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Getting a Job in the Philippines:
The Transition from Unemployment to Work among Filipino Jobseekers*

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ABSTRACT

Unemployment remains a significant development challenge in the Philippines. This paper investigates the dynamics of transition from unemployment to employment of jobseekers in the Philippine labor market. Using an individual level panel data constructed from two nationally representative surveys, this paper examines how employment prospects of Filipino jobseekers are affected by their personal characteristics and by their unemployment income as well as by household composition, local labor market conditions, and unemployment duration. Influential factors to transition from unemployment to work were identified from the estimated duration and ordered logistic regression models.

Keywords: duration analysis, grouped data, unemployment, Philippines

1. **Introduction**

The Philippines has had a stubbornly high open unemployment rate for almost a decade now. Official figures[3] show that the unemployment rate just hovered above 7.0 percent since 2006. Although the unemployment rate had fallen albeit steadily in recent years, it remains the highest among the five largest economies in the Association of Southeast Asian Nations or ASEAN 5[4]. In 2013, there are roughly 2.9 million unemployed Filipinos.

The Department of Labor and Employment (DOLE, 2011) acknowledges in its 2011-2016 Labor and Employment Plan (LEP) that while unemployment is a serious social problem, its relevance for a developing country like the Philippines where there is a significant share of self-employed and unpaid family workers[5] in the labor force is somewhat diminished arguing that "unemployment as an indicator is ***less sensitive*** to the developments in the economy and labor market." [Emphasis in the original] However, the economic and non-economic costs of unemployment cannot be downplayed.

The cost of unemployment for the broader economy is foregone output or simply the goods and services that the unemployed would have produced had they been gainfully

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[3]The Labor Force Survey (LFS) had gone through several changes since it was first conducted in the Philippines in 1956. There had been several breaks in the data series due to changes pertaining to the survey's reference period, coverage, population projection benchmark, and unemployment definition. The latest comparable data series starts from 2006 (BLES, 2011).
[4]Indonesia, Malaysia, Philippines, Singapore, and Thailand
[5]Also known in literature as vulnerable employment and currently one of the Millennium Development Goal (MDG) indicators being monitored by the national government; as of 2013, it is estimated to be 38.0 percent of total employment.

employed. Unemployment also results to reductions in potential revenue for the government in terms of losses in social contributions of employees and employers, direct taxation on income, and indirect taxation on consumption (Gerard, Valsamis, & Van der Beken, 2012). Correspondingly for individuals, the cost of being unemployed is foregone earnings that they would have spent for consumption or put into savings. Unemployment also wears down household assets through using up of savings and aggravates household debt through increased borrowing or falling behind on loan or rent payments (Nichols, Mitchell, & Lindner, 2013).

Aside from the direct economic impact on individuals and the economy, unemployment also entails other, probably more damaging, non-pecuniary effects which are often overlooked when accounting for the real cost of unemployment. Unemployment takes a heavy toll on the psychological and physical health of individuals (Linn, Sandifer, & Stein, 1985; Murphy & Athanasou, 1999; see McKee-Ryan, Song, Wanberg, & Kinicki, 2005 for an excellent summary). It is well documented in literature that the unemployed are more likely to experience "boredom, alienation, shame and stigma, [and] increased social isolation (McClelland & MacDonald, 1998)."

Just as the ranks of the jobless suffer, their families and communities also bear the brunt. Unemployment is linked to strained family relationships, rise in cases of alcohol and substance abuse, and increase in crime and suicide rates (Swinney, 1983; Broman, Hamilton, & Hoffman, 1996; Gerard et al., 2012). Yet, the most detrimental outcome of being out-of-work is its impact on human capital and (re-) employability of individuals. Unemployment erodes confidence, self-esteem, and work skills which are crucial factors in job search, eventual re-employment, and post-unemployment wages (Clark, Georgellis, & Sanfey, 2001; Arulampalam, Gregg, & Gregory, 2001). Furthermore, employers might view long bouts of unemployment as a negative signal of unobserved productivity in jobseekers and in doing so, attach stigma to history of long-term unemployment (Biewen & Steffes, 2010). The longer the unemployment spell, the worse the effects become.

Considering the policy relevance of unemployment for the Philippines, it is imperative to take a closer look at the factors that drive the transition from unemployment to work and understand how these factors interplay; because after all unemployment remains a development challenge (NEDA, 2011). This paper aims to describe and analyze the patterns of transitions from unemployment to employment in the Philippine labor market by examining how demographic and socio-economic characteristics of Filipino jobseekers affect the length of their unemployment spell and their likelihood of exiting to employment. Equally important, this paper intends to determine if the amount of time individuals already spent without a job hurts their chances of exiting to employment.

The rest of the paper is organized as follows: Section 2 provides an overview of the job search-theoretic framework that underpins the econometric analysis of labor market transitions and unemployment duration; Section 3 describes in detail the methodology applied in this paper; Section 4 describes the data used for this study; Section 5 discusses the empirical results; and the last section draws some conclusions.

2. **Theory of Job Search and Unemployment Duration**

The neoclassical theory of labor supply also known as the income-leisure choice model (Mortensen, 1986), while useful in explaining why people choose to be active as wage earners for a certain period of time, falls short of addressing why unemployed individuals actively seek jobs. Apparently, there is no reason for unemployment to exist in a neoclassical labor market that implicitly assumes perfect information with respect to jobs and wages. However, Stigler (1962) pointed out that imperfect information indeed exists in the labor market. Hence, a jobseeker surveys the labor market in order to find the highest wage rate in exchange for his or her services very much like when a buyer canvasses various sellers to determine the lowest price. Stigler (1961) aptly labeled this process as "search". Building on earlier work of Stigler (1962) on fixed sampling approach to job search, McCall (1970) and Mortensen (1970) first developed the sequential job search model based on the optimal stopping approach to explain the behavior of a jobseeker who has imperfect information about the labor market. Their work on the dynamic job search model was in fact the precursor of the modern job search framework. The theory of job search did not contradict instead, in a complementary way, improved upon the neoclassical theory of labor supply by acknowledging the relevance of the time and cost of looking for work in explaining unemployment.

The basic job search theory and its extensions served as the theoretical foundation for the empirical analysis of the employment/unemployment transitions and unemployment duration. In a nutshell, the basic model of job search states that in a stationary environment the search for job will continue until a job offer is received after which the choice of whether to accept or reject the job offer will be decided by comparing the wage offer with the reservation wage (or the lowest wage at which a jobseeker will accept a job). If the offered wage is greater than or equal to the reservation wage, the search will cease. In contrast, if the wage offer is less than the reservation wage, the search will resume. In an extended version of the job search model in which labor market transitions[6] are taken into account, the reservation wage w_R is determined by a variety of factors such as unemployment benefits/gains from domestic production while unemployed[7] b, cost of search effort[8] c, arrival rate of job offers λ, discount rate r, rate of job loss q, offered wage w, and the known probability density of wage offers $f(w)$. The reservation wage can be expressed as:

$$w_R = z + \frac{\lambda}{r+q}\int_{w_R}^{+\infty}(w - w_R)f(w)dw, \tag{1}$$

where $z = b - c$ or the net instantaneous income in unemployment. By evaluating the integral, the reservation wage can also be expressed as:

$$w_R = z + \frac{\lambda}{r+q}[E_w(w|w \geq w_R) - w_R][1 - F(w_R)] \tag{2}$$

where $E_w(w|w \geq w_R) = \frac{\int_{w_R}^{+\infty} wf(w)dw}{\int_{w_R}^{+\infty} f(w)dw}$ and $1 - F(w_R) = \int_{w_R}^{+\infty} f(w)dw$ and (2) can be further simplified as:

$$w_R = z + \frac{\lambda}{r+q}(w - w_R)[1 - F(w_R)] \tag{3}$$

Since a jobseeker becomes employed when he or she receives a job offer which occurs at rate λ and the offered wage is at the very least equal to his or her reservation wage which occurs with probability $[1 - F(w_R)]$, the hazard rate (exit rate) from unemployment is given as:

[6]Job to job, employed to unemployed, and employed to inactive (out of the labor force)
[7]Refers to the sum of unemployment benefits (if there are any) and the monetary value of home production and "leisure" net of losses due to unemployment per se (e.g. stigma, low self-esteem)
[8]Refers to the sum of out-of-pocket costs of job search and the opportunity cost of time devoted to search

$$\Theta = \lambda[1 - F(w_R)] \quad (4)$$

Assuming that the hazard rate Θ is constant[9], the probability that a jobseeker is still unemployed after a spell of length t is:

$$S(t) = e^{-\Theta t} \quad (5)$$

Consequently, the average unemployment duration T_u can be derived as follows:

$$T_u = \int_0^{+\infty} t\Theta e^{-\Theta t} dt = \frac{1}{\Theta} = \frac{1}{\lambda[1-F(w_R)]} \quad (6)$$

The unemployment duration depends on both the reservation wage w_R and the job offer arrival rate λ. Meanwhile, the arrival rate of job offers depends on search intensity, state of the labor market, and individual characteristics. Assuming that search intensity is uniform throughout the search period and hence λ is constant, it can be surmised from (6) that higher reservation wage leads to longer duration of unemployment. Conversely, suppose that λ is allowed to vary, it is expected that more frequent offers lead to shorter duration. However, this may not be necessarily true since higher arrival rate of job offers means the jobseeker can afford to be more selective and in the process raises his or her reservation wage (Rogerson, Shimer, & Wright, 2005). Besides, the more sensitive the reservation wage is to the arrival rate the longer is the duration (Zaretsky & Coughlin, 1995). To sum up, the search-theoretic framework postulates that the exit rate from unemployment will be a function of variables that affect the probability of receiving a job offer and variables that affect the probability of accepting the job offer.

3. **Econometric Models**

3.1. *Duration Model*

Since we have no actual observations of the reservation wage of jobseekers, Lancaster & Nickell (1980) propose that the second best approach in studying unemployment duration is modeling the variation in the hazard function $\theta\,(x^*, t)$ or the conditional probability of leaving unemployment, denoted as θ, expressed as a function of a set of variables, represented by a vector x^*, and the length of time an individual has already been out of work t albeit the fact that job offer arrival rate λ may vary (Lancaster, 1979). The hazard function can indicate the relationship of unemployment duration with time already spent out of work. This relationship is referred to in the literature as duration dependence. For instance if there is a positive duration dependence or $\theta'(t) > 0$, the chances of escaping unemployment rises with the amount of time t already spent unemployed. On the other hand, if there is a negative duration dependence or $\theta'(t) < 0$, the likelihood of exiting from unemployment falls with the length of time t already spent out of job. In fact for policy-making, it is crucial to distinguish between a situation where unemployment begets unemployment (negative duration dependence) from a situation where individual characteristics lead to longer unemployment spells (Pedersen & Westergird-Nielsen, 1993).

This study uses an unemployment duration model following the specifications set by Lancaster (1979):

$$\theta(t) = \theta_0(t)\theta_1(x), \quad (7)$$

[9]The implied distribution of unemployment durations is exponential.

where the hazard rate from unemployment is both a function of time t and a function of other explanatory variables x. Considering that the hazard rate cannot take negative values, (7) can be re-written as:

$$\theta(t|x) = \theta_0(t)\exp(x'\beta), \tag{8}$$

where $\theta_0(t)$ is the baseline hazard function describing the duration dependence in the hazard rate, x is a vector of k covariates pertaining to individual, household, and community characteristics and β is a vector of k unknown parameters to be estimated.

Lancaster & Nickell (1980) stress that knowing the complete set of variables x^* and determining the functional form of the distribution of unemployment durations is crucial in generating reliable estimates of the parameters of θ by standard maximum likelihood techniques. In other words, the problem of omitted variables and the misspecification of the duration dependence may result to significant bias in the estimates of the parameters in the duration model. It is possible that there are other factors other than the observed variables (such as work ethic or drive, differing preference for leisure and extent of social network) that could significantly affect the distribution of unemployment durations. This phenomenon is referred to in the literature as unobserved heterogeneity. The data on unemployment duration may not be representative of individuals experiencing unemployment due to length-biased sampling. Jobseekers with favorable characteristics may have escaped unemployment quickly and were not captured by the survey, and so the sample of the unemployed is biased by jobseekers who are less likely to exit unemployment and experiencing longer bouts of joblessness. Ignoring heterogeneity especially if it accounts for large unexplained variation in the model results in an estimated hazard rate that is either falling faster or rising more slowly than the actual hazard rate and the proportional impact of a change in x_j being smaller and now depends on t and no longer of the proportional hazard type (Cameron & Trivedi, 2005).

Some authors such as Kupets (2006) argues that the failure to account for unobserved heterogeneity do not significantly bias results if the baseline hazard is assumed to be nonparametric. Considering that the proportional hazard model proposed by Cox (1972) could estimate the relationship between the hazard rate and explanatory variables without specifying the shape of the baseline hazard function (Jenkins, 2005), several of the previous studies reviewed from transition and developing economies (e.g. Foley, 1997; Rõõm, 2002; Kupets, 2006; Dendir, 2007) used the semi-parametric Cox proportional hazard model. On the other hand, in a case where unobserved heterogeneity was controlled for, the Mixed Proportional Hazard (MPH) model was employed (see Lubyova & Van Ours, 1999) wherein a random variable v_j entered the hazard function additively and assumed to have a discrete distribution. Also, some researchers who are interested in the shape of the baseline hazard such as Foley (1997), Lubyova & Van Ours (1999), Galiani & Hopenhayn (2001), Grogan & Van den Berg (2001), and Tansel & Taşçı, (2010) used models with flexible baseline hazard that assumed the duration dependence function to have a piecewise constant specification (i.e., the hazard rate is assumed to be constant within duration intervals but is allowed to vary between duration intervals), except for Foley (1997) who modeled the duration dependence as a fourth-order polynomial. Nevertheless, Cameron & Trivedi (2005) suggest that the heterogeneity issue should be approached with caution. They favor the use of parsimonious models over models saturated with heterogeneity parameters to avoid the problems of over-parameterization and uninterpretability.

Another important methodological issue to consider in estimating unemployment duration models is the discrete nature of unemployment spell data. Recall that in theory, unemployment duration is a continuous random variable; however in practice, unemployment duration data are usually expressed in intervals of weeks or even months. This is referred to in the literature as grouped data. The use of discrete hazard models offers more flexibility and a better fit to actual data aside from making model estimation more straightforward (Cameron & Trivedi, 2005). Galiani & Hopenhayn (2001) and Tansel & Taşçı (2010) used the discrete time (grouped duration data) proportional hazard model in their analysis of unemployment duration in Argentina and Turkey, respectively.

Taking into consideration the methodological issues previously discussed, this paper employs a single risk discrete time (grouped data) proportional hazard model with flexible baseline hazard following the specifications set by Blake, Lunde, & Timmerman (1999) in Cameron & Trivedi (2005). Suppose in a grouped data, t_a refers to intervals with $a = 1, \dots, A$ and t is within the interval $[t_{a-1}, t_a)$. Given that regressors are constant within the interval but can vary across intervals, and $\theta_0(t)$ can vary within the interval, the discrete hazard function can be expressed as:

$$\theta_d(t_a|x) = 1 - \exp\ [-\exp(\gamma_a + x(t_{a-1})'\beta)], \tag{9}$$

where $\gamma_a = \log \int_{t_{a-1}}^{t_a} \theta_0(u)du$ is the integrated baseline hazard function. Furthermore, (9) can also be expressed alternatively as:

$$\theta_{ij} = 1 - \exp\ \left[-\exp(\alpha D_{ij} + \beta x_{ij})\right] \tag{10}$$

where θ_{ij} is the probability that individual i has left unemployment during interval j, D_{ij} is a vector of functions of the cumulative duration by interval j with coefficients α, and x_{ij} is a vector of covariates with coefficients β. The baseline hazard function αD_{ij} is specified to be a step function,

$$\alpha D_{ij} = \alpha_1 D_1 + \alpha_2 D_2 + \cdots + \alpha_q D_q \tag{11}$$

where $D_1, \dots, D_q$ are dummies for time intervals $j = 1, \dots, q$ and q is the maximum observed event time. However, to ensure that there are events occurring within each of the time intervals primarily because the hazard cannot be estimated for values of j with no events, the time intervals will be specified as groups or piecewise constants wherein the hazard is assumed to be constant over longer intervals.

The ideal form for analyzing unemployment durations is where a group of *n* individuals all become unemployed at the same time say t_0, and these individuals are followed through time until they have left unemployment. However, available data from labor force surveys have censored durations for at least part of the sample. Data containing both completed and incomplete spells is typically used to analyze unemployment durations (Bazen, 2011). The shortcomings of collecting information on unemployment duration from unemployed individuals in periodic surveys have implications in the analysis of the data itself. Conventional statistical methods such as the ordinary least squares (OLS) estimation procedure cannot handle censoring or the presence of incomplete durations very well (Jenkins, 2005). Linear models with completed and incomplete durations generally yield biased and inconsistent estimates. Even if the whole sample is consisted of completed spells, time-varying independent variables poses a challenge in estimating linear models of duration data (Kiefer, 1988). Furthermore, in the case of job search models, the OLS can only estimate models that are formulated in terms of completed spell lengths and not in terms of observed transitions from unemployment to employment (Jenkins, 2005). Therefore, analysis of duration data requires methods that consider the sequential nature of the data and can handle censoring and time-varying explanatory variables.

Previously, Prentice & Gloeckler (1978) has demonstrated that if the data are generated by a continuous-time proportional hazards model, the grouped data duration model (10) is equivalent to the binary response model with complementary log-log link function as its link function or linearizing transformation,

$$\log(-\log(1-\theta_{ij})) = \alpha D_{ij} + \beta x_{ij} \tag{12}$$

As expounded by Jenkins (2005), given that time is measured in discrete intervals indexed by positive integers and suppose that each interval is month long, then a jobseeker's i's spell from month $k = 1$ through the end of jth month can be observed and at this moment i's spell is either complete ($c_i = 1$) or right-censored ($c_i = 0$). The discrete hazard can be written as:

$$\theta_{ij} = \mathrm{P}(T_i = j | T_i \geq j) \tag{13}$$

The likelihood contribution for a right-censored spell is given by the discrete time survivor function:

$$\mathcal{L}_i = \mathrm{P}(T_i > j) = S_i(j) \tag{14}$$

$$= \prod_{k=1}^{j}(1-\theta_{ik}) \tag{15}$$

and the likelihood contribution for each completed spell is given by the discrete time density function:

$$\mathcal{L}_i = \mathrm{P}(T_i = j) = f_i(j) \tag{16}$$

$$= \theta_{ij} S_i(j-1) \tag{17}$$

$$= \frac{\theta_{ij}}{1-\theta_{ij}} \prod_{k=1}^{j}(1-\theta_{ik}) \tag{18}$$

The likelihood for the whole sample is:

$$\mathcal{L} = \prod_{i=1}^{n}[\mathrm{P}(T_i = j)]^{c_i}[\mathrm{P}(T_i > j)]^{1-c_i} \tag{19}$$

$$= \prod_{i=1}^{n}\left[\left(\frac{\theta_{ij}}{1-\theta_{ij}}\right)\prod_{k=1}^{j}(1-\theta_{ik})\right]^{c_i}\left[\prod_{k=1}^{j}(1-\theta_{ik})\right]^{1-c_i} \tag{20}$$

$$= \prod_{i=1}^{n}\left[\left(\frac{\theta_{ij}}{1-\theta_{ij}}\right)^{c_i}\prod_{k=1}^{j}(1-\theta_{ik})\right]. \tag{21}$$

Recall that c_i refers to a censoring indicator defined such that $c_i = 1$ if a spell is complete and $c_i = 0$ if a spell is right-censored. This implies that:

$$\log\mathcal{L} = \sum_{i=1}^{n} c_i \log\left(\frac{\theta_{ij}}{1-\theta_{ij}}\right) + \sum_{i=1}^{n}\sum_{k=1}^{j}\log(1-\theta_{ik}) \tag{22}$$

Given a new dummy indicator variable $a_{ik} = 1$ if jobseeker i exits unemployment in month k, and $a_{ik} = 0$ otherwise. That is:

$$c_i = 1 \implies a_{ik} = 1 \text{ for } k = T_i, a_{ik} = 0 \text{ otherwise} \tag{23}$$

$$c_i = 0 \Rightarrow a_{ik} = 0 \text{ for all } k \tag{24}$$

Thus, (22) can be re-written as:

$$\log\mathcal{L} = \sum_{i=1}^{n}\sum_{k=1}^{j} a_{ik}\log\left(\frac{\theta_{ij}}{1-\theta_{ij}}\right) + \sum_{i=1}^{n}\sum_{k=1}^{j}\log(1-\theta_{ik}) \tag{25}$$

$$= \sum_{i=1}^{n}\sum_{k=1}^{j}[a_{ik}\log\theta_{ik} + (1-a_{ik})\log(1-\theta_{ik})] \tag{26}$$

Notice that (26) can now be considered as a standard likelihood function for a binary regression model in which a_{ik} is the dependent variable and in which the data structure has been transformed from having one record per spell (i.e., person data) to having one record for each month that a person is at risk of exiting from unemployment (i.e., person-month data). Hence with the necessary data transformation, the model can be estimated using any standard binary dependent regression approaches such as the logistic model and the complementary log-log model.

For this study, the complementary log-log model was selected as the estimation procedure due to the following reasons: (1) at low hazard values, the logistic and complementary log-log functions are virtually identical; and (2) it builds in a proportional hazards assumption similar to the Cox regression model where the estimated parameters (i.e., exponentiated coefficients) can be interpreted as hazard ratios. Hosmer, Lemeshow, & May (2008) emphasized that the manipulations of the likelihood in (13) – (26) are meant to cast the interval-censored data problem in a form that would allow likelihood analysis by existing software. They pointed out that the problem is not a binary regression problem in the usual sense of the primary outcome variable being a dummy variable but we manipulated the problem to make it look like one.

3.2. *Baseline Hazard Specification*

Ideally, the smaller the ratio of the length of intervals used for grouping relative to the average spell length, the more appropriate it is to use a continuous time specification however if the data is characterized by large grouping and numerous 'tied' survival times then it is more appropriate to use a non-parametric specification that accounts for interval-censoring (Jenkins, 2005).

In most grouped duration data analyses, the number of intervals and the interval size are often determined based on an exogenous observation scheme (Ryu, 1994) and in theory, the intervals need not be of equal length (Jenkins, 2005) for as long as the intervals are the same for all the subjects (Hosmer et al., 2008). In practice, the determination of interval length largely depends on the data itself. Galiani & Hopenhayn (2001) truncated their unemployment duration data to two years and used four intervals: 0-3 months, 3-6 months, 6-12 months, and 12-24 months. Tansel & Taşçı (2010), who used quarterly rotating panel data, assigned twelve intervals: three-month intervals until the end of the second year, six-month intervals until the end of the third year and twelve-month interval until the end of the fourth year and a final group which includes the unemployment durations of more than four years. Sueyoshi (1995) considered spells longer than 40 weeks as artificially right-censored and used period-specific constants in his duration models i.e, 40 periods corresponding to 40 weeks.

Recall that when estimating a model with fully non-parametric baseline hazard, it is crucial to check whether events occur at each value of the spell period at risk because the hazard cannot be estimated for values of the spell period at risk with no events. To address the estimation issue arising from spell periods with no events occurring (i.e., exit to employment), Jenkins (2005) proposes to either specify the spell periods as groups (or piecewise constants) wherein the hazard is assumed to be constant over longer intervals or drop the relevant person periods from the estimation. The latter makes it impossible to describe the hazard in the periods in which no event occurred, hence, the more practical approach is to implement the former.

In the estimation of the discrete-time proportional hazards model of local employment hazard, the baseline hazard estimated in this paper is specified as piecewise constants represented by 4 dummy variables corresponding to 4 intervals: 3 six-month intervals until end of the 81st week (i.e., 1-27 weeks, 28-54 weeks, 55-81 weeks), and a final group which includes unemployment spells of more than 81 weeks (i.e., 82 weeks and greater). This specification takes interval-censoring explicitly into account.

3.3. *Ordered Logistic Regression Model*

Besides duration analysis techniques which were borrowed from the biological sciences, Jenkins (2005) proposed using binary dependent regression models such as logit and probit to model whether or not someone made a transition to a certain state (e.g., from unemployment to employment). This approach addresses both issues on censored observations and structural modeling. However, even if accounting for differences in time in which each individual is at risk of experiencing event by modeling whether a transition occurred within some pre-determined time interval using logit or probit models, still a fairly large amount of information is lost in the process in particular pertaining to when the transition occurred. Notwithstanding the loss in information, this paper models the transition from unemployment to having work using the ordered logistic regression model.

The transition of unemployed individuals to employment may be characterized by a set of outcomes. For instance, the post-transition status may be one of the following three outcomes: no work, had work at least one hour in past week, or had work at least one hour in past quarter. It is apparent that there is a natural ordering of states hence a model that accounts for this ordering is deemed the most suitable. Given a latent regression model describing an underlying continuous, yet unobservable, post-transition employment status as y^*,

$$y_i^* = \mathrm{x}_i'\beta + \varepsilon_i \tag{27}$$

where x does not include an intercept, as y^* traverses a series of increasing unknown thresholds we move up the ordering of unemployment outcomes i.e., for very low y^* the status is still unemployed, for $y^* > \alpha_1$ the status is employed in the past week, and lastly for $y^* > \alpha_2$ the status is employed in the past quarter. Following the discussions of Cameron & Trivedi (2005) and Greene & Hensher (2009), the probabilities associated with the observed outcomes in an m-alternative ordered model are,

$$\mathrm{Prob}[y_i = j|\mathrm{x}_i] = \mathrm{Prob}\big[\varepsilon_i \le \alpha_j - \mathrm{x}_i'\beta\big] - \mathrm{Prob}\big[\alpha_{j-1} - \mathrm{x}_i'\beta\big], j = 0,1,\dots,J \tag{28}$$

where $y_i = j$ if $\alpha_{j-1} < y_i^* \le \alpha_j$ and $\alpha_0 = -\infty$ and $\alpha_m = +\infty$.

Furthermore, (28) can also be expressed as,

$$\mathrm{Prob}[y_i = j|\mathrm{x}_i] = F\big(\alpha_j - \mathrm{x}_i'\beta\big) - F\big(\alpha_{j-1} - \mathrm{x}_i'\beta\big), \tag{29}$$

where F is the cumulative distribution function of ε_i. For an ordered model with three outcomes, the probabilities are,

$$\text{Prob}[y_i = 0|\text{x}_i] = F(0 - \text{x}_i'\beta) - F(-\infty - \text{x}_i'\beta) = F(-\text{x}_i'\beta) \tag{30}$$

$$\text{Prob}[y_i = 1|\text{x}_i] = F(-\text{x}_i'\beta) - F(\alpha_1 - \text{x}_i'\beta) \tag{31}$$

$$\text{Prob}[y_i = 2|\text{x}_i] = F(+\infty - \text{x}_i'\beta) - F(\alpha_1 - \text{x}_i'\beta) = 1 - F(\alpha_1 - \text{x}_i'\beta) \tag{32}$$

The estimates of the parameters β and the (m-1) threshold parameters $\alpha_1, \dots, \alpha_{m-1}$can be derived by maximizing the log-likelihood function,

$$\log\mathcal{L} = \sum_{i=1}^{n}\sum_{j=1}^{k} m_{ij} \log\left[F\left(\alpha_j - \text{x}_i'\beta\right) - F\left(\alpha_{j-1} - \text{x}_i'\beta\right)\right] \tag{33}$$

where $m_{ij} = 1$ if $y_i = j$ and 0 otherwise. For the ordered logit model, ε is logistic distributed with $F(z) = e^z/(1 + e^z)$. The sign of the parameter estimates $\hat{\beta}$ can be interpreted as indicating whether or not the latent variable y^* increases with regressor x.

4. **Data Description and Variables**

The data used in this research comes from the Philippine Labor Force Survey (LFS). The LFS is a nationwide sample survey regularly conducted by the Philippine Statistics Authority (PSA; formerly the National Statistics Office) four times a year every January, April, July and October. The LFS gathers data on demographic and socio-economic characteristics of the population and serves as the basis for the official labor force statistics on levels and trends of employment, unemployment, and underemployment of the country and its administrative regions. Starting July 2003, the LFS used the 2003 Master Sample (MS) constructed from the results of the 2000 Census of Population and Housing (CPH). The number of samples was increased from 41,000 to about 51,000 households across the country to ensure more precise and reliable estimates at the regional level. Like all household surveys, the LFS is subject to the problem of proxy respondents which may affect the accuracy of the data. This research also used data from the Philippine Family Income and Expenditure Survey (FIES). The FIES is also a nationwide household-based survey regularly conducted (in two visits every 3 years starting 1985) by the PSA as a rider survey of the LFS. The FIES is the primary source of income and expenditure data in the Philippines which include among others consumption levels and patterns as well as sources of income. The official poverty statistics of the country is based on the income data collected in the FIES.

The rotation design used for the LFS results in only 50% of housing units remaining in the sample for two quarters one year apart. During years when the FIES is not conducted, the quarterly rotation of the full sample is completed within the year. On the other hand, during years when FIES is carried out, 100% of sample housing units are retained during the first and second visits of the said survey (i.e. July and January the following year). All housing units visited in July of the current FIES year were re-visited in January of the following year which means, subject to a certain level of attrition, most of the households residing in these sample housing units were interviewed a maximum of two times. This study took advantage of this sample rotation scheme so as to construct panel data at the individual level and household level. In particular, the individual-level panel data is crucial in the determination of completed unemployment spells and labor market transitions. Matched July 2009 and January 2010 LFS data were specifically used in this paper. Moreover, the matched LFS datasets were also linked with the 2009 FIES data.

This study is restricted to individuals aged 15 to 64 years old (compulsory retirement age is 65) who were unemployed and were actively looking for work in July 2009. The sample consists of 2,896 observations. There are at least 2,269 individuals whose labor market statuses were observed in both survey periods i.e., July 2009 and January 2010. However, 627 individuals attrited in the January 2010 survey which means they only have a single data point. These observations were treated as right-censored. On the other hand, among those individuals who were observed twice 892 (of 2,269) were employed, 750 were unemployed, 578 were not in the labor force, and 49 individuals were reported to have been employed overseas in the January 2010 survey (see Table 1). Considering that this paper focuses on estimating the probability of transitioning into employment in the local labor market, individuals who were employed abroad were also considered as right-censored observations in addition to the unemployed and individuals who left the labor force. Thus, 69.2 percent of the matched July 2009 LFS and January 2010 LFS datasets are right-censored observations. Meanwhile, 84 households (consisting of 162 unemployed individuals) were not able to complete the 2009 FIES hence the final sample size of the linked LFS datasets and the 2009 FIES dataset is 2,734 (67.5 percent of which are right-censored observations).

Table 1. Labor Market Transitions

Labor Market Status in January 2010	No.	%
Total Unemployed in July 2009	2,896	100.0
Of which:		
Employed	892	30.8
Still Unemployed	750	25.9
Left the Labor Force	578	20.0
Employed Overseas	49	1.7
Attrited	627	21.7

Source: Authors' computations

Table 2 presents the official labor market statistics during the survey periods of the LFS datasets used in this paper. It shows that the labor market situations are very similar in July 2009 and January 2010. The labor force participation rate and underemployment rate are virtually steady in both survey periods while the unemployment rate is slightly lower by 0.3 percentage points in January 2010 compared to July 2009.

Table 2. Labor Force Statistics

Philippines	July 2009	January 2010
Population 15 years and over (in '000)	59,512	60,208
Labor Force Participation Rate (%)	64.6	64.5
Employment Rate (%)	92.4	92.7
Unemployment Rate (%)	7.6	7.3
Underemployment Rate (%)	19.8	19.7

Source: PSA

Currently, the Philippine Statistics Authority (PSA) does not have an official definition of unemployment duration. The said organization only reports through its annual Yearbook of Labor Statistics a statistical table on "Unemployed Persons Looking for Work by Region and Number of Weeks Looking for Work". However, unemployment duration is defined internationally as either the duration of job search, duration of joblessness, or whichever is shorter of the two. In the case of the Philippines, the duration of job search can be ascertained from the question, "How many weeks has _____ been looking for work?"

(Line Number 34 of the Philippines LFS questionnaire). It should be noted though that this question is only asked to unemployed persons who reported to have looked for work or tried to establish a business during the past week or to jobseekers. Meanwhile, the duration of joblessness cannot be determined from any of the questions in the Philippines LFS questionnaire. It is possible to derive information on incomplete and completed unemployment spells from a panel LFS data. As previously mentioned, individuals were only asked about the duration of their job search if they were unemployed and looking for work at the time of the survey. On the other hand, employed individuals at the time of the survey were not asked exactly when they started working at their current job though it can be determined if a person worked during the past week and/or the past quarter (last three calendar months preceding the interview).

At the time when the first interview was conducted (i.e., July 2009), the information on elapsed unemployment duration, as drawn from the retrospective question on job search length (in number of weeks), is available. Let's denote this jobseeker's elapsed unemployment spell as t_0 weeks. Using the information on employment status in the second interview conducted six months (or 26 weeks) after the first interview (i.e., January 2010) and assuming that the sample of unemployed only experienced a single continuous spell[10] during the fixed time interval, the observed unemployment spells can be determined whether it ended in employment or otherwise. The length of unemployment spell of individuals who are still unemployed, left the labor force, or were employed overseas during the past reference week prior to the date of the second interview is computed as $t_1 = t_0 + 26$. These incomplete spells are considered as right-censored observations. For individuals who got employed in the past week prior to the second interview, the length of unemployment duration is defined as $t_2 = t_0 + 26 - \omega$, where $0 \leq \omega \leq 26$. Although it is not possible to determine exactly when these persons exited unemployment, it can be surmised that their unemployment spell ended within the interval $[t_0 , t_0 + 26 - \omega]$. These completed spells are considered as interval-censored observations. However, for individuals who attrited or were not observed during the second interview, the unemployment duration is given as $t_3 = t_0$ comprising only of right-censored observations. This sampling scheme where jobseekers are randomly selected from the stock of unemployed and then interviewed after some interval has elapsed is labeled by Lancaster (1992, p.183) as stock sampling with observations over a fixed interval.

The average duration of job search (i.e., number of weeks looking for work) of the sample of the sample jobseekers in July 2009 is estimated to be 5.4 weeks. Meanwhile, the average completed and incomplete duration of unemployment of the sample jobseekers from the derived unemployment duration data is estimated to be 7.1 months and 5.4 months, respectively[11].

Related literature provides a set of variables that can influence the probability of an individual exiting unemployment. These explanatory variables or covariates in survival analysis parlance can be divided into four main categories, namely, personal characteristics, family composition, local labor demand and income variables (Lancaster & Nickell, 1980). In particular, personal characteristics and local labor demand affect the probability of receiving a job offer while family composition and income variables affect the probability of accepting a job offer. Variables on personal characteristics include age, sex, marital status, and

[10]Consistent with related literature, the possibility of several unemployment spells occurring during the unobserved periods is discounted (Foley, 1997; Galiani & Hopenhayn, 2001; Grogan & Van den Berg, 2001; Tansel & Taşçı, 2010).

[11]However, note that these figures do not take into account interval censoring.

educational attainment. The other explanatory variables included in the proposed models are local unemployment rate, local minimum wage, schooling status, number of dependents (both young and old) and employed members, presence of an informal worker in the household, as well as the amount of cash receipts from abroad, assistance from domestic source, credit from other families, withdrawal from savings, and household savings rate (proxy variables for unemployment income). Furthermore, previous work experience and job search method (as proxy for training) which can both affect the probability of receiving a job offer were likewise considered in model building.

Age is an important factor that can affect unemployment duration. Age is often used by employers as an indicator of likely productivity of a worker. In the case of young workers aged 15-24 years old, they may experience difficulty landing a job because of limited skills and occupational experience. Studying is also likely to impact on their decision to work. On the other hand, based on mainly anecdotal evidence, older workers face barriers in recruitment through stipulations of specific age limits or salary levels in advertisements for job vacancies based on employers' prejudice against older workers being slow, non-creative, and less productive (Gust, 2006). Furthermore, employers prefer hiring younger workers because of lower cost in terms of salary paid and benefits extended.

Women and men have very different labor market experiences. Although Filipino women have surpassed the men in terms of education, have increased their labor force participation, and mostly comprised the sectors of education, health services, and the civil service, they still face discrimination in terms of employment opportunities and remuneration (Gust, 2006). The relevance of the marital status of a jobseeker is closely related to his or her sex. There had been reported cases of firings of pregnant women or married women being replaced by single women in Philippine Export Processing Zones (EPZs) (Gust, 2006). This situation is largely tied to the additional cost for firms in providing pregnancy-related and maternity benefits to married female workers. Moreover, some employers perceive that family obligations of married women may interfere with their job and hence lower their productivity. Meanwhile, married males may be more intensive in their job search compared to females because of the cultural norm that the "man of the house" should provide for the family's needs.

The educated unemployed is a notable feature of labor markets in most developing countries including the Philippines. Individuals who have tertiary education accounted for 41.2 percent of the total number of unemployed persons in 2010. Fan & Stark (2007) found evidence suggesting that the 'educated unemployment' is an intended response to increasing outward flow of labor from the developing countries to the developed countries because workers from the former find it optimal to acquire more human capital as returns to human capital are higher in the latter. They further added that if these jobseekers fail to secure a highly-paid job overseas, they may well decide to remain unemployed and continue their search for more highly-paid employment abroad. Highly-educated individuals, most of which are young and unmarried members of households, have higher reservation wages and can afford to wait for better job offers because they may get financial support from their families while searching for a job (ILO, 2012). From the perspective of employers, education is often used as an indirect measure of worker productivity therefore we would expect that more educated jobseekers will receive more job offers than their less educated counterparts. Moreover, in the case of college graduates in particular, the program/course that they completed may also be influential in determining their chances of finding a job because employers look for skills and experience in jobseekers from certain educational background.

These clearly illustrate that an individual's educational background is closely linked to his or her personal decisions and outcomes pertaining to job search.

The composition of the family as described by the number of young (0-14 years old) and old (65 years old and above) dependents may influence a jobseeker's decision of whether to accept a job offer or not. Women are disproportionately affected because traditionally they are expected to take the nurturing role in their families. The demands of childbearing and childrearing especially amongst married females takes precedence over participation in the labor market. Furthermore, care of the elderly is not uncommon in Filipino families because of the traditional high regard for older persons. The number of employed members in the family may also be influential on making decisions on whether to accept a job offer or not. Clearly, a jobseeker belonging to a family where there are employed members may be less pressured to accept a job offer than a counterpart who belongs to a family where there is no one working. An indicator for the presence of informal workers or self-employed persons and unpaid family workers in the household was also included as an explanatory variable. Considering that informal workers earn less compared to their formal counterparts, jobseekers in households with informal workers are more likely to accept a job offer in order to make ends meet.

The local unemployment rate is the proxy variable for labor market conditions. Areas with high unemployment rates are locales where the quantity of labor supplied by households is greater than the quantity of labor demanded by firms. In other words, when unemployment is high, a lot of people who want to work cannot find jobs. Conversely, places with low unemployment rates are regions where the quantity of labor demanded by businesses is greater than the quantity of labor supplied by households. Stronger labor demand means more recruitment/hiring or an increase in number of job offers. The provincial minimum wage as a proxy variable for reservation wage was also considered as an explanatory variable.

As of this writing, there is no legislation or institution providing for unemployment insurance in the Philippines thus there is no direct measurement for income of jobseekers while unemployed. The amount of cash transfers from domestic and international sources, loans from other families, and withdrawal from savings in bank deposits were used as proxy variables for unemployment income. The said income variables were log-transformed to "normalize" the highly skewed data distribution or stabilize its variance. Moreover, household savings rate or the percent of total household savings, which is total household income less total household expenditure, to total household income is also used as proxy variable for unemployment income. Simply put, higher unemployment income means there are more resources available for jobseekers to spend while looking for a job. The job search theory predicts that if the unemployment income is high, the reservation wage rises. As the jobseeker can afford to stay unemployed, the time he or she spends being jobless is prolonged.

Based on a survey[12] covering 7,061 establishments with 20 or more workers nationwide, shortage of applicants with the right competencies/skills, too few applicants applying for the job, and lack of years of experience in the job were the primary reasons cited by businesses behind the difficulty in filling job vacancies in the country. Employers look at work experience (or lack of it) as an indicator of the jobseekers unobserved productivity. Past labor market experience of jobseekers may affect unemployment duration through the probability of receiving a job offer. Likewise, training history is an influential factor in the

[12] The 2011/2012 BLES Integrated Survey (BITS) by the Philippine Statistics Authority (PSA)

likelihood of escaping unemployment because lack of training could result to fewer job offers. The job search methods such as being registered in a public employment agency (e.g. Public Employment Service Office or PESO) or a private employment agency as proxy variables for having attended trainings were included as explanatory variables. It should be noted that one of the functions of the PESO is to "undertake employability enhancement trainings/seminars for jobseekers as well as those who would like to change career or enhance their employability." This function is currently being supervised by the Technical Education and Skills Development Authority (TESDA).

Table 3 presents the description and summary statistics of the explanatory variables used in the duration and ordered logistic regression models.

Table 3. Definition and Descriptive Statistics of Explanatory Variables

Variable	Definition	Mean	Std. dev.
Personal characteristics			
Age			
age	age in years	25.723	8.704
age squared	age squared	737.388	581.080
Age Group			
aged 15-24 (base)	=1 if 15 to 24 years old, =0 otherwise	0.596	0.491
aged 25-34	=1 if 25 to 34 years old, =0 otherwise	0.263	0.440
aged 35-44	=1 if 35 to 44 years old, =0 otherwise	0.084	0.278
aged 45-54	=1 if 45 to 54 years old, =0 otherwise	0.043	0.203
aged 55-64	=1 if 55 to 64 years old, =0 otherwise	0.013	0.115
Sex			
female	=1 if female, =0 male	0.424	0.494
Marital Status			
ever married	=1 if married, widowed/er, divorced/separated, annulled, =0 if never married	0.272	0.445
Interaction Term			
female x ever married	interaction term for sex and marital status	0.111	0.314
Education			
pre-primary/primary (base)	=1 if completed at most primary education, =0 otherwise	0.099	0.299
secondary incomplete	=1 if did not complete secondary education, =0 otherwise	0.110	0.313
secondary complete	=1 if completed secondary education, =0 otherwise	0.324	0.468
tertiary incomplete	=1 if did not complete tertiary education, =0 otherwise	0.233	0.423
tertiary complete	=1 if completed tertiary education, =0 otherwise	0.233	0.423
general major	=1 if completed general program, =0 otherwise	0.002	0.042
education major	=1 if completed education program, =0 otherwise	0.033	0.180
humanities major	=1 if completed humanities and arts program, =0 otherwise	0.001	0.026
social sciences major	=1 if completed social sciences, business, and law program, =0 otherwise	0.059	0.235
science major	=1 if completed science program, =0 otherwise	0.027	0.163
engineering major	=1 if completed engineering, manufacturing, and construction program, =0 otherwise	0.070	0.256
agriculture major	=1 if completed agriculture program, =0 otherwise	0.008	0.089
health major	=1 if completed health and welfare program, =0 otherwise	0.004	0.062
services major	=1 if completed services program, =0 otherwise	0.029	0.169

<u>*Job Search Duration*</u>			
Less than 10 weeks (base)	=1 if no. of weeks looking for work is less than 10, =0 otherwise	0.872	0.335
10-19 weeks	=1 if no. of weeks looking for work is between 10 and 19, =0 otherwise	0.081	0.273
20-29 weeks	=1 if no. of weeks looking for work is between 20 and 29, =0 otherwise	0.032	0.175
30 weeks and longer	=1 if no. of weeks looking for work is 30 weeks or greater, =0 otherwise	0.016	0.125
Local labor demand			
unemployment rate	provincial unemployment rate (Oct 2008 - Jul 2009 ave.)	8.996	3.741
Reservation wage (proxy)			
minimum wage	provincial minimum wage (as of end-2009)	287.075	58.546
Previous work experience			
no work experience	=1 if did not work at any time before, =0 otherwise	0.352	0.478
Trainings (proxy)			
public employment agency	=1 if registered in public employment agency, =0 otherwise	0.057	0.232
private employment agency	=1 if registered in private employment agency, =0 otherwise	0.146	0.353
other job search methods (base)	=1 if approached employer directly , approached relatives or friends, placed or answered advertisements, or did other active job search methods not elsewhere classified, =0 otherwise	0.797	0.402
Schooling status			
attending school	=1 if currently attending school, =0 otherwise	0.019	0.137
Household composition			
young household member	number of household members aged 0-14	1.342	1.419
old household member	number of household members aged 65 and above	0.346	0.619
employed household member	number of employed household members	1.808	1.194
informal sector	=1 if there is at least one informal worker* in the household, =0 otherwise	0.375	0.484
Unemployment income (proxy)			
assistance from abroad	natural logarithm of cash receipts, gifts, support, and relief and other forms of assistance from abroad	3.727	5.146
assistance from local	natural logarithm of cash receipts, gifts, support, and relief and other forms of assistance from domestic source	4.277	4.607
loans from other households	natural logarithm of loans from other families	1.434	3.256
withdrawal from savings	natural logarithm of withdrawal from savings in bank deposits	2.555	4.241
savings rate	total household Income less total household expenditure as percent of total household income	7.994	21.212

Notes: Unweighted estimates from the Jul'09 LFS person data (N=2,896) except for the income variables which were estimated from the linked Jul'09/Jan'10 LFS-2009 FIES data (N=2,734).
*Self-employed persons and unpaid family workers
For dummy variables, the mean reflects the proportion of "1s" in the data.
Source: Authors' computations

In order to estimate the grouped data hazards model, the person data consisting of 2,734 observations was transformed to person-period data using the prsnperd user-written Stata® do-file[13] based on the piecewise constants baseline hazard specification. The said data transformation increased the final sample size for duration analysis to 4,658 observations with 890 failures (i.e., total number of exit-to-employment events).

5. **Estimation Results**

Five duration models fitting the discrete-time (grouped data) proportional hazards model in a single risk framework to the sample of person-period unemployment duration data were estimated using the complementary log-log regression. In addition to duration models, structural models of post-unemployment outcomes were also estimated using the ordered logistic regression. The explanatory variables used in the structural models are the same set of variables used in the duration models which includes personal characteristics, variables that may affect the probability of receiving a job offer, and variable that may influence the probability of accepting a job offer. The results of the said estimations are discussed accordingly in this section.

The first model (specification 1) includes the baseline hazard specified as a piecewise constant function. The second model (specification 2) includes the baseline hazard and explanatory variables related to individual characteristics such as age, sex, marital status, and educational attainment. The third model (specification 3) contains the same set of variables as the second model but with the interaction between marital status and sex and specific variables on tertiary programs. The fourth model (specification 4) now includes the rest of the variables that may influence the probability of receiving a job offer such as past work experience, job search method (as proxy for training), and local unemployment rate (as proxy for local labor market condition). Lastly, the fifth model comprises all variables previously stated except the unemployment rate which was replaced by local minimum wage plus other related variables that may influence the probability of accepting a job offer such as schooling status, household composition and unemployment income (specification 5).

Without controlling for any covariates, the estimated hazard rates on the piecewise constant baseline hazard as represented by 4 interval dummy variables increases initially at around 28 to 54 weeks and then declines monotonically thereafter. The shape of the hazard suggests that the probability of exiting to employment rises over time and then falls at a certain point (see Table 4, Model 1). Recall that if $\theta_j > \theta_{j+1}$, it implies a negative duration dependence between intervals j and $j+1$ and vice versa. The inclusion of explanatory variables, as shown in Models 2 to 5 of Table 4, does not alter the shape of the baseline hazard. The initial positive duration dependence indicates that it is difficult to find and start a new job which is common among those individuals who are first-time jobseekers and have no previous work experience or jobseekers can afford to wait for what they think is a “good” job offer. It also suggests that jobseekers tend to keep their reservation wages but only for a certain amount of time spent unemployed and then eventually accept job offers with lower wages than they initially decided to accept. On the other hand, the negative duration dependence that followed indicates that as the time spent unemployed increases even further the hazard of exiting to employment actually decreases. One possible explanation is that employers view longer bout of joblessness in jobseekers as a negative signal of their productivity. Galiani & Hopenhayn (2001) found strong negative duration dependence in the

[13]Included in the dthaz (Discrete-Time Hazard and Survival Probability Estimates) package Version 2.0.1 (updated as of 26 March 2012) written by Alexis Dinno. The said package is available at http://www.doyenne.com/stata. The results in this paper were obtained using Stata® Special Edition 12.1.

case of Argentina. In Slovakia, Lubyova & Van Ours (1999) observed an inverse U-shaped duration dependence. On the other hand, Tansel & Taşçı (2010) found the duration dependence among the Turkish unemployed as slightly U-shaped.

The signs of the coefficients of the quadratic age terms (in specifications 2 and 3) imply that the likelihood of exiting unemployment initially increases as jobseekers become older but begins to decline after the ages of 35-36[14], holding other variables constant. Younger jobseekers may have higher reservation wages than older jobseekers. They opt to remain unemployed to search for better and suitable job opportunities that fit their qualifications. On the other hand, lower exit rates to employment among older jobseekers can be explained by fewer job offers due to age discrimination in hiring. Employers associate ageing with mental and physical decline and see hiring of older jobseekers as costly in terms of providing health insurance and retirement benefits even though these jobseekers are qualified for the job positions. The finding that older workers are at a disadvantage when it comes to escaping unemployment has also been observed in Argentina (Galiani & Hopenhayn, 2001), Russia (Foley, 1997; Grogan & Van den Berg, 2001), Slovak Republic (Lubyova & Van Ours, 1999), Turkey (Tansel & Taşçı, 2010), and Ukraine (Kupets, 2006).

Female jobseekers are more unlikely to exit unemployment compared to male jobseekers. Females, in general, were estimated to face 0.867 of the hazard of males or they have 13.3 percent smaller hazard than males. A hazard ratio of less than one indicates that exiting from unemployment is occurring slower for females than for males. Ever-married jobseekers, in general, were estimated to face 1.205 of the hazard of their never-married counterparts or they have 20.5 percent higher hazard than the never-married. For females, being married is associated with lower hazard to employment. On the other hand, for males it is the opposite. In particular, married women are at disadvantaged because they were estimated to face 0.866 (exponent of $\beta_{female} \times 1 + \beta_{married} \times 1 + \beta_{femalexmarried} \times 1$ from specification 3) of the hazard of married men or they have 13.4 percent smaller hazard than married men. The most plausible explanation is that married women may receive fewer job offers than married men. Married women are often discriminated against during the hiring process because employers have to provide additional benefits such as, in the case of the Philippines, entitlement to special leave following surgery caused by gynecological disorders and maternity leave following childbirth. Married men, on the other hand, have higher exit rates to employment most probably because they are under greater pressure to find employment compared to married women. In a country where men are seen as the breadwinners of the family, male jobseekers are expected to be more intensive in their job search. Cross-country findings on the effect of sex of an individual on likelihood of leaving unemployment are uniform. Argentine, Estonian, Russian, Slovak, and Turkish females have lower exit rates from unemployment to employment compared to their male counterparts (Galiani & Hopenhayn, 2001; Rõõm, 2002; Foley, 1997; Lubyova & Van Ours, 1999; Tansel & Taşçı, 2010). In particular, married women in Russia and Turkey experience significantly longer unemployment spells before exiting to employment (Foley, 1997; Tansel & Taşçı, 2010).

The coefficients of the dummy variables for incomplete tertiary education and completed tertiary education are statistically significant with a negative sign (in specification 2) suggesting that jobseekers who are college undergraduates or graduates are less likely to exit unemployment compared to jobseekers with complete primary education or with even lower level of educational attainment. College undergrads and college grads face 0.710 and

[14]With reference to models 2 and 3, the peaks can be derived using the formula: $-\beta_{age}/2\beta_{agesq}$

0.647 of the hazard of primary graduates or they have 29.0 percent and 35.3 percent smaller hazard than primary grads, respectively. Most of these college educated jobseekers have high reservation wages and can afford to be unemployed or wait for better job offers (DOLE, 2011). In terms of courses/programs, college graduates who are either engineering or services majors spend more time unemployed compared to primary grads. Graduates of engineering and services programs face 0.535 and 0.342 of the hazard of primary grads or they have 46.5 percent and 65.8 percent smaller hazard than the reference group, respectively (in specification 3). These findings are in contrast to what were found in other more developed countries. In Argentina (Galiani & Hopenhayn, 2001), Russia (Grogan & Van den Berg, 2001), Slovak Republic (Lubyova & Van Ours, 1999), Turkey (Tansel & Taşçı, 2010), and Ukraine (Kupets, 2006), for example, less educated individuals have lower probability of exiting to employment than individuals with higher level of education. Fan & Stark (2007) noted that a strong negative relationship between unemployment and educational attainment had been observed in developed countries, which is opposite to the phenomenon of "educated unemployment" in developing countries such as the Philippines.

The duration model estimated (specification 4) shows that coefficient of the local labor demand as proxied by the provincial unemployment rate enters negatively into the equation as expected and was found to be statistically significant at conventional levels of significance. For every 1 percent increase in unemployment rate, the hazard to employment decreases by 2.7 percent. Previous studies in Russia (Foley, 1997), Slovak Republic (Lubyova & Van Ours, 1999), Turkey (Tansel & Taşçı, 2010), and Ukraine (Kupets, 2006) also found the local unemployment rate to be negatively associated with the probability of exiting from unemployment to employment. In addition, regional dummies and the indicator for urbanity of the *barangay* (village) where the jobseeker resides were found to be confounding factors to the variable on local unemployment rate. This implies that the local labor market condition already takes into account geographical differences and hence no additional controls were further needed[15].

The signs of the coefficients of the variables pertaining to the schooling status and household composition such as the number of young and old dependents although turned out as expected, their relationships with the likelihood of exiting unemployment to employment were found to be not statistically significant at conventional levels of significance. However, the indicator for an informal worker in the household was found to have a significant and positive effect on hazard to employment. Compared to jobseekers belonging to households with no informal worker, on the average, jobseekers living with an informal worker in the household have 13.4 percent higher hazard to employment. In contrast, the negative effects of the provincial minimum wage and the number of employed members in the household on the probability of exiting unemployment were found to be statistically significant. For every 10-peso increase in minimum wage, the hazard to employment decreases by about 2 percent and for every additional employed member in the household, the hazard to employment falls by 9.9 percent.

Results also show that as the amount of cash assistance received from local sources and from overseas increases, the exit rate to employment from unemployment falls. In particular, as the amount of assistance received from abroad and domestic source increases by 10 percent, the hazard to employment falls by 35 percent and 20 percent, respectively. This finding suggests that cash assistance from outside the household may lead to higher

[15] In 2010, NCR and Region IV-A (highly urbanized regions) posted unemployment rates of 11.5% and 9.5% respectively.

reservation wages for jobseekers as they can afford to be out-of-work compared to those that did not receive any assistance from external sources such as family members working abroad, other households, government, or the private sector. The “disincentive effect” to accept a job offer is more prominent among jobseekers who receive cash receipts from abroad probably because the amount of remittances is larger compared to cash transfers from domestic sources. On the contrary, jobseekers who accessed credit from other households are more likely to exit unemployment. As the amount of loans from other families increases by 10 percent, the hazard to employment rises by 26 percent. Intuitively, jobseekers who took loans from other families may be under greater financial pressure to look for a job and pay back their obligations unlike jobseekers who received financial assistance with no strings attached. In Ethiopia (Dendir, 2007), relying on relative’s help was found to have a negative effect on the probability of exit from unemployment to employment. Reliance on sources of income while unemployed such as casual work, household income, and pension was also found to be negatively associated with exit rates from unemployment in Ukraine (Kupets, 2006). Results also show that for every 10 percent increase in savings rate, the hazard to employment increases by 3 percent.

Jobseekers who have no prior work experience were less likely to escape to employment compared to jobseekers who already have occupational experience. Inexperienced jobseekers were estimated to face 0.674 of the hazard of experienced jobseekers or they have 32.6 percent smaller hazard than their experienced counterparts (from specification 5). Tansel & Taşçı (2010) found that first-time jobseekers in Turkey have lower exit rates compared to jobseekers who have looked for work at any time before. These findings demonstrate that the lack of experience is penalized in the job market as new entrants to the labor force may be offered fewer jobs. In terms of job search method, results indicate that jobseekers who registered in a public employment agency have higher exit rates compared to jobseekers who either approached employer directly, friends or relatives, placed or answered advertisements, or did some other methods of finding work. Jobseekers who registered in public employment agency were estimated to face 1.329 of the hazard of jobseekers who did some other methods of finding work aside from registering in a private employment agency or they have 32.9% higher hazard than the reference group. It is possible that the trainings or assistance provided by government employment agencies benefit jobseekers in terms of increased employability and job offers.

Results of the estimated proportional odds models of post-unemployment outcomes (refer to Table 5) show that longer time spent looking for work is associated with less likelihood of getting employed. Personal characteristics of jobseekers such as being female and highly educated have negative effects on the probability of being employed. Being female and married is associated with less likelihood of getting employed. Having no previous work experience reduces the probability of getting employed while training (as proxied by registration to an employment agency) increases the chances of finding work.

Certain household characteristics are also influential factors in employment transitions. For instance, as the number of employed members in the household increases, the likelihood of an unemployed member to exit to employment decreases. In the same way, the more reliant a household is on assistance from abroad or domestic sources, the less likely it is for its job seeking members to be employed. On the other hand, higher savings rate is associated with higher likelihood of getting employed. Results also show that the higher the minimum wage the less likely it is for a jobseeker to escape from unemployment.

Table 4. Parameter Estimates (Hazard Ratios) for Grouped Duration Proportional Hazards Models of Independent Employment Hazard

Variable	Model 1	Model 2	Model 3	Model 4	Model 5
Baseline Hazard					
interval 1 (1-27 weeks)	0.057	0.040	0.036	0.081	0.140
	(0.004)***	(0.014)***	(0.013)***	(0.031)***	(0.061)***
interval 2 (28-54 weeks)	0.482	0.339	0.313	0.716	1.186
	(0.018)***	(0.116)***	(0.108)***	(0.270)	(0.507)
interval 3 (55-81 weeks)	0.304	0.214	0.206	0.483	0.809
	(0.092)***	(0.098)***	(0.094)***	(0.234)	(0.424)
interval 4 (>=82 weeks)	0.154	0.110	0.096	0.231	0.390
	(0.154)*	(0.117)**	(0.102)**	(0.248)	(0.425)
Covariates					
age		1.042	1.047	1.015	1.023
		(0.023)*	(0.024)**	(0.024)	(0.025)
age squared		0.999	0.999	1.000	1.000
		(0.000)*	(0.000)**	(0.000)	(0.000)
female		0.867	0.984	0.988	1.025
		(0.062)**	(0.085)	(0.085)	(0.089)
ever married		1.205	1.488	1.451	1.533
		(0.110)**	(0.161)***	(0.156)***	(0.171)***
secondary incomplete		0.736	0.738	0.758	0.749
		(0.105)**	(0.105)**	(0.108)*	(0.108)**
secondary complete		0.779	0.763	0.789	0.785
		(0.090)**	(0.089)**	(0.092)**	(0.094)**
tertiary incomplete		0.710	0.691	0.723	0.758
		(0.088)***	(0.086)***	(0.091)***	(0.099)**
tertiary complete		0.647			
		(0.082)***			
education major			0.704	0.731	0.747
			(0.151)	(0.159)	(0.165)

humanities major	0.961	1.316	1.539
	(0.979)	(1.345)	(1.594)
social sciences major	0.764	0.782	0.826
	(0.131)	(0.135)	(0.149)
science major	0.756	0.789	0.866
	(0.175)	(0.184)	(0.205)
engineering major	0.535	0.592	0.641
	(0.094)***	(0.106)***	(0.120)**
agriculture major	0.830	0.902	0.885
	(0.310)	(0.339)	(0.334)
health major	1.463	1.595	1.916
	(0.644)	(0.705)	(0.868)
services major	0.342	0.360	0.368
	(0.095)***	(0.101)***	(0.105)***
female x ever married	0.591	0.598	0.548
	(0.093)***	(0.094)***	(0.087)***
no work experience		0.694	0.674
		(0.058)***	(0.057)***
public employment agency		1.269	1.329
		(0.179)*	(0.189)**
private employment agency		1.108	1.121
		(0.110)	(0.112)
unemployment rate		0.973	
		(0.009)***	
minimum wage			0.998
			(0.001)***
attending school			0.683
			(0.210)
no. of young household member			0.979
			(0.025)
no. of old household member			0.916
			(0.053)

no. of employed household member					0.901
					(0.031)***
informal sector					1.134
					(0.086)*
assistance from abroad					0.965
					(0.007)***
assistance from local					0.980
					(0.008)***
loans from other households					1.026
					(0.011)**
withdrawal from savings					1.003
					(0.009)
savings rate					1.003
					(0.002)*
No. of observations	4,828	4,828	4,821	4,821	4,652
No. of failures	892	892	892	892	890
Log likelihood	-1,898.46	-1,881.71	-1,866.85	-1,852.04	-1,808.35

Notes: Base categories: male, never married, completed primary education or below, worked at any time before, approached employer directly, relatives or friends, placed or answered advertisements, and did other job search methods, currently not attending school, no informal worker in the household
Exponentiated form of the coefficients are presented, standard errors in parentheses
*** denotes $p<0.01$, **$p<0.05$, *$p<0.10$ (two-tailed tests)
The variable for general major is a perfect predictor hence its observations were dropped in the estimation of Model 3, Model 4, and Model 5.
The dependent variable is a dummy variable indicating whether or not an exit to employment occurred for jobseeker *i* in the interval *k*. The variable is coded 1 if the event occurred and coded 0 otherwise. Mean (Std. dev) of the dependent variable in the final sample is 0.191 (0.393). Values of all explanatory variables are taken at the time of the first survey interview.

Table 5. Parameter Estimates (Odds Ratios) for Proportional Odds Models Using Employment Status as an Ordered Response with Three Categories

Explanatory Variables	Model 1	Model 2	Model 3	Model 4	Model 5
job search duration 10-19 weeks	0.700	0.712	0.716	0.712	0.662
	(0.110)**	(0.113)**	(0.114)**	(0.114)**	(0.108)**
job search duration 20-29 weeks	0.552	0.547	0.552	0.551	0.542
	(0.144)**	(0.143)**	(0.145)**	(0.145)**	(0.145)**
job search duration 30 weeks and longer	0.773	0.740	0.782	0.792	0.773
	(0.262)	(0.253)	(0.269)	(0.273)	(0.271)
aged 25-34		1.105	1.089	0.985	0.980
		(0.111)	(0.110)	(0.103)	(0.107)
aged 35-44		1.141	1.142	1.033	0.975
		(0.183)	(0.185)	(0.170)	(0.169)
aged 45-54		1.376	1.341	1.220	1.157
		(0.288)	(0.283)	(0.260)	(0.259)
aged 55-64		1.598	1.471	1.333	1.075
		(0.547)	(0.510)	(0.464)	(0.385)
female		0.772	0.832	0.843	0.927
		(0.065)***	(0.083)*	(0.085)*	(0.096)
ever married		1.210	1.438	1.393	1.615
		(0.128)*	(0.186)***	(0.181)**	(0.221)***
secondary incomplete		0.737	0.746	0.763	0.742
		(0.129)*	(0.131)*	(0.134)	(0.134)*
secondary complete		0.775	0.767	0.785	0.791
		(0.112)*	(0.111)*	(0.114)*	(0.120)
tertiary incomplete		0.694	0.686	0.701	0.745
		(0.106)**	(0.105)**	(0.108)**	(0.122)*
tertiary complete		0.709			
		(0.110)**			
education major			0.868	0.883	0.839
			(0.224)	(0.230)	(0.227)
humanities major			1.980	2.803	2.712
			(2.821)	(4.003)	(3.884)

social sciences major	0.901	0.926	0.969
	(0.188)	(0.196)	(0.218)
science major	0.746	0.768	0.810
	(0.206)	(0.214)	(0.236)
engineering major	0.579	0.633	0.644
	(0.120)***	(0.134)**	(0.145)*
agriculture major	0.957	0.999	1.095
	(0.441)	(0.463)	(0.522)
health major	2.375	2.554	2.884
	(1.482)	(1.604)	(1.861)
services major	0.350	0.370	0.347
	(0.110)***	(0.117)***	(0.113)***
female x ever married	0.654	0.646	0.530
	(0.123)**	(0.122)**	(0.103)***
no work experience		0.708	0.655
		(0.069)***	(0.066)***
public employment agency		1.361	1.539
		(0.236)*	(0.277)**
private employment agency		1.119	1.189
		(0.134)	(0.146)
unemployment rate		0.983	
		(0.011)	
minimum wage			0.999
			(0.001)*
attending school			0.652
			(0.228)
no. of young household member			0.967
			(0.031)
no. of old household member			0.924
			(0.065)
no. of employed household member			0.857
			(0.036)***

informal sector						1.076 (0.100)
assistance from abroad						0.956 (0.009)***
assistance from local						0.965 (0.009)***
loans from other households						1.022 (0.014)
withdrawal from savings						1.011 (0.011)
savings rate						1.005 (0.002)**
N		2,896	2,896	2,891	2,891	2,730
Chi^2 (df)		11.06 (3)	49.07 (13)	70.66 (21)	88.39 (25)	156.95 (35)
Pseudo R^2		0.00	0.01	0.02	0.02	0.04
Log likelihood		-1,981.00	-1,962.00	-1,949.35	-1,940.49	-1,843.15
Likelihood-ratio test of proportionality of odds across response categories	Test statistic	2.45	18.23	25.26	25.03	39.69
	p-value	0.4853	0.1489	0.2360	0.4609	0.2690

Notes: Base categories: job search duration less than 10 weeks, aged 15-24, male, never married, completed primary education or below, worked at any time before, approached employer directly, relatives or friends, placed or answered advertisements, and did other job search methods, currently not attending school, no informal worker in the household

Exponentiated form of the coefficients are presented, standard errors in parentheses, cut-off values are not shown

*** denotes p<0.01, **p<0.05, *p<0.10 (two-tailed tests)

The variable for general major is a perfect predictor hence its observations were dropped in the estimation of Model 3, Model 4, and Model 5.

The dependent variable is a categorical variable indicating whether a jobseeker is still unemployed, got employed in the past week (prior to the second interview), or got employed in the past quarter. The categories are coded from 1 to 3 respectively. Mean (Std. dev) of the dependent variable in the final sample is 1.632 (0.920). Values of all explanatory variables are taken at the time of the first survey interview.

6. **Conclusions**

This paper set out to examine the determinants of the probability of exiting from unemployment to employment in the Philippines and to determine whether an individual's length of time already spent without a job may actually prolong their joblessness for even a longer period of time using an individual-level panel data constructed from the July 2009 and January 2010 rounds of the Labor Force Survey (LFS).

Based on the results of this study, several personal, household, and community attributes were identified as influential factors to transition from unemployment to work and duration of unemployment. The probability of transitioning from unemployment to employment is lower among young and older jobseekers compared to their prime-age counterparts. Married women have lower exit rates to employment than married men. College graduates looking for work are less likely to leave unemployment than less educated jobseekers. Jobseekers with no work experience are less likely to find work compared to experienced jobseekers. Individuals looking for a job in areas with high unemployment rates have lower chances of finding work compared to jobseekers searching in regions with lower unemployment rates. Higher amounts of cash transfers from external sources are associated with lower exit rates to employment while larger amounts of money and goods borrowed from other families are related to higher exit rates to employment. Results also indicated a duration dependence that initially rises but steadily falls thereafter.

The aforementioned findings on labor market transitions in particular from unemployment to employment clearly have broader policy implications. First, given that unemployment is mainly a youth problem in the Philippines, the finding that the youth are less likely to leave unemployment makes it more daunting. Therefore, preparing our youth for their entry to the labor force is desirable. Second, longer unemployment spells for married women means limited job opportunities and increased pressure to leave the labor force considering that historically female labor participation rate has been significantly lower than that of males. Giving employment opportunities to married women may improve the labor force participation of women in general. Third, the lower exit rate to employment of relatively well educated jobseekers especially engineering majors and services majors indicates queuing for "decent" jobs which may be attributed to the high reservation wage of highly-educated jobseekers expecting more favorable return to investment on their education. Lastly, cash transfers may have possible disincentive effect for individuals to work. Considering, that the disincentive effect is more prominent among jobseekers who belong to households that receive assistance from abroad, this finding implies that remittances can affect albeit unintentionally the labor supply decisions of the left-behind relatives of migrants.

The pattern of duration dependence indicates that in the medium- and long-term, unemployment begets unemployment. It is possible that employers are using unemployment duration as a criterion in the screening of potential hires. Although, there are legislations and regulations in place to protect the rights of workers to equal opportunity and treatment in employment the results of this study indicate that stricter enforcement of these laws is needed. It will be therefore beneficial to expand government-sponsored skills development programs to medium- and long-term unemployed to keep their work skill set relevant to the demands of the labor market.

The ILO Deputy Director-General in a speech[16] stressed the importance of improving labor market statistics for policymaking especially in developing countries in terms of "gender-disaggregated data and information on the duration, security and quality of employment and the level of wages and earnings." In the Philippines, for instance, the present design of the LFS questionnaire does not address the current demand for labor force statistics that will accurately capture the dynamics and movements in and out of the labor market (Ybañez, 2000). The current rotation design of the LFS wherein 50% of housing units are contacted in 2 quarters a year apart (except in FIES years when the in-between period is 6 months) was meant to refine the year-on-year survey estimates and not for tracking the changes in the labor market status of individuals per se. Moreover, the survey instrument in its current form is limited in terms of determining the transitions in the labor market status of persons in-between survey periods. Hence, a review of the LFS' current design and questionnaire should be seriously considered by the PSA.

[16] Keynote Address by Mr. Greg Vines, ILO Deputy Director-General delivered in the ILO New York City office last 17 June 2013

References

Arulampalam, W., Gregg, P., & Gregory, M. (2001). Unemployment scarring. *The Economic Journal*, *111*(475), 577–584. doi:10.1111/1468-0297.00663

Bazen, S. (2011). *Econometrics Methods for Labour Economics*. Oxford: Oxford University Press. doi:10.1093/acprof:oso/9780199576791.001.0001

Biewen, M., & Steffes, S. (2010). Unemployment persistence: Is there evidence for stigma effects? *Economics Letters*, *106*(3), 188–190. doi:10.1016/j.econlet.2009.11.016

BLES. (2011). Primer on Labor Force Survey. Bureau of Labor and Employment Statistics.

Broman, C. L., Hamilton, V. L., & Hoffman, W. S. (1996). The impact of unemployment on families. *Michigan Family Review*, *2*(2), 83–91. Retrieved from http://hdl.handle.net/2027/spo.4919087.0002.207

Cameron, A., & Trivedi, P. (2005). *Microeconometrics: methods and applications*. New York: Cambridge University Press.

Clark, A., Georgellis, Y., & Sanfey, P. (2001). Scarring: The psychological impact of past unemployment. *Economica*, *68*(270), 221–241. Retrieved from http://www.jstor.org/stable/3548835

Cox, D. (1972). Regression Models and Life-Tables. *Journal of the Royal Statistical Society. Series B (Methodological)*, *34*(2), 187–220.

Dendir, S. (2007). Unemployment duration in poor developing economies: Evidence from urban ethiopia. *The Journal of Developing Areas*, *40*(1), 181–201. Retrieved from http://muse.jhu.edu/journals/journal_of_developing_areas/v040/40.1dendir.html

DOLE. (2011). *The Philippine Labor & Employment Plan 2011-2016: Inclusive Growth Through Decent and Productive Work*. Manila: Department of Labor and Employment.

Fan, C. S., & Stark, O. (2007). International migration and “educated unemployment.” *Journal of Development Economics*, *83*(1), 76–87. doi:10.1016/j.jdeveco.2006.05.002

Foley, M. (1997). *Determinants of unemployment duration in Russia* (No. 81). Retrieved from http://wdi.umich.edu/files/publications/workingpapers/wp81.pdf

Galiani, S., & Hopenhayn, H. A. (2001). *Duration and risk of unemployment in Argentina* (No. 476). Retrieved from http://deepblue.lib.umich.edu/bitstream/handle/2027.42/39861/wp476.pdf?sequence=3

Gerard, M., Valsamis, D., & Van der Beken, W. (2012). *Why invest in employment ? A study on the cost of unemployment*. Brussels. Retrieved from http://www.federgon.be/fileadmin/MEDIA/pdf-fr/etudes-enquetes/Report__Study_on_the_cost_of_unemployment__January_2013_English.pdf

Greene, W., & Hensher, D. (2009). Modeling ordered choices. *Unpublished Manuscript*, 1–285. doi:10.1037/0021-9010.91.1.97

Grogan, L., & Van den Berg, G. (2001). The duration of unemployment in Russia. *Journal of Population Economics*, *14*(3), 549–568. Retrieved from http://link.springer.com/article/10.1007/s001480000029

Gust, G. A. (2006). *Equality at Work: Philippines* (No. 12). Retrieved from http://www.ilo.org/wcmsp5/groups/public/---asia/---ro-bangkok/---ilo-manila/documents/publication/wcms_126069.pdf

Hosmer, D., Lemeshow, S., & May, S. (2008). *Applied Survival Analysis: Regression Modeling of Time-to-Event Data* (2nd ed.). New Jersey: John Wiley & Sons Inc.

ILO. (2012). *Decent Work Country Profile The PHILIPPINES*. Geneva: International Labour Organization. Retrieved from http://www.ilo.org/wcmsp5/groups/public/---dgreports/---integration/documents/publication/wcms_190710.pdf

Jenkins, S. P. (2005). *Survival Analysis*. Retrieved from https://www.iser.essex.ac.uk/files/teaching/stephenj/ec968/pdfs/ec968lnotesv6.pdf

Kiefer, N. (1988). Economic duration data and hazard functions. *Journal of Economic Literature*, *26*(2), 646–679.

Kupets, O. (2006). Determinants of unemployment duration in Ukraine. *Journal of Comparative Economics*, *34*(2), 228–247. doi:10.1016/j.jce.2006.02.006

Lancaster, T. (1979). Econometric methods for the duration of unemployment. *Econometrica: Journal of the Econometric Society*, *47*(4), 939–956.

Lancaster, T. (1992). *The Econometric Analysis of Transition Data* (Paperback.). New York: Cambridge University Press.

Lancaster, T., & Nickell, S. (1980). The analysis of re-employment probabilities for the unemployed. *Journal of the Royal Statistical Society. Series A (General)*, *143*(2), 141–165. Retrieved from http://www.jstor.org/stable/2981986

Linn, M. W., Sandifer, R., & Stein, S. (1985). Effects of unemployment on mental and physical health. *American Journal of Public Health*, *75*(5), 502–6. Retrieved from http://www.ncbi.nlm.nih.gov/pmc/articles/PMC1646287/pdf/amjph00281-0056.pdf

Lubyova, M., & Van Ours, J. (1999). Unemployment durations of job losers in a labour market in transition. *Economics of Transition*. Retrieved from http://onlinelibrary.wiley.com/doi/10.1111/1468-0351.00030/abstract

McCall, J. (1970). Economics of Information and Job Search. *The Quarterly Journal of Economics*, *84*(1), 113–126. Retrieved from http://www.rand.org/pubs/research_memoranda/RM5745.html?src=mobile

McClelland, A., & MacDonald, F. (1998). *The social consequences of high unemployment*. Retrieved from http://www.bsl.org.au/pdfs/social.pdf

McKee-Ryan, F., Song, Z., Wanberg, C. R., & Kinicki, A. J. (2005). Psychological and physical well-being during unemployment: a meta-analytic study. *The Journal of Applied Psychology*, *90*(1), 53–76. doi:10.1037/0021-9010.90.1.53

Mortensen, D. (1970). A Theory of Wage and Employment Dynamics. In E. Phelps, G. Archibald, & A. Alchian (Eds.), *Microeconomic Foundations of Employment and Inflation Theory* (pp. 124–166). New York: W.W. Norton & Company, Inc.

Mortensen, D. (1986). Job search and labor market analysis. *Handbook of Labor Economics*, *1*. Retrieved from http://www.kellogg.northwestern.edu/research/math/papers/594.pdf

Murphy, G., & Athanasou, J. (1999). The effect of unemployment on mental health. *Journal of Occupational and …*, *72*(1), 83–99. doi:10.1348/096317999166518

NEDA. (2011). *Philippine Development Plan 2011-2016*. Retrieved from http://www.neda.gov.ph/wp-content/uploads/2013/09/CHAPTER-8.pdf

Nichols, A., Mitchell, J., & Lindner, S. (2013). *Consequences of long-term unemployment*. Washington D.C. Retrieved from http://www.urban.org/uploadedpdf/412887-consequences-of-long-term-unemployment.pdf

Pedersen, P., & Westergird-Nielsen, N. (1993). Unemployment: A Review of the Evidence from Panel Data. *OECD Economic Studies*.

Prentice, R. L., & Gloeckler, L. A. (1978). Regression Analysis of Grouped Survival Data with Application to Breast Cancer Data. *Biometrics*, *34*(1), 57–67.

Rogerson, R., Shimer, R., & Wright, R. (2005). Search-theoretic models of the labor market: a survey. *Journal of Economic Literature*, *XLIII*(December), 959–988.

Rõõm, M. (2002). *Unemployment and Labour Mobility in Estonia: Analysis Using Duration Models* (No. 7). Retrieved from http://www.eestipank.ee/sites/default/files/publication/en/WorkingPapers/2002/index_1.pdf

Ryu, K. (1994). Group Duration Analysis of the Proportional Hazard Model: Minimum Chi-square Estimators and Specification Tests. *Journal of the American Statistical Association*.

Stigler, G. (1961). The economics of information. *The Journal of Political Economy*, *69*(3), 213–225. Retrieved from http://www.jstor.org/stable/1829263

Stigler, G. (1962). Information in the labor market. *The Journal of Political Economy*, *70*(5), 94–105. Retrieved from http://www.jstor.org/stable/1829106

Sueyoshi, G. T. (1995). A Class of Binary Response Models for Grouped Duration Data. *Journal of Applied Econometrics*, *10*, 411–431. doi:10.2307/2285055

Swinney, D. (1983). Documenting the Social Cost of Unemployment. *Labor Research Review*, *1*(3). Retrieved from http://digitalcommons.ilr.cornell.edu/lrr/vol1/iss3/5

Tansel, A., & Taşçı, H. M. (2010). Hazard analysis of unemployment duration by gender in a developing country: The case of Turkey. *Labour, 24*(4), 501–530. doi:10.1111/j.1467-9914.2010.00480.x

Ybañez, J. R. (2000). *Labor Force Indicators of the Philippines*. Retrieved from http://www.ilo.org/wcmsp5/groups/public/---asia/---ro-bangkok/documents/genericdocument/wcms_143036.pdf

Zaretsky, A., & Coughlin, C. (1995). An introduction to the theory and estimation of a job-search model. *Federal Reserve Bank of St. Louis Review*, (January/February), 53–65. Retrieved from http://ideas.repec.org/a/fip/fedlrv/y1995ijanp53-65.html