects dynamic probit (Model I) estimates, which allow for unobserved heterogeneity, but treat the initial condition as exogenous. The third column (Model II) shows more reasonable estimates because of the addition of the equation to control for the initial condition by implementing the Wooldridge (2005) style method. The last column (Model III) shows the estimates of the model, including interaction variables. We can see that there is no significant difference in the estimated coefficients and those signs by the three specifications, after controlling for the initial condition problem and unobserved heterogeneity. Here, the estimated coefficients mean average probability effects (APES; see footnote 19).

As mentioned in section 2, we grouped the explanatory variables into four different categories. The first category of variables is related to individual demographic characteristics, including their gender, age, and marital status. In Model II of table 4, the estimated coefficients on variables related to demographic information are positive and statistically significant except for age. The estimated coefficient for age is positive, albeit statistically insignificant, implying that age is not likely to matter in determining unemployment probability. We can also observe that males are more likely to experience unemployment than females.[14] Household characteristics (marital status) have a significant influence on unemployment probability; single and divorced or widowed individuals increase the probability of experiencing unemployment. This could be interpreted as a signal of weaker productivity because of lower job-hunting intensity.

The second category measures the household background through growth region, household wealth, father's educational level, and parents' work types in their teens. It is interesting that all of the household background

[14] We are indebted to an anonymous reviewer for the following explanation. One important reason why we see more males are unemployed than females is because while the males seeks full time jobs, whereas females may only seek part-time or non-regular jobs (Yu, 2002; Okamura and Islam, 2009; Ahn, 2010), and hence are more likely to have less persistent unemployment. In Appendix, we separately have estimated the unemployment probability function by gender and have found that the magnitude of state dependence is greater for females than for males.

variables were found to have a significant effect on the unemployment probability. The results show that individuals who grew up in a metropolis, grew up in a wealthy family, with higher level of father's education, and with their parents employed as wage workers increase the probability of being in employment.[15)] This implies that people who grew up in a wealthy family are likely to have a higher education level, and may have more efficient job search methods and more motivation. So, they can appear to be more attractive to firms, and also are likely to have various opportunities to start up their own business. Thus the coefficients on the household background variables confirm that individuals who come from good families may be less likely to experience unemployment states from the beginning.

The third category measures the effects of cognitive personalities, proxied by educational level, on unemployment probabilities. The estimated coefficient on the individual's education level shows a negative value but is significant statistically. This implies that cognitive abilities do not matter in determining unemployment probabilities.

The fourth category represents the effects of non-cognitive personalities, proxied by the individual's propensity to a current living environment and one's job hunting effort. The estimated coefficients on both satisfaction with family income and social familiarities are positive and statistically significant, implying that people who have high satisfaction with both current family income and social contact with other people show increased probability of being unemployed.[16)] On the other hand, people who have positive propensity to satisfaction with leisure decrease the probability of unemployment. We can say that individuals with high satisfaction on leisure are more likely to be employed. This implies that high dissatisfaction with leisure might be a considerable factor that increases unemployment persistence. However, the satisfaction score variables of residential environment, family relations, and near relatives do not have

[15)] Metropolis refers to the current seven metropolitan cities in Korea.
[16)] This is because theoretically, some people who are highly satisfied with their wealth could develop a greater attraction for leisure as well as less sincerity toward work, and less motivation or ambition.

significant influence on the unemployment probability.

The job search effort variable, which reflects the individual's perseverance, sincerity, and social networking abilities, has a significant negative effect on the probability of unemployment. Therefore, a person of perseverance and sincerity is more likely to be employed. In addition, if we capture the job search effort as one's social network ability, then that strong influence of the job-hunting channel on unemployment has an important implication, so that in order to increase the probability of transition from unemployment to employment, it could be helpful to make efficient use of personal connections with the formal channels. This is consistent with the positive relationship between personality with positive reciprocity, and work effort, as reported in Dohmen *et al*. (2010).

The estimated coefficients of lagged unemployment and initial unemployment state variables are highly significant, which demonstrates that unemployment has a positive state dependence. Other things being equal, the results show that an individual experiencing unemployment in the previous period has a higher probability of being unemployed in the current period, than somebody who was at work. This result of state dependence is consistent with the presence of a stigma or scarring effect, with unemployment experience having a significant effect on future labor market behavior.[17)] Specifically, the coefficients of the lagged dependent variable lie between 0.48 and 1.57, according to each variant.

With respect to the model specification, it should be noted that the coefficient associated with state dependence is higher in the first column than in the others. This result can be explained by the fact that in the pooled dynamic probit model, the effect of state dependence could be over-estimated relative to the random effects dynamic model, by ignoring the heterogeneity and initial unemployment condition problem. Another important result is

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17) Unemployment incidence, as mentioned by Pissarides (1992), reduces individual human capital, and may be considered as an indicator of lower productivity. In a similar perspective, previous studies such as Phelps (1972), Lockwood (1991), and Blanchard and Diamond (1994) also support the phenomenon that employers use an individual's unemployment history as a screening device.

the significance of the coefficient attached to the initial condition. We can therefore reject the null hypothesis that the initial condition is not independent of the heterogeneity term. Then the importance of the individual heterogeneity term can be demonstrated by the value taken by the share of the total variance attributed to the heterogeneity term (ρ), which is relatively important (32.6%, 34.0% and 32.8%, respectively, for the three specifications).[18] Moreover, the null hypothesis that this coefficient is not significantly different from 0 is rejected for all specifications. This means that estimating the unemployment equation by panel data brings more information than a simple probit.

5.2. Marginal Probability Effects[19]

In practical terms, the estimated coefficients with the random effects dynamic probit model do not directly offer marginal effects. So it is

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[18] The rho $(\rho = \sigma_v^2 / (\sigma_v^2 + 1))$ is the proportion of the total variance contributed by the panel level variance component. When ρ is zero, the panel-level variance component is unimportant, and the panel estimator is not different from the pooled estimator.

[19] There are two types of marginal effects in the probit model: marginal effects at the mean (MEMS, or average probability effects) and marginal probability effects (MPES). In linear regression, if the coefficient on X_i is $\beta_{i,}$ then a 1-unit increase in X_i increases dependent variable Y by β_i. But in the probit model, the marginal impact of change in a variable is not constant. To look at this, suppose a simple probit model such as $\Pr(Y = 1 | X) = \Phi(X^T \beta)$, where Pr denotes probability, X^T is a row vector of regressor values, β is a column vector of regression coefficients, and Φ is the cumulative distribution function of the standard nominal distribution. In this case, the marginal effects of X_i are given by $\partial \Pr(Y = 1) / \partial X_i = \beta_i \times \phi(X^T \beta)$. From this, we can easily confirm that marginal effects depend on not just β_{ii} but on the values of X_i and all other variables X_j. A typical option to get the marginal effects is to set all variables to their means, which is called, marginal effects at the mean (MEMS). The MEMS for continuous variables measure the instantaneous rate of change, holding all other variables at their means. However, we should note that the marginal effects will differ at other values of X_S. Another approach, MPES, is to fix the X_j and let X_i vary from its minimum to maximum values, i.e., $\partial \Pr(Y = 1) / \partial X_i = \beta_i \times \phi(X^T \beta)$. Then, we can plot how the marginal effects of X_i changes across its observed range of values.

necessary to compare the predicted probabilities conditional on the different unemployment status (unemployed at *t*–1 or not) on the previous time. However, since we are using panel data, it is required to take into account the fact that individuals may have different unemployment propensities, considering the presence of unobserved heterogeneity. In connection with this problem, Chamberlain (1984) suggested a mean effect method to compute the marginal effects for each individual and thereafter taking the mean on the whole sample. Specifically, to estimate marginal probability effects, we first compute the predicted probability for each individual, assuming that they have known unemployment at *t*–1. Secondly, we compute the predicted probabilities for each individual, assuming they were in employment at *t*–1. Then we can calculate the difference in the predicted probabilities for each individual, which shows the amount of genuine state dependence. When taking the mean of these differences, we can obtain a genuine state dependence measure, which explains the part of the unemployment persistence.

In this study, we can estimate the parameters by marginalization of the likelihood function with respect to ν, if we assume that the conditional distribution of $U_{i,t}$ on α_i, $X_{i,t}$, $\bar{X}_i$, then $U_{i,t-1}$ is independent normal. That is, we use the mean values of all the independent variables as the baseline probability of unemployment. The marginal effects of the variables computed for each of the specifications can be seen in table 5. The marginal probability effects (MPES) represent an increase by a factor of unemployment, relative to the probability of unemployment for an average individual, as predicted by the model. However, the estimates are conditional on previous employment status, and thus uncover the role of certain personalities in unemployment transitions. In the first row of table 5, state dependence explains that a randomly chosen individual experiencing unemployment at *t*–1 will be 41.7, 38.4, and 12.5 percentage points more likely to be unemployed again at t by the specifications, respectively, than an individual who was employed at *t*–1.

The positively significant MPEs of lagged unemployment (U_{t-1}) and initial

Table 5 Marginal Probability Effects

Variable \ Variant	Random Effects Dynamic Probit					
	Without Initial Condition (I)		With Initial Condition (II)		With Initial Condition and Interactions (III)	
U_{t-1}	0.417***	(0.007)	0.384***	(0.008)	0.125***	(0.030)
U_1	–	–	0.152***	(0.008)	0.146***	(0.008)
GEN	0.249***	(0.008)	0.218***	(0.008)	0.212***	(0.008)
$\ln AGE$	0.029	(0.070)	0.080	(0.071)	0.063	(0.070)
S_m	0.060***	(0.009)	0.072***	(0.009)	0.070***	(0.009)
D_m	0.061***	(0.013)	0.062***	(0.013)	0.060***	(0.013)
HW_{14}	–0.013***	(0.004)	–0.012***	(0.004)	–0.011***	(0.004)
$\ln EDY_F$	–0.015**	(0.006)	–0.015**	(0.007)	–0.015**	(0.006)
GR_{14}	–0.015**	(0.007)	–0.016**	(0.008)	–0.016**	(0.007)
JT_P	–0.026***	(0.008)	–0.024***	(0.008)	–0.024***	(0.008)
$\ln EDY$	–0.067	(0.072)	–0.064	(0.072)	–0.064	(0.071)
S_{FI}	0.075***	(0.004)	0.074***	(0.004)	0.047***	(0.005)
S_{LE}	–0.054***	(0.004)	–0.052***	(0.004)	–0.059***	(0.006)
S_{RE}	–0.004	(0.004)	–0.004	(0.004)	–0.016	(0.006)
S_{FR}	0.004	(0.005)	0.004	(0.005)	0.008	(0.007)
S_{NR}	–0.010*	(0.006)	–0.010*	(0.006)	–0.023*	(0.008)
S_{SF}	0.041***	(0.006)	0.039***	(0.005)	0.043***	(0.008)
JH_P	–0.120***	(0.010)	–0.022***	(0.010)	–0.070***	(0.010)

Note: Estimated by unemployment probability assuming $v_t = 0$ at means of all covariates.

unemployment state (U_1) in all specifications show the strong state dependence of unemployment. This finding is consistent with the scarring effect of unemployment of an individual's previous unemployment experience having implications for their future labor market behavior. Therefore, it is important to escape quickly from unemployment status.[20)]

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20) This is because according to the signaling hypothesis, high productivity people move from job to job without any experience of unemployment, or exit unemployment faster. Blanchard and Diamond (1994) also pointed out that wages are higher with ranking, because the currently employed and the more recently unemployed have a better chance of being re-employed than the longer-term unemployed.

Table 6 Conditional Marginal Probability Effects (using specification II)

Condition	Variable	Random Effects Dynamic Probit Model with Initial Condition					
		All		Male		Female	
		CMPE	S.E.	CMPE	S.E.	CMPE	S.E.
$U_{t-1}=1$	U_{t-1}	0.2 33***	(0.005)	0.116***	(0.005)	0.367***	(0.007)
	U_1	0.092***	(0.005)	0.046***	(0.003)	0.145***	(0.008)
	GEN	0.132***	(0.005)	0.066***	(0.002)	0.208***	(0.011)
	$\ln AGE$	0.049	(0.043)	0.024	(0.021)	0.077	(0.068)
	S_m	0.044***	(0.006)	0.022***	(0.003)	0.069***	(0.009)
	D_m	0.037***	(0.008)	0.019***	(0.004)	0.059***	(0.012)
	HW_{14}	–0.007***	(0.003)	–0.004***	(0.001)	–0.011***	(0.004)
	$\ln EDY_F$	–0.009**	(0.004)	–0.005**	(0.002)	–0.015**	(0.006)
	GR_{14}	–0.010**	(0.005)	–0.005**	(0.002)	–0.016**	(0.007)
	JT_P	–0.015***	(0.005)	–0.007***	(0.001)	–0.023***	(0.007)
	$\ln EDY$	–0.039	(0.043)	–0.019	(0.022)	–0.061	(0.069)
	S_{FI}	0.045***	(0.002)	0.022***	(0.001)	0.070***	(0.004)
	S_{LE}	–0.032***	(0.002)	–0.016***	(0.001)	–0.050***	(0.004)
	S_{RE}	–0.002	(0.002)	–0.001	(0.002)	–0.004	(0.004)
	S_{FR}	0.003	(0.003)	0.001	(0.002)	0.004	(0.005)
	S_{NR}	–0.006*	(0.003)	–0.003*	(0.002)	–0.010*	(0.005)
	S_{SF}	0.024***	(0.003)	0.012***	(0.002)	0.038***	(0.005)
	JH_P	–0.043***	(0.006)	–0.022***	(0.003)	–0.068***	(0.010)
$U_{t-1}=0$	U_{t-1}	0.582***	(0.007)	0.555***	(0.012)	0.516***	(0.006)
	U_1	0.230***	(0.013)	0.219***	(0.012)	0.204***	(0.012)
	GEN	0.330***	(0.012)	0.314***	(0.009)	0.293***	(0.010)
	$\ln AGE$	0.121	(0.107)	0.116	(0.102)	0.108	(0.095)
	S_m	0.109***	(0.014)	0.104***	(0.013)	0.097***	(0.013)
	D_m	0.094***	(0.019)	0.089***	(0.018)	0.083***	(0.017)
	HW_{14}	–0.018***	(0.006)	–0.017***	(0.006)	–0.016***	(0.006)
	$\ln EDY_F$	–0.023**	(0.010)	–0.022**	(0.009)	–0.021**	(0.009)
	GR_{14}	–0.025**	(0.011)	–0.024**	(0.011)	–0.022**	(0.010)
	JT_P	–0.037***	(0.012)	–0.035***	(0.011)	–0.033***	(0.010)
	$\ln EDY$	–0.097	(0.109)	–0.092	(0.103)	–0.086	(0.096)
	S_{FI}	0.112***	(0.006)	0.106***	(0.005)	0.099***	(0.005)
	S_{LE}	–0.080***	(0.006)	–0.076***	(0.005)	–0.071***	(0.005)
	S_{RE}	–0.006	(0.006)	–0.006	(0.006)	–0.005	(0.005)
	S_{FR}	0.006	(0.008)	0.006	(0.007)	0.006	(0.007)
	S_{NR}	–0.015*	(0.009)	–0.015*	(0.008)	–0.013*	(0.008)
	S_{SF}	0.059***	(0.008)	0.057***	(0.008)	0.053***	(0.007)
	JH_P	–0.108***	(0.016)	–0.103***	(0.015)	–0.096***	(0.014)

Note: CMPE stands for conditional probability effects.

Individuals, with rich family backgrounds and active job hunting, are more likely to be employed, the MPE for a one standard deviation increase in these variables being 1.2 and 2.2 percentage points, respectively, in specification II.

In addition, as confirmed above, the coefficients on the gender variable show that males are more likely to experience unemployment. In order to see the differences of the conditional MPES in terms of both employment condition and gender, we calculate the change in the predicted likelihood associated with a change in explanatory variable when variables representing the unemployment condition or gender take the value of either zero or one. That is, we use mean values of all the independent variables, except for lagged unemployment and gender, as a baseline probability of unemployment. Table 6 reports the conditional marginal effects of the explanatory variables computed for the model with the initial condition (Model II) of the unemployment equation.

The main points to note about the predicted probabilities reported in table 5 are as follows. First, the conditional MPES are larger for the variables representing household background, and job hunting efforts, and those for the state dependence are greater for females than for males. Second, the conditional MPES for the state dependence are stronger under the employment condition in $t-1(U_{t-1}=0)$ than under the unemployment condition in the same period $(U_{t-1}=0)$. Third, the estimated signs of conditional MPES do not differ from the restrictions of gender and unemployment conditions.

6. CONCLUDING REMARKS

In this study, we examined the determinants of unemployment persistence among Korean individuals using a random effect dynamic probit model, controlling for both unobserved heterogeneity and the initial condition problem. This work provides some answers to the important question of whether or not there exists state dependence in unemployment, by estimating binary panel data models of unemployment incidence. Interestingly, the results show that one's demographic characteristics, household background, and non-cognitive personalities play crucial roles in determining unemployment persistence.

The main findings of the paper are as follows. First, the results strongly suggest the presence of state dependence in unemployment persistence, even after controlling for unobserved heterogeneity and the initial condition problem. Second, the individual's demographic condition (i.e., gender, marital status) and household background (i.e., household wealth, growth region, educational level of parents, and father's job type) have strong influences on unemployment probabilities. However, age is not likely to matter in determining unemployment probabilities. Third, surprisingly, one's cognitive abilities proxied by educational level does not matter in determining unemployment probabilities, however, non-cognitive abilities proxied by variables show significant influence on unemployment probabilities, such as satisfaction with family income, leisure satisfaction, social familiarities, and job-hunting effort. Thus, we can reasonably state that the lower the satisfaction with one's family income, the higher the leisure satisfaction, and the stronger the job hunting efforts, then the greater the probability of being employed.

The estimations of unemployment persistence in Korea suggest that over the sample period, though the probability of an individual escaping unemployment is strongly related to the demand of the labor market and the business cycle, non-cognitive personalities, as well as household background, have important roles in employment transition. Therefore, the following measures are recommended, to fight against unemployment. First, the finding that previous unemployment experience increases the probability of current unemployment has important implications for a separate unemployment policy, than the policy of reducing the macroeconomic unemployment rate or natural rate of unemployment. That is, unemployment policies reducing short-term unemployment incidence will have longer run effects, by reducing the stigma effect of unemployment. Among other things, it is important to appropriately aid young people in their transitions between school and employment in order for unemployment to be their first experience in the labor market. Second, to increase the efficiency of unemployment policies, which typically focus on market institutions and cognitive personalities, they may critically differ among individuals with different unobserved personalities. This is because of the importance of non-cognitive personalities on unemployment persistence. Third, our findings also suggest that policies aimed at preventing long-term impact on aggregate unemployment are also needed, such as promoting education and training, especially for individuals with poor family backgrounds. Those successful public policies targeting low-income families should lead to some important implications for the reducing the role of the difference of non-cognitive personalities and their determination during childhood and early adulthood.

Throughout the paper, we have found that there exists strong state dependence in the labor market and that non-cognitive personalities play significant roles in the unemployment persistence. However, much more research is required in order to compare inter-country differences in both state dependence and non-cognitive factors in determining unemployment persistence, which could not be conducted because of the lack of usable data.

APPENDIX

Table A1 Coefficient Estimates by Gender

Variable \ Variant	Random Effects Dynamic Probit with Initial Condition (II)			
	Male		Female	
U_{t-1}	1.199***	(0.037)	1.531***	(0.025)
U_1	0.328***	(0.052)	0.599***	(0.040)
lnAGE	0.300	(0.448)	0.760**	(0.360)
S_m	–0.687***	(0.054)	0.863***	(0.049)
D_m	–0.286***	(0.078)	0.429***	(0.061)
HW_{14}	–0.054***	(0.022)	–0.051**	(0.022)
lnEDY_F	–0.067*	(0.035)	–0.058**	(0.025)
GR_{14}	–0.032**	(0.041)	–0.099**	(0.038)
JT_P	–0.043	(0.043)	–0.065*	(0.034)
lnEDY	–0.128	(0.420)	–0.187	(0.351)
S_{FI}	0.432***	(0.023)	0.221***	(0.018)
S_{LE}	–0.073***	(0.024)	–0.279***	(0.018)
S_{RE}	–0.012	(0.025)	–0.024	(0.019)
S_{FR}	0.053*	(0.031)	–0.022	(0.024)
S_{NR}	–0.049	(0.037)	–0.039	(0.028)
S_{SF}	0.202***	(0.035)	0.121***	(0.026)
JH_P	–0.452***	(0.055)	–0.099*	(0.056)
Constant	1.282***	(0.528)	–2.520***	(0.493)
Log of Variance $(\ln \sigma_v^2)$	–0.956	(0.098)	–0.607	(0.067)
Standard Deviation (σ_v)	0.620	(0.030)	0.738	(0.025)
$\rho(= \sigma_v^2 / (\sigma_v^2 + 1))$	0.278***	(0.020)	0.352***	(0.015)
LR Test of $\rho = 0$, $\chi^2(1)$	305.62***		797.00***	
Wald $\chi^2(32)$	2,843.51***		6,504.94***	
Log-likelihood	–6,216.69		–11,452.64	
Observations	26,622		29,819	

Note: Refer to the table 4.

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