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Equitable Redistribution without Taxation: A lesson from East Asian Miracle countries

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Abstracts

Does uncertainty of labor earning over the life-time increase income inequality? – This paper finds that there is a direct positive relationship between life-time uncertainty and income inequality. Earlier studies single out the effect of uncertainty to pin point the effects of predictable factors (i.e. education, family background, etc.), whereas the uncertainty is treated as uncontrollable factor. This paper finds that, the degree of earning uncertainty is predictable to a large extent, which is one of the corner-stones of life cycle models with stochastic earnings. Therefore, the uncontrollable *uncertainty* can be influenced by policy decisions. The EAM countries have set examples of such policies and have shown that despite their rapid economic growth, inequality has been decreased in those countries. The degree of earning uncertainty can be reduced by creating more jobs in less volatile *Dependent Employment*. In other words, by giving a worker higher opportunity to find a less volatile job, earning uncertainty can be reduced. And reduced earning uncertainty eventually results in reduced income inequality.

Key words: Inequality, Redistribution.

JEL Codes: D15, D33, E24.

1. Introduction

The conventional policies for equitable redistribution of income are taxes and subsidies (or minimum wage increase). Apart from tax, subsidy, or other conventional policies, this paper proposes a new policy tool for equitable income distribution – that we call *reducing uncertainty*[1] to income. In other words, we can say

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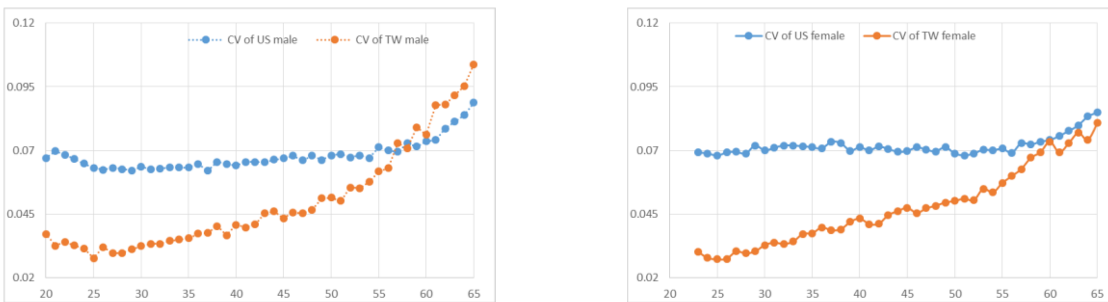
[1] Uncertainty is the future or expected volatility or shocks to labor earning, which is measured in Life-cycle models by variance of earning less the variance of individual fixed effects at each age group. Since an individual worker moves from one age to next age, the earning-variance profile gives us measures of current inequality, as well as expected future uncertainties of a worker.

less volatile income reduces income inequality. This finding comes from the comparisons of contemporary cross-country data between United States and Taiwan (one of the EAM countries) provided by Luxembourg Income Study (LIS, 2017).

In earlier literature, it has been found that despite their rapid economic growth East Asian Miracle[2] (EAM) countries have successfully contained their income inequality (Stiglitz, 1996). This success of EAM countries is attributed to land policy, labor policy, industrial policy, and education policy etc. However, these policies create a relatively indirect channel to income redistribution compared to tax or subsidy policies. We argue that if Stiglitz's policies reduces income *uncertainty* then these policies have a direct relationship with income inequality through *uncertainty*. Figure 1 explains the relationship in simple and easy way.

Figure 1 Labor-Earning uncertainty in US and Taiwan



Coefficient of variation of log-earning (male) by age in the US and Taiwan

Coefficient of variation of log-earning (female) by age in the US and Taiwan

Note. We measure the uncertainty to labor income by the coefficient of variation at each age. The figures have been constructed using LIS (2017) database. We use the datasets available for 2004 (for Taiwan 2005), 2007, 2010 and 20013 for both countries. In relevant literature uncertainty often measured as variance of log-earnings. In this figure we place CV to make two countries comparable.

The above figure (Figure – 1) shows that labor earning uncertainty is higher in United States compared to Taiwan; moreover the income inequality is higher in United States compared to Taiwan (CIA, 2017)[3]. The question is '*does income uncertainty increase income inequality?*' To answer this question through Figure – 1, we need to provide two convincing arguments. First, the main source of income inequality in the OECD countries is labor-earning inequality. In case of United States more than 80 % of total income inequality is attributed to labor earning inequality (OECD, 2012, p. 186 : Figure 5.3), which implies reducing labor earning inequality reduces overall income inequality. Second, uncertainty is a measure of inequality in life-cycle models (Deaton & Paxson, 1994; Blundell & Preston, 1998) whereas Lorenz curves or Gini coefficients are usual measures in other studies of income inequality (Atkinson, 1970). It can also be said that, uncertainty is the expected future inequality. Inequality is the dispersion of current income while uncertainty is the measure of expected inequality of next period or periods afterwards. By using the argument of Deaton (1985) a direct relationship can be established between usual (cross – sectional) measures of inequality (Lorenz curve) and uncertainty of labor earning over the working life.

[2] EAM countries include Hong Kong, Indonesia, Japan, Malaysia, Singapore, South Korea, Taiwan, and Thailand.
[3] CIA's (Central Intelligence Agency of United States) The World Factbook reports that the Gini index of United States is 45 (in 2007) and that of Taiwan is 33.4 (in 2014).

Based on Figure – 1, for the time being let us assume, earning[4] uncertainty increases earning inequality. Then the question remains, *how does Taiwan reduce earning uncertainty in the early working life?* Following tables (Table – 1 and Table – 2) provide the answer (see Appendix A1 as well). According to LIS database guidelines, in every country workers are segregated into two broad groups (see Appendix A4); *Independent Employees (IE) and Dependent Employees (DE)*. The data (LIS, 2017) show that *DE*s in every country have less volatile earnings compared to that of *IE*s over the life cycle. In case of Taiwan, there are more workers in *DE* than in United States which results in less overall uncertainty to earning in early working life.[5].

Table 1 Change in average uncertainty from early to mid-working life

(1)	(2)	Early working life (20 – 39) (3)	Mid working life (40 – 59) (4)	Change in Uncertainty (5)
United States	Male	0.0643	0.0678	0.0035
	Female	0.0702	0.0705	0.0003
Taiwan	Male	0.0338	0.0532	0.0194
	Female	0.0334	0.0516	0.0182

Note. In this table we measure uncertainty as the average of CVs (coefficient of variation) of the respective age groups. *Source:* Author's calculation from LIS (2017)

Although, Taiwan has a notable success to reduce earning uncertainty in early working life, in mid-working life, overall uncertainty of Taiwan is very close to that of U.S. Therefore, the change in uncertainty from early to mid-working life in Taiwan is much higher than in the U.S. (Table – 1, col 5).

Table 2 Proportion of *DE*s (in percent) among total workers by age group and gender

(1)	(2)	Early working life (20-39) (3)	Mid working life (40-59) (4)	% change from early to mid-working life (5)	Late working life (60-64) (6)
United States	Male	83	79	4	69
	Female	84	84	0	77
Taiwan	Male	90	68	22	43
	Female	94	80	14	51

Source: Author's calculation from LIS (2017)

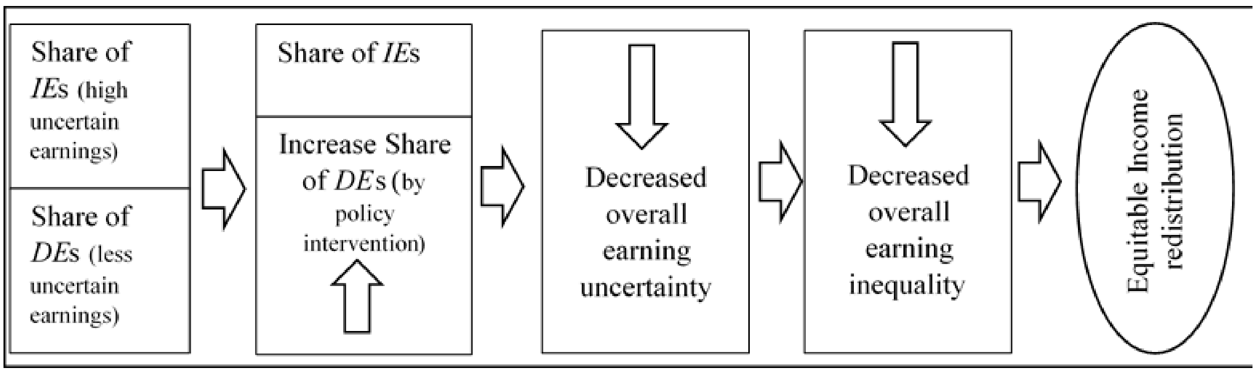
Table – 2 shows that changes in share of *DE*s from early to mid-working life is very high in Taiwan, whereas in the United States the change is negligible (col – 5). From the facts given in Table – 1 and Table – 2 we can say that, higher uncertainty in Taiwan's mid-working life compared to its early working life can be explained by the sharp fall in the share of *DE*s. Consequently, it can be argued that share of *DE*s not only

[4] Let us differentiate between income and earnings. Whereas income implies the total annual income of an individual, the earning implies the part of total income that an individual receives from her labor input only. That is income from capital or other transfers are excluded here.

[5] Note that, the earning uncertainty of *DE*'s in Taiwan is less than that of US. Let us take this as Taiwan's country specific characteristic, which has an impact on overall uncertainty to earning of workers. Country – specific characteristics can be affected or changed by Stiglitz's policies. However, to emphasize on the effect of proportion of dependent employees, it can be said that, within Taiwan (i.e. keeping the country specific characteristics unchanged) proportion of *DE* has a conspicuous effect on earning uncertainty of early working life compared to mid or late working life.

creates the difference in uncertainty across the countries (between US & Taiwan), moreover, it also creates the difference in uncertainty within the country across working age. In following diagram (Figure – 2), we describe a plausible process, how share of *DE*s can affect the overall earning uncertainty and ultimately impact the redistribution of income.

Figure 2 Diagram of equitable redistribution without taxation



Total workers in the economy | Policy Intervention | Desired outcome

In the following section we describe the methodology and data of our research. Section – 3 reviews the related literature. The fourth section sets up the benchmark life cycle model and the fifth analyzes the differential policy interventions. Finally we conclude the paper in Section – 6.

2. Methodology and Data

At the beginning of this section we revisit our research questions:

a) *Does uncertainty or future volatility to labor earning increase the inequality today*?
b) *Can we reduce uncertainty to labor earning by creating more jobs in dependent employment system*?

The future uncertainty of a young worker is the realized inequality of an older worker today. For example the realized inequality of age cohort 21 today, is the expected future uncertainty of the age cohort 20 which will be faced in following period. There will be a calendar year effect between these two periods which can be corrected by econometric operations. These earning uncertainties over the life time of a worker is analyzed by a life-cycle model.

However, for our research we find it difficult to study life-time uncertainty through usual life cycle models in existing literature. In existing models uncertainty of all the individuals comes from a single source. In other words the degree of uncertainty is same for all workers in the economy of a particular age. In this paper we argue that sources of uncertainties are diverse, which implies *IE*s have more uncertain earnings than that of *DEs*. To fit-in our argument in usual life-cycle models we follow the argument of Rahman (2017), which provides empirical evidence of heterogeneous shock processes. Subsequently to answer the research questions, we set up a hypothesis in the following subsection that we call *proportion and uncertainty hypothesis*.

Proportion and Uncertainty Hypothesis (PUH)

Assume an economy where all individuals, who are macroeconomic agents, work either as *IE*s or *DE*s. *IE*s have low average earning and high uncertainty. On the other hand, *DE*s have high average earning and low uncertainty. Then we formulate the hypothesis in two components: 1) earning uncertainty or future volatility increases earning inequality and thus increases overall income inequality, and 2) earning uncertainty can be attenuated by increasing the proportion or share of less volatile dependent employment.

Methodology

To test the hypothesis we set up our benchmark life-cycle model in Section – 4 following the argument of Rahman (2017). The model parameters are estimated by using Method of Simulated Moments (MSM). To evaluate the performance of the benchmark model, estimated parameter values are compared with the parameter values of existing literature. Then we perturb the benchmark model with different policy interventions to test the *proportion and uncertainty hypothesis*.

The Data

Luxembourg Income Study (LIS) database (LIS, 2017), which is one of the largest harmonized[6] database for household and individual income surveys across the world, provides data for more than 50 countries across the world for several decades. We select the United States and Taiwan for our research in this paper[7] (since we follow Rahman (2017)). In this paper we define a worker if her labor earning is positive. We pool the cross-section data that are available for 2004 (2005 for Taiwan), 2007, 2010 and 2013 respectively and separate them according to sex. Then we regress the labor earning with year dummies and remove the year effects from the individual earnings. Afterwards, observations are top coded and bottom coded according to the highest and lowest one percent in the data. We take log of the earnings and then construct the variance profiles for every ages.

A pseudo – panel is constructed following Deaton (1985) and Deaton & Paxson (1994) from the repeated cross-sectional data. We construct a cohort of individuals consisting members of the same age, or born in the same year. The heterogeneity of these cohorts comes from two sources: income year effects, and birth year effects (Rahman, 2017). The calendar year or income year effects are corrected by controlling for year dummies and birth year effects are assumed to be individual specific fixed effects. Then variations in labor earnings that come from the birth year-effect is constant over ages and it does not affect the persistence of earning shocks (see Appendix A3).

Assuming population belonging to a particular cohort is fixed through time (Deaton A. , 1985), the cohort mean and cohort variance can be estimated from the micro survey data given that the sample size is large. In this paper following Rahman (2017) we create age-cohort for every age. For the United States the cohort sizes are greater than 1000, and for Taiwan it is over 300. We rule out further adjustments (Deaton A. , 1985) assuming that the cohort sizes are large enough.

3. Literature review

Uncertainty to labor earning is a future event whereas inequality is a current event. The earning uncertainty over the life-time is studied in life-cycle models with stochastic earning process (Blundell & Preston, 1998; Deaton & Paxson, 1994). In these models earning uncertainty is measured as the variance of earning shocks at each age group. The underlying assumption is that an individual who starts her working life at age 20 passes through the age-specific uncertainties throughout her working life. The underlying assumption originates from the Permanent Income Hypothesis (Friedman, 1957), which is later on adopted by many literature of similar studies (Deaton & Paxson, 1994; Storesletten, Telmer, & Yaron, 2004).

[6] The database is harmonized across countries and across years, that is why it is easy to compare across times or places. The variable definitions are also standardized and easy to understand.
[7] U.S. and Taiwan are compared because in many related literature a comparison between U.S. and Taiwan is often observed (Deaton & Paxson, 1994; Deaton & Paxson, 1995; Deaton & Paxson, 1997).

The life cycle models not only predict the uncertainty, they also predict the average earning profile of a worker. In general the average earning profiles over the life cycle are hump-shape (Ben-Porath, 1967; Friedman, 1957; Mincer, 1974). Exception is also observed, for example in case of female average earning the average earning profile is M – shape in Japan (Lise, Sudo, Suzuki, Yamada, & Yamada, 2014). Nevertheless, the predictability of average earning and the predictability of degree of uncertainty are the key features of life – cycle models. If the earning shock is highly persistent, it is conspicuous that uncertainty evolves in a linear profile over the life cycle.

Labor earning shocks are persistent over the life-cycle (Meghir & Pistaferri, 2004). If earning shocks are persistent over the working life, then the degree of uncertainty is predictable, which is the novel and important tool we use in this paper. There are different conflicting arguments and findings regarding the persistence of labor earning shocks in literature. Nonetheless, it is widely accepted that labor earning shock is an AR (1) process and has a persistent component in it (Meghir & Pistaferri, 2004). Some literature find highly persistent (Storesletten, Telmer, & Yaron, 2004a) earning shocks over the life cycle while some other differ (Guvenen, 2007; Allerano, Blundell, & Bonhomme, 2017; Karahan & Ozkan, 2013) the argument and claim persistent is low.

Since the earning shocks can be heterogeneous (Browning, Hansen, & Heckman, 1999) the persistent parameter is not the only determinant of uncertainty (Rahman, 2017). The cross-sectional variance at each age group is also determined by intragroup uncertainty, intergroup uncertainty and the proportion of groups among workers (Guiso, Jappelli, & Pistaferri, 2002). Moreover, Carroll, & Samwick (1997) has found that in the United States the distribution of labor earning shock differs across occupation as well as age. It opines that largest distribution of shock (or uncertainty) is faced by Farmers, Service workers and Self-employed managers. This group is followed by Laborers, Clerical workers, and Managers. The least distribution of shock is experienced by Professionals and Craftsmen.

Earlier studies separate the effect of uncertainty to target the effect of predictable factors such as education, family background etc. (Cunha & Heckman, 2007). Some life cycle literature also document uncertainty over the life cycle and uncertainty at the beginning of the working life (Huggett, Ventura, & Yaron, 2011). The idea behind pinning down uncertainty is to treat it as an uncontrollable factor. However, overall uncertainty is a composition of group specific uncertainties (Guiso, Jappelli, & Pistaferri, 2002). It is rare in literature to observe that, policies influencing the overall uncertainty by targeting the composition of groups and group specific uncertainties.

Therefore, to influence overall uncertainty, we need to predict group-specific uncertainties through a life cycle model with heterogeneous shock process. Then the predicted life-time uncertainties can be transformed into cross-sectional inequality by using the argument of Deaton (1985), which implies that a panel data set can be constructed by pooling a series of cross-sectional data sets (see Section – 2). Exploiting this argument, we also can show that, a panel data can also be considered as a cross-sectional data, assuming that all the age-cohorts co-exist on the same point of time. Then using the cohort specific uncertainties and inter-cohort differences, we calculate the overall inequality on a particular time point.

In a separate string of literature, inequality is assumed to be influence by economic growth. It has been argued that higher economic growth is accompanied by higher inequality in the initial stage of development, and later when the countries reach a certain level of development inequality decreases (Kuznets, 1955). By Kuznets' argument the inequality profile should take a reverse – U shape along the path of economic development. However, as more and more data are being available in recent decades from countries across the world, many studies have found that this argument is not always true.

Among many others there are two major critics of Kuznets' hypothesis. First, Joseph E. Stiglitz found that while the East Asian miracle countries including Japan, Taiwan, South Korea, Singapore, Hong Kong, Malaysia, Indonesia, and Thailand were enjoying highly rapid growth, their inequality did not rise (Stiglitz, 1996), rather inequality has been decreased in these countries. Second, Piketty (2013) and Piketty & Saez (2003) argue that, despite being in the advanced level of development, income inequality is still increasing in the United States. Moreover, Piketty (2013) states that slower economic growth increases inequality.

Piketty's argument is observed in many countries, including the East Asian countries. After the decades of rapid growth, East Asian countries have lost their pace to economic growth in recent decades. Along with slower growth, income inequality is also rising in these countries. After 1990, inequality has continued to rise in these countries including Japan and Taiwan (Jain-Chandra, Kinda, Kochhar, Piao, & Schauer, 2016).

We argue that *uncertainty-inequality relationship* can give suitable explanations to both Stiglitz's (1996) and Piketty's (2013) arguments. According to Stiglitz (1996), by land, labor, industrial and other policies, EAM countries have successfully reduced inequality. However, we state that, if Stiglitz's policies help to create more jobs in dependent employment (see Appendix A1: proportion of Taiwan's male and female workers), then by increasing the share of *DE*s, EAM countries have reduced income inequality. On the other hand for Piketty's argument it can be said that, when economic growth slows down, the job creation rate in dependent employment is also abated[8]. Which implies increased share of independent employees create extra uncertainty to overall labor earning. In this channel the uncertainty to labor earning increases and thus leads to higher income inequality.

4. Benchmark Life Cycle Model

4.1. Our Life-Cycle Model

In this section we set up a life-cycle model of job-choices where the labor earning shock depends on employment status of the individual. According to this model, by maximizing her life-time utility, an individual chooses to work either as an Independent or a Dependent employee in the beginning of her career. A dependent employee (*DE*) faces an age-dependent separation probability along with the career path. On the other hand an independent employee (*IE*) has an age-specific probability to obtain a dependent employment conditional on her employment status. We detail the process in the following subsections.

4.1.1. Demographics and preferences

A model period is one year long and each individuals working life spans T_r periods. We do not claim that the labor market is segmented (Reich, Gordon, & Edwards, 1973), rather it is a choice of an individual to work dependent or independently. The individual who chooses to be a dependent employee in the beginning of the career face age-specific separation probability. In the United States job finding rate and job separation rate monotonically decrease throughout the life-time (Esteban-Pretel & Fujimoto, 2014). We assume that a *DE* faces an age-specific separation probability which is similar to the job separation rate. On the other hand, given the separation[9] rate, we estimate the conditional probability of an *IE* to get a job in *DE* from the model.

[8] It has been found that the job separation rate in the United States remained steady for many decades irrespective of recession or expansion (Hall, 2005).

[9] The job separation rate in the U.S. has been steady for many decades (Hall, 2005). Therefore if the job separation rate is proportionally attributed to all types of jobs, then it can be said that *DE*s face the same separation probability as the overall separation rate documented in literature.

At age t an individual's occupation o_t can be either *IE* ($o_t = 1$) or *DE* ($o_t = 2$). The employment status evolves according to the process defined in equations (15) and (16), *i.e.* one's employment status depends on her/his employment status in previous period and current age.

$$\pi_t^F(o_{t=2}|\, o_{t=1}) = \begin{cases} \upsilon_1 + \omega_1\, t & for\ t \le t_1 \\ \upsilon_2 t^{\omega_2} & for\ t_1 < t \le t_2 \\ 0 & otherwise \end{cases} \quad \dots \quad (15a)$$

$$\pi_t^F(o_{t=2}|\, o_{t=1}) = \begin{cases} \upsilon_0 - \upsilon_1\, t + \upsilon_2\, t^2 & for\ t \le t_1 \\ \omega_0 - \omega_1\, t - \omega_2\, t^2 & for\ t_1 < t \le t_2 \\ 0 & otherwise \end{cases} \quad \dots \quad (15b)$$

$$\pi_t^S(o_{t=1}|\, o_{t=2}) = \upsilon t^{\omega} \quad \dots \quad (16)$$

where π_t^F is the conditional probability of an IE to find a job in dependent employment, and π_t^S is the separation rate that a dependent employee faces conditional of her/his employment. Equation (15a) is for male workers and equation (15b) for female workers.

Individuals who do not participate in the labor market have zero labor earnings and not observed in our model. The job separation rate remains steady in the United States irrespective of major economic events like expansions or recessions (Hall, 2005). We assume the age-specific separation rates are also stable over time. We also assume that number of individuals who move out of working status to non-working (unemployed plus out of labor force) status is immediately and exactly replaced by the number of individuals that move into the working status. Thus we expect the conditional probability of getting a dependent employment for an *IE* remains steady across time (though it varies across ages).

Individual's employment status affects her/his productivity and disutility of work (θ) in dependent employment relative to independent employment. We assume agent's discount factor β is constant across ages. The agent is endowed with one unit of time that is indivisible labor supply in either of the employments. We set the preferences of agents over consumption take the following form:

$$u(c_t, o_t) = \frac{c_t^{1-\gamma}}{1-\gamma} - \theta \mathbf{1}_{\{\boldsymbol{o_t=2}\}} \quad \dots \quad (17)$$

where $\mathbf{1}_{\{.\}}$ is an indicator function which is equal to one if its argument is true and zero otherwise, θ is the utility cost of dependent employment relative to independent jobs and γ is risk aversion coefficient.

4.1.2. Labor income and human capital

The labor earning of the individual is employment dependent (see Appendix A3). The labor earning y_t and the idiosyncratic productivity z_t takes the following forms:

(1) For dependent employees

$$\log y_t^{DE} = \mathcal{H}^{DE}(h, t|o = 2) + {z_t}^{DE} + {\eta_t}^{DE} \quad \dots \quad (18)$$

$$z_t = \rho z_{t-1} + \varepsilon_t^{DE} \quad \dots \quad (19)$$

where $\varepsilon_t^{DE} \sim N(0, \sigma_{\varepsilon DE}^2)$ and $\eta_t^{DE} \sim N(0, \sigma_{\eta DE}^2)$ are the persistent and transitory components of the idiosyncratic productivity. The deterministic part of earning is a function of human capital (h) which evolve with experience conditional on the employment status in the following expression.

$$\mathcal{H}^{DE}(h, t|o = 2) = \phi + h + a_{DE} t - b_{DE}\, t^2 \quad \dots \quad (20)$$

where, ϕ is the earning premium for the dependent employees relative to independent employees[10] (Blundell, Dias, Meghir, & Shaw, 2016). We assume that the earning premium is additive in log-earning.

(2) For independent employees, similarly

$$\log y_t^{IE} = \mathcal{H}^{IE}(h, t|o = 1) + z_t{}^{IE} + \eta_t{}^{IE} \quad ... \quad (21)$$

$$z_t = \rho z_{t-1} + \varepsilon_t^{IE} \quad ... \quad (22)$$

where $\varepsilon_t^{IE} \sim N(0, \sigma_{\varepsilon IE}^2)$ and $\eta_t^{IE} \sim N(0, \sigma_{\eta IE}^2)$ are the persistent and transitory components of the idiosyncratic productivity. The deterministic part of earning is a function is given as:

$$\mathcal{H}^{IE}(h, t|o = 1) = h + a_{IE} t - b_{IE}\, t^2 \quad ... \quad (23)$$

In some literature initial distribution of earning has been attributed to the human capital distribution (Huggett, Ventura, & Yaron, 2011) and this distribution carried over throughout life cycle. In this paper we add a tiny change to it. We argue that, to estimate the human capital distribution we use unconditional distribution of earning whereas the variance profile we observe in the data is constructed from the conditional variance on working. Following Storesletten, et.al. (2004) we estimate the inequality due to human capital and transitory component together as $(\sigma_\eta^2 + \sigma_\alpha^2)$.

4.1.3. Timing of the model

The timing of the model is as follows. We assume a period unit consists of one year. At the beginning of the career the agent decides (o_t) whether to work dependent or independently based on one's asset and human capital. Those who are employed as dependent (*DE*) choose to remain dependent employees, although at the end of each period they face a separation probability from the job.

Those who choose to work independently, at the beginning of each period enjoy chances to be employed as dependent employees conditional on their current status. Taking the information into account, the agent chooses to work dependently or independently. For male workers, until mid-twenties every period they have higher chances than previous period. Since mid-twenties chances monotonically decline every period. After the mid-fifties the chance of getting a *DE* disappears. However, for female workers, as they approach 30 their chances of DE fall and after 30 till 40 chances increase. After 40 chances fall monotonically similar to male workers.

After age 60, in addition to separation probability the dependent employees face retirement probabilities from their career jobs. After the formal retirement many individuals work as independent employees which increases the share of independent employees in the end of working life.

[10] In Blundell, et.al. (2016) the coefficient has been used a return to experience conditional on education or skill. The assumption implies that human capital maps into earning one-to-one so agent accumulates human capital based on skill or education. However, we assume that same amount of human capital can yield differential earning profile depending on the employment status (see Appendix A3). For example, the same individual earns different amount of income depending on her employment status even though her human capital remains unchanged. Suppose Ms. X, a University Professor, takes 2 periods (years) leave for her newborn and during that time works as an online tutor. According to Blundell, et.al. (2016) her human capital is heavily depreciated for 2-periods and she cannot recover this for rest of her working life. However, in reality when she joins her job two periods later, she immediately returns to the same earning profile where she left it. Upon this situation we assume that though human capital grows following Ben-Porath (1967) equation, earning is not solely determined by human capital. Earnings depend on the experience or human capital an individual accumulates as well as the occupation she is working on.

The working life of an individual span from age 20 to age 65 (25 to 65 for female workers) which ends deterministically at 65. After the full retirement individual do not work. And an individual lives for another 10 years after full retirement.

4.1.4. The optimization problem

We simplify the agent's optimization problem by assuming that after retirement everyone receives the same retirement benefit (pb). Therefore the amount received at the end of working life does not impact the individual's decision to choose an employment at the beginning of her career[11].

The agent optimizes her life-time utility given her asset, human capital and a persistent shock to her earnings. As she employs full of her labor endowment as a worker, leisure is not a choice in this model. She choose to consume c_t and save k_{t+1} for the future periods. Conditional on the employment status the human capital evolves deterministically, implicating that she has full information of her human capital and thus her corresponding earnings at time (t).

She solves the following problem recursively and chooses to work as dependent or independently at the beginning of her career.

Independent Employees:

$$V_t^{IE}(k_t, h_t, \varepsilon_t) = \ max_{\{c_t, k_{t+1}\}}\{u(c_t, o_t) + \ \beta\ E[W_{t+1}^{IE}(k_{t+1}, h_{t+1}, \varepsilon_{t+1})]\} \ \dots \quad (24)$$

$$W_{t+1}^{IE}(k_{t+1}, h_{t+1}, \varepsilon_{t+1}) = \ \pi_t^F\left[max_{o\epsilon\{IE,DE\}}\{V_{t+1}^o(k_{t+1}, h_{t+1}, \varepsilon_{t+1})\}\right] + \ (1-\pi_t^F)[\{V_{t+1}^{IE}(k_{t+1}, h_{t+1}, \varepsilon_{t+1})\}]$$

Subject to the budget constraint given as:

$$k_{t+1} = \ k_t(1+r) + \ y_t^{IE} + pb\mathbf{1}_{\{\boldsymbol{t\geq 65}\}} - \ c_t$$

Dependent Employees:

$$V_t^{DE}(k_t, h_t, \varepsilon_t) = \ max_{\{c_t, k_{t+1}\}}\{u(c_t, o_t) + \ \beta\ E[V_{t+1}^{DE}(k_{t+1}, h_{t+1}, \varepsilon_{t+1})]\} \ \dots \quad (25)$$

Subject to the budget constraint:

$$k_{t+1} = \ k_t(1+r) + \ y_t^{DE} + pb\mathbf{1}_{\{\boldsymbol{t\geq 65}\}} - \ c_t$$

where, V_t^{DE} and V_t^{IE} are the value functions respective to dependent and independent employment. pb is the common pension benefit, β is the common discount factor for all the agents and r is the returns to non-human capital.

4.2. Model parameters estimation

We estimate the parameters in two steps. Initially we estimate some of the parameters outside the model and take some of them from existing literature. In second step we calibrate the model and estimate the parameters from the simulated sample by targeting the data moments.

4.2.1. First step estimation

Without solving the model the first collection of parameters are set by borrowing from existing literature. We report these parameters in Table 3 along with their corresponding sources. These parameters mainly govern the demographics and preferences.

[11] This assumption gives us additional benefit that the part of labor earning variance created by the pension payment (which is in some literature accounted as labor earning) is eliminated.

Table 3 Parameter Values: Taken from other sources

Category	Symbol	Parameter Value	Sources
Demographics	(T, T_R)	(55, 40)	Hugget, et.al. (2011)
Preferences	(β, γ)	(0.98, 2)	Storesletten, et.al (2004a)
Return to non-human capital	(r)	0.04	Hugget, et.al. (2011)
Persistence Parameter	(ρ)	0.99	Storesletten, et.al.(2004)

Demographics – Following Hugget, et.al. (2011) we set the demographics as (T, T_R) using model period of one year. An agents working life starts at real age 20 and she lives until real age 75. After age of 60 agents start retiring (Huggett, Ventura, & Yaron, 2011) form work and at age 65 everyone decides to retire (Storesletten, Telmer, & Yaron, 2004).

Preferences – The value of discount factor is set to be 0.98 and the value for risk aversion is taken as 2. Storesletten, et.al. (2004a) along with Hugget, et.al. (2011) uses these values in respective analyses. The value of the risk aversion parameter ($\gamma = 2$) is mid-value of the range of estimates based upon micro data (Browning, Hansen, & Heckman, 1999).

Return on capital – We set the parameter to be $r = 0.04$ which is used by Hugget, et.al. (2011) as equilibrium real return to capital. A similar value is also used by Storesletten, et.al. (2004) as an equilibrium outcome.

Persistence – The persistence parameter is very close to one (Rahman, 2017). In this study, this is one of our major research objectives. We set $\rho = 0.99$ which is argued by Storesletten, et.al. (2004). It has estimated the value of the persistence parameter 0.9989.

Table 4 Parameter Values: Estimated outside the model

Category	Symbol	Parameter Values
Separation Rate (for both)	(υ, ω)	(0.1176, -0.606)
	For Male workers	
Human Capital accumulation (DE)	(a_{DE}, b_{DE})	(0.074,0.0012)
Human Capital accumulation (IE)	(a_{IE}, b_{IE})	(0.095, 0.0016)
Initial condition (at age 20)	$\psi \sim LN(\mu_h, \sigma_h^2)$	(9.62,0.25)
	For Female workers	
Human Capital accumulation (DE)	(a_{DE}, b_{DE})	(0.0271, 0.0006)
Human Capital accumulation (IE)	(a_{IE}, b_{IE})	(0.0416, 0.0008)
Initial condition (at age 25)	$\psi \sim LN(\mu_h, \sigma_h^2)$	(10.15,0.15)

Note. The separation rate parameters are estimated from the age specific separation rates (see Table – 5 and Figure – 3) given in Table – 2 of Gervais et.al. (2016). Other parameters in this table are estimated from LIS(2017).

In Table 4 we report the parameter values that we estimate from data outside the model. However, the separation rate we do not estimate from LIS (2017) data, rather we take it from Gervais, Jaimovich, Siu, & Yedid-Levi (2016), which estimates the life cycle job separation rate in the U.S. (from Current Population Survey (CPS) data) over the life-cycle using various methods including Shimer (2005).

Separation rate – We assume that the probability of separation from a dependent employment evolves as a function of age, and we estimate the parameters from the profile constructed by Gervais et.al. (2016) using Shimer's (2005) method from CPS data (see Figure – 3 and Table – 5). Though Shimer's method has certain limitations, it provides a suitable framework for this paper. According to this method workers move only between the status of employment and unemployment. Movement in and out of the labor force is not taken into account.

Similarly, to simplify our model, we assume that workers move between the status of dependent and independent employments. A non-worker in our model could be unemployed or a person out of labor force[12], who has zero labor earning. We also assume that whenever a worker moves out of working status, she is immediately replaced by her lookalike.

Hall (2005) finds that the job-separation rate in the United States remains steady for many decades. Considering this fact, we argue that a dependent employee faces a separation probability over her life cycle which is age dependent but remains stable across time. Upon this argument we take Gervais et.al. (2016) profile of separation rate as given and estimate separation rate function.

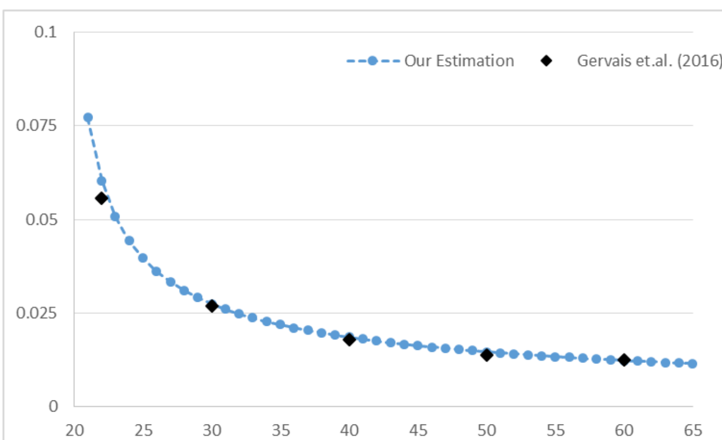
Table 5 Job separation rate profile of dependent employees in the United States

	20-24	25-34	35-44	45-54	55-64
Gervais et.al. (2016)	5.58	2.70	1.79	1.39	1.26
Our estimation	5.82	2.94	1.90	1.48	1.25

Note. The separation rate profile has been taken from Table 2. in Gervais et.al. (2016), which is constructed by using Shimer (2005) approach from CPS data.

Several literature find that the job-separation rate in the United States monotonically decreases (Esteban-Pretel & Fujimoto, 2014; Gervais, Jaimovich, Siu, & Yedid-Levi, 2016) over the life cycle. We estimate parameters using a non-linear regression (a power function) from Gervais et.al. (2016) profile given in Table 5. The fitted regression line is given in Figure – 3.

Figure 3 Separation rate profile of dependent employees in the United States



Note. The age-group specific separation rates (black squares) are taken from Table – 2 of Gervais et.al (2016) and the blue line shows age specific separation rates (author's estimation).

[12] In support of the assumption we can say that, if the movement in and out of the working status remains steady in the population then this movement does not impact the conditional probability of an independent employee to receive an opportunity of dependent employment. We acknowledge that this is a crude measure of conditional probability and can often lead to misleading conclusion (if the movement differ significantly), however, it not only provides a very simple and strong framework, but also provides an unbiased and consistent estimate of the conditional probabilities.

Human capital accumulation – Following Ben-Porath (1967) we argue that an agent's human capital accumulation creates a hump-shape profile which we estimate as a quadratic function. In Hugget et.al. (2011) and Blundell et.al. (2016) human capital accumulation is a monotone increasing function along with a depreciation of human capital. We use a quadratic function which accommodate an age-dependent human capital depreciation and a constant rate of accumulation over the working life. Hugget et.al. (2011) and Blundell et.al. (2016) argue that human capital is accumulated at a decreasing rate and depreciates at a constant rate, whereas we argue that human capital is accumulated at a constant rate and depreciates at increasing rates as the working life moves on. In the end both the arguments produce similar profile for life cycle human capital.

Initial Condition – In many literature it is assumed that human capital follows a log-normal distribution (Hugget, et.al. 2011). Since we only observe the conditional distribution workers' of earning at age 20 (initial stage of the male agent's career; for female agents at age 25), we assume that an agent's log-earning can be a proxy of her human capital and it would follow a normal distribution if there is no self-selection in the sample (Heckman, 1979). If it is reasonable that only those that have lower human capital do not work, then the selection only affect one side of the distribution.

We can say without the selection the median of the distribution coincides with mean, which is distorted by the selection. We set the median of the distribution to be unconditional mean and estimate the variance by the six-sigma (6σ) rule of normal distribution. The initial unconditional variance we estimate as 0.25 (for male workers) whereas Hugget, et.al. (2011) claims the initial distribution to be 0.213.

4.2.2. Second step estimation

In the second step of estimation process we set the parameters to be fixed that we obtain in first step. Rest of the model parameters we estimate from the model by simulated method of moments. Some study target the data moments by minimizing the squared difference between data and model moments (or squared distance of log moments of the two (Huggett, Ventura, & Yaron, 2011)).

However, to do so we found that it is computationally expensive. And some moments are very large compared to other data moments, so the relative weights of the minimization problem also becomes an issue. To avoid these costs, we simulate the model several times and target the data moments in phases. The parameters estimated by method of simulation are given in Table 6.

Utility cost – In first phase, we target the proportion of dependent and independent male-employees at age 20 (for female at 25). We let the individual solve the recursive problem and choose whether to work dependent or independently. By simulating the model to and forth we estimate the utility cost (θ) of dependent employment relative to independent employment[13].

Conditional probability – In the following phase we target the share of the independent employees among the total workers at every age throughout the working life (see Figure – 4). We estimate the parameters of conditional probability function. Esteban-Pretel & Fujimoto (2014) and Gervais, et.al. (2016) opine that job finding rate monotonically declines with age in the United States. Our estimated parameters construct a similar profile, however, in the beginning of the working life the conditional probability for male workers

[13] We use a fixed utility cost for dependent employment relative to independent employment. However, an age dependent θ can be a better argument as the utility cost of dependent employment should increase with age. When individuals grow older they feel the cost of dependent employment is higher than that at younger ages. The age dependent θ will also change our measure of conditional probability to obtain a dependent job for an independent employee. However, it does not change our conclusion regarding the persistence of the earning shocks, which is employment dependent. Therefore, to keep the model simpler we use a fixed utility cost throughout the working life.

increases until mid-twenties[14] ($t_1 = 25$). Probably because in the beginning of the working life, the independent employees complete education and gradually enter the dependent employment. Moreover, after mid-fifties ($t_2 = 57$) an independent employee cannot find a job in dependent employment. For female workers ($t_1 = 40$) which implies after age 40 the conditional probability for a female IE decreases monotonically. However, from 25 to 40 the conditional probability curve takes a U-shape. Probably because, for child bearing, until age 30 they gradually leave *DE* and after 30 they gradually again start working in *DE*.

Table 6 Parameter Values: Estimated within the model

Category	Symbol	Parameter Values
	For Male workers	
Variance of Persistent component	$(\sigma^2_{\varepsilon DE}, \sigma^2_{\varepsilon IE})$	(0.0044, 0.0121)
Variance of transitory component	$\left(\sigma^2_{\eta DE} + \sigma^2_{\alpha DE}\right)$	(0.28)
(including fixed effect)	$(\sigma^2_{\eta IE} + \sigma^2_{\alpha IE})$	(0.49)
Conditional probability of IE	(υ_1, ω_1)	(0.22, 0.0143)
(to get a DE)	(υ_2, ω_2)	(0.17, 0.0411)
Earning premium (DE)	(ϕ)	(0.47)
Utility cost (DE)	(θ)	(0.0027)
	For Female workers	
Variance of Persistent component	$(\sigma^2_{\varepsilon DE}, \sigma^2_{\varepsilon IE})$	(0.0016, 0.0072)
Variance of transitory component	$\left(\sigma^2_{\eta DE} + \sigma^2_{\alpha DE}\right)$	(0.34)
(including fixed effect)	$(\sigma^2_{\eta IE} + \sigma^2_{\alpha IE})$	(0.56)
Conditional probability of IE	$(\upsilon_0, \upsilon_1, \upsilon_2)$	(0.2, 0.012, 0.005)
(to get a DE)	$(\omega_0, \omega_1, \omega_2)$	(0.12, 0.0003,0.0003)
Earning premium (DE)	(ϕ)	(0.7)
Utility cost (DE)	(θ)	(0.46)

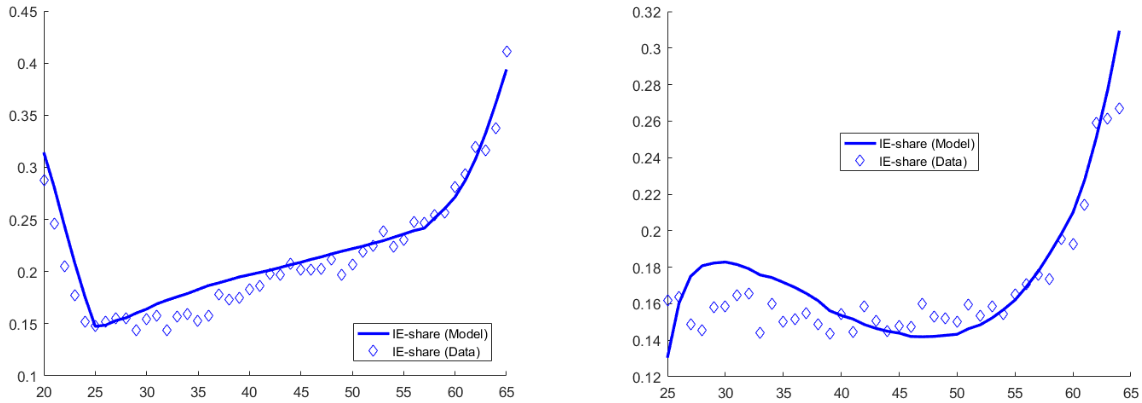
Note. The parameters in the table are estimated by using the Method of Simulated Moments (MSM). We match the data moments (obtained from LIS (2017)) with the moments obtained by simulating the model.

Earning premium (DE) – After matching the *IE*'s share among the workers we target the average log-earning profiles of *IE*'s and *DE*'s (see Figure – 5). In this stage we set the initial average earning of a worker with no experience and an earning premium for the *DE*'s. We estimate the *DE*'s earning premium for male workers as an additive constant to the log-earning ($\phi = 0.47$). However, in level it accounts for 60 percent additional earning for a *DE* compared to that of an *IE*. For female workers ($\phi = 0.7$) which accounts for almost double income of a *DE* compared to an *IE* in the level.

Distribution of earning shocks – When the average earning profile is matched, it is easier to adjust the variance of persistence and transitory components as they do not affect the average earning profiles (see Figure – 6). In the final phase of simulation we target the persistence ($\sigma^2_{\varepsilon DE}$) and transitory $\left(\sigma^2_{\eta DE} + \sigma^2_{\alpha DE}\right)$ components (see appendix A3) of the dependent employees. In the end we match the overall variance profile by setting the parameters for independent employees earning shocks.

[14] For male workers t_1 and t_2 are reported age real age of 25 and 57. In the model they are 6 and 38 respectively.

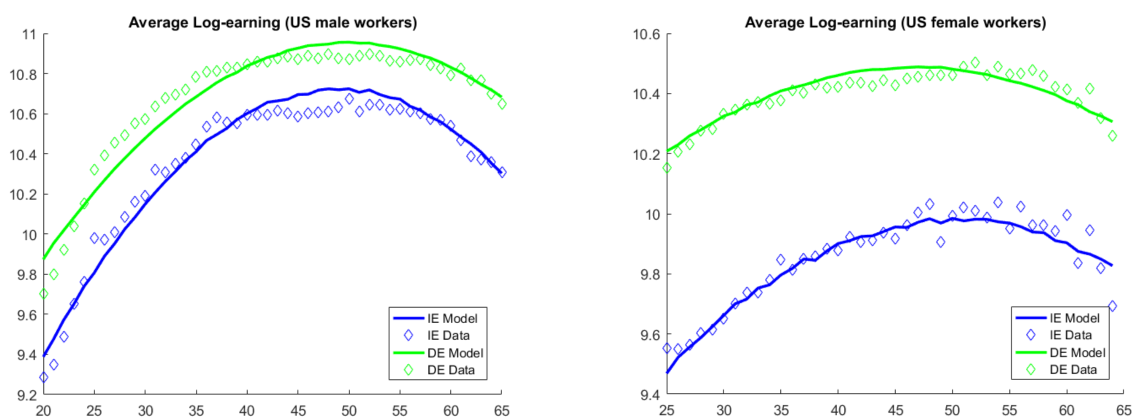
Figure 4 Share of independent employees among total workers in the US



(a) Share of IE's among male workers (b) Share of IE's among female workers

Note. The blue squares represents the age – specific independent employee shares (author's calculation) obtained from LIS (2017). The blue lines are derived by simulating the benchmark model. We change the relevant parameters (see Table – 6) until the data moments and the model moments are matched.

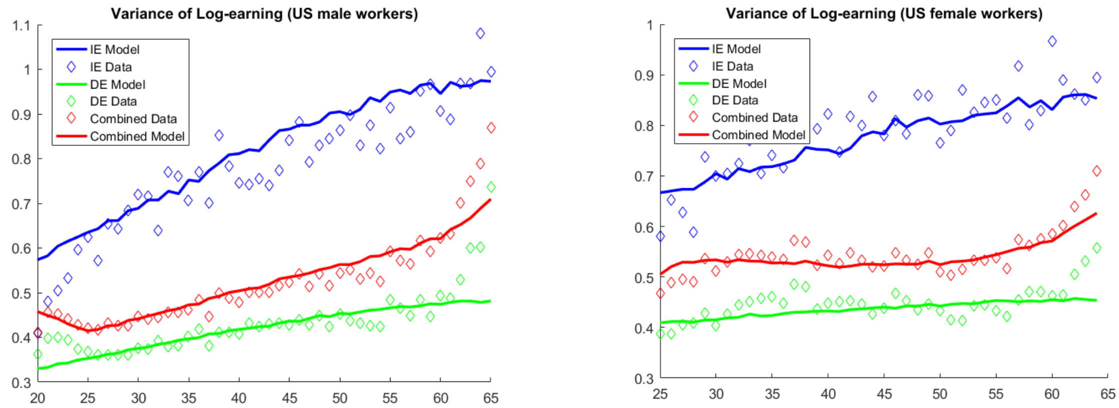
Figure 5 Average log-earning profile of dependent and independent employees



(a) Average log-earnings of US male workers (b) Average log-earning of US female workers

Note. The squares represents the age – specific average of log labor earnings (author's calculation) obtained from LIS (2017). The blue squares represent average log-earning of IEs in the U.S. whereas the green squares represent the DE's average log-earnings. The lines are derived by simulating the benchmark model. We change the relevant parameters (see Table – 6) until the data moments and the model moments are matched. The blue lines represent average log-earning of IEs in the U.S. and the green lines represent the DE's average log-earnings.

Figure 6 Log-earning variance profiles in the United States



a) Log-earning variance profile (male) b) Log-earning variance profile (female)

Note. The squares represents the age – specific variances of log labor earnings (author's calculation) obtained from LIS (2017). The blue squares represent log-earning variances of IEs in the U.S. whereas the green squares represent the DE's log-earning variances. The red squares represent the overall log-earning variances in the data. The lines are derived by simulating the benchmark model. We change the relevant parameters (see Table – 6) until the data moments and the model moments are matched.

4.3. Performance of the benchmark model

In Table – 7 we compare our estimates for male workers with existing literature, however there is not enough study that documents the earning shock distribution for female workers. Therefore, we leave it for future studies. By using PSID data Storesletten et.al. (2004) estimates the variance of the persistent component to be $\sigma_\varepsilon^2 = 0.0166$, whereas our estimates for dependent and independent employees are $\sigma_{\varepsilon DE}^2 = 0.0044$ and $\sigma_\varepsilon^2 = 0.0121$ respectively. For the variance of transitory component including individual fixed effects in Storesletten et.al. (2004) is $\sigma_\alpha^2 + \sigma_\eta^2 = 0.2735$. However, our results are $\sigma_{\alpha DE}^2 + \sigma_{\eta DE}^2 = 0.28$ and $\sigma_{\alpha IE}^2 + \sigma_{\eta IE}^2 = 0.49$ respectively.

Table 7 Comparison of our estimates (for male workers) with previous studies

	Our Estimates	**Storesletten et.al.** (2004)
Distribution of persistent shock	$\sigma_{\varepsilon DE}^2 = 0.0044, \sigma_\varepsilon^2 = 0.0121$	$\sigma_\varepsilon^2 = 0.0166$
Distribution of transitory shock (including fixed effect)	$\sigma_{\alpha DE}^2 + \sigma_{\eta DE}^2 = 0.28$ $\sigma_{\alpha IE}^2 + \sigma_{\eta IE}^2 = 0.49$	$\sigma_\alpha^2 + \sigma_\eta^2 = 0.2735$
		Hugget, et.al. (2011)
Initial human capital distribution	$\sigma_h^2 = 0.25$	$\sigma_h^2 = 0.213$

In the following chapter, we calibrate the benchmark model that has been set up here. We use different policy interventions and compare the outcomes of different policies with that of the benchmark model of this chapter.

5. Policy Simulation

To investigate Stiglitz's (1996) argument in the benchmark model we add more chances for independent employees to find a dependent job. And we compare the inequality of benchmark model with that of the new scenario. Similarly to review Piketty's argument we set that independent employees have less chance compare to benchmark model to find a dependent job. We compare the inequality measures between both scenarios.

5.1. Analysis and Findings

From the benchmark life-cycle model that we set up in Chapter – 2, we generate a simulated sample of N individuals who are observed for T years. Which implies that in total we have $N \times T$ individual – year observations. These individuals are present in the economy for T years whereas inequality is usually measured on a particular period in time. The question is – *how much significance does it carry if we measure the inequality from all these individual – year observations*?

The question can be answered by using the argument in Deaton (1985). According to Deaton (1985) a panel data can be created from a series of cross-sectional data sets. Using this same argument, we can show that from a panel data set we can also create a cross-sectional data set.

Suppose we eliminate the calendar year effect on labor earning from a panel data set. Then let us assume that all these individuals are being surveyed on the same period and are separated in different age groups. If in the panel data we only observe a particular age-cohort for T periods, then it can be argued that the birth year effect is same for all individuals.

Given the argument in the above paragraph we can say that, we can consider the hypothetical panel data set created by the benchmark model simulation as a cross-sectional data. In this cross-section data the earning inequality is net of calendar year effects and birth-year effects. Nonetheless, this data set provides us enough information for policy simulation and observe the results of policy interventions.

We take all the observations as observations of a particular time and measure the earning inequality from the benchmark model. The benchmark model reports the Gini coefficient for earning inequality to be 39.71 percent, while the Gini coefficient for overall income inequality in the United States was 45 percent in 2007 (CIA, 2017). We argue that the estimate from the benchmark model is not unrealistic, since income inequality is higher than earning inequality and also mostly contributed by earning inequality. In our benchmark scenario, the earning Gini coefficient accounts for 88 percent of income Gini coefficient of U.S. in 2007.

Table 8 Benchmark model and policy interventions

	Gini coefficient
Overall income inequality in US (2007)	45.00
Earning inequality in benchmark model	39.71
Earning inequality *(5% more chance to find a job in DE by an IE)*	38.71
Earning inequality *(15% more chance to find a job in DE by an IE)*	37.88
Earning inequality *(15% less chance to find a job in DE by an IE)*	43.50
Earning inequality *(if all workers are dependent employees)*	36.72

We experiment three different policy scenarios. First we increased the chances of an *IE* to find a job in *DE* by 5 % (for all ages). Second we increase the chance further to 15 % compared to the benchmark scenario. Finally, we decreased the chances of an *IE* to find a job in *DE* by 15 % than that of the benchmark model.

We find that when the chances of finding a job in *DE* by an *IE* is higher than the benchmark scenario, earning inequality reduces. In addition when the chances are low inequality rises. Which implies increased chances of finding a job in *DE* by an *IE* increases the share of *DE*s among all workers. And an increased share of *DE*s decreases the overall earning uncertainty[15] (Rahman, 2017; Guiso, Jappelli, & Pistaferri, 2002). Thus we can say that, earning inequality is reduced because of reduced earning uncertainty, which completes the proof of *proportion and uncertainty hypothesis* (PUH).

Figure – 7 shows the Lorenz curves for the policy interventions along with the benchmark scenario. The Lorenz curves in the figure is consistent with the measures of earning inequality given in Table – 8. Comparing the results of policy interventions, we can say that our Proportion and Uncertainty Hypothesis (PUH) is true. Increased job opportunity in dependent employment, increases the share of *DE*s among the workers in the economy. An increased share of *DE*s, reduces the overall earning uncertainty. And which through the earning inequality reduces the income inequality.

In Taiwan (and other EAM countries like Japan), for young workers, opportunity to work in dependent employment sector in very high. As a result more than 90 percent (see Table – 2) workers work in dependent employment in their early working life. Probably the high opportunities for dependent employment are created by Stiglitz's policies such as land policy, industrial policy, labor policy, education policy etc.

Moreover, if the opportunity to work in dependent employment is reduced or the share of *DE*s is decreased, more workers are susceptible to high uncertain earnings, which results in higher inequality through the same channel mentioned in earlier paragraph. Probably this statement can explain Pikkety's argument that 'slower growth raises inequality' given that, share of *DE* is decreased by slow growth or recession.

6. Conclusion

6.1. Summary of findings

Although the flagship finding of this paper is '*less uncertainty, less inequality*', the overall findings are many folds. It is found that labor earning shock (for both male and female workers) is highly persistent – in other words, if an individual receives a high earning shock in current period, she is highly likely to receive a similar high shock in next period.

In addition, it is observed that, Deaton (1985) and Deaton & Paxson (1994) give a strong evidence that, life-cycle models with stochastic earning can be studied by using cross-sectional data. This finding is important, because, most of the studies in life-cycle models with stochastic earning are based on panel data. However, in most of the countries across the world panel data are not only scarce, but also they are not as good as PSID. Our findings can encourage more researchers to study life-cycle models with stochastic earning by using cross-sectional data sets.

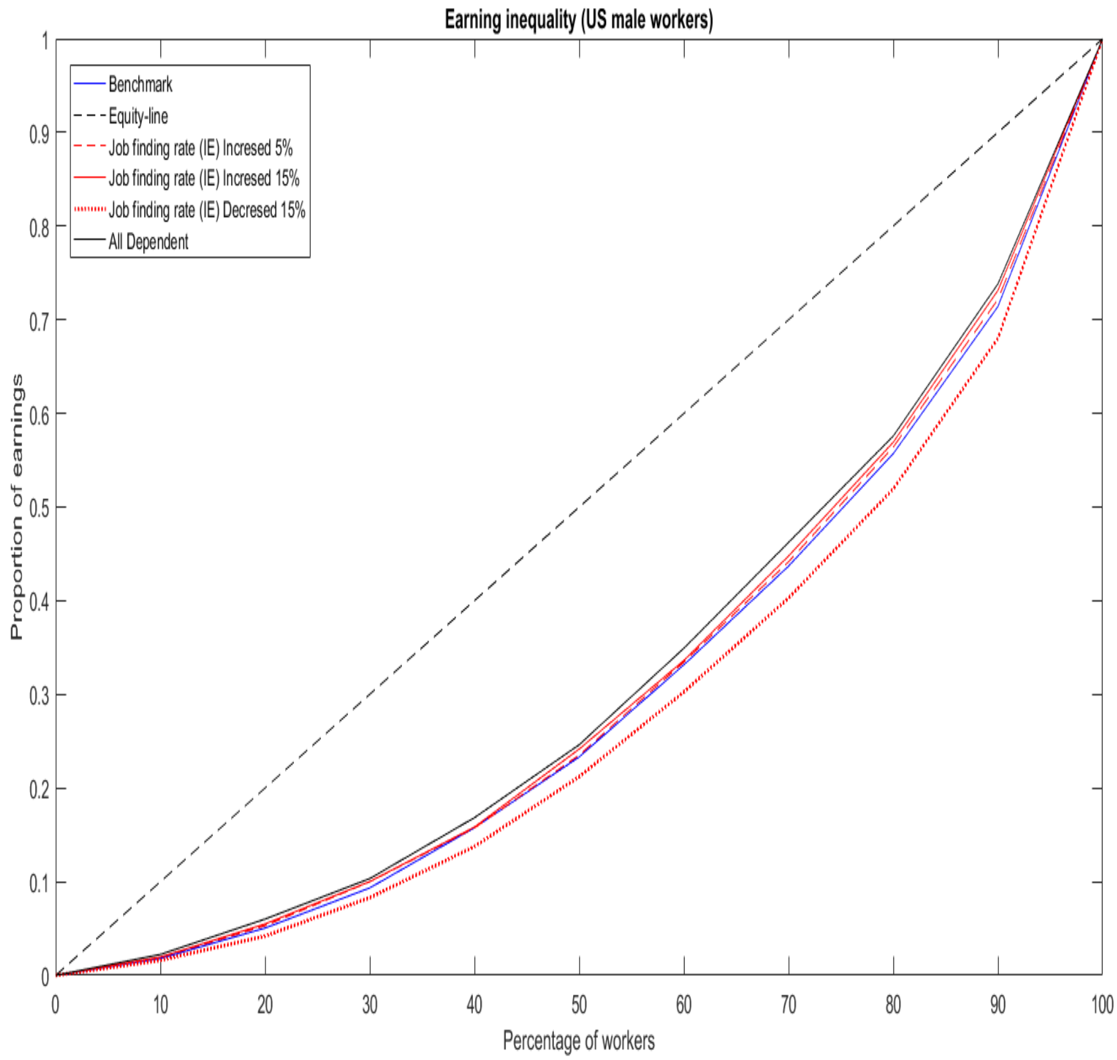
6.2. Policy recommendations

The policy recommendations are more or less obvious. Irrespective of countries or economies across the world, policymakers along with academicians or researchers should acknowledge that *uncertainty* is a source of income inequality. How to address the group specific uncertainties – is not the focus of this paper. The ways of addressing group specific uncertainties can vary across countries or across times. However, one policy that fits for all countries and in all times is to increase the share of less volatile dependent

[15]Since the DEs face low uncertainty compared to IEs, an increase in DEs share reduces the share of IEs. Therefore, the uncertainty of the overall economy which composed of all the workers reduces.

employment for more equitable income redistribution. Nonetheless, this paper emphasizes only on the direct channel between uncertainty and income inequality.

Figure 7 Lorenz curves for benchmark model and policy interventions



6.3. Policy concern

Policymakers should be careful that, some inappropriate policies may also increase DE – share and reduce inequality: for example – pushing some IEs out of political boundary, or compelling some IEs to get rid of labor force, etc.

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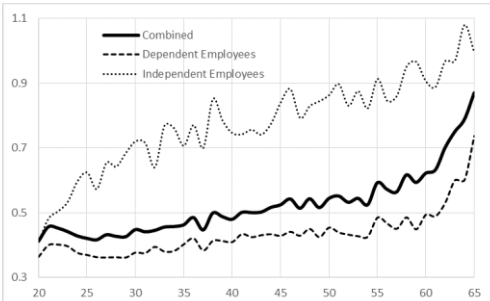
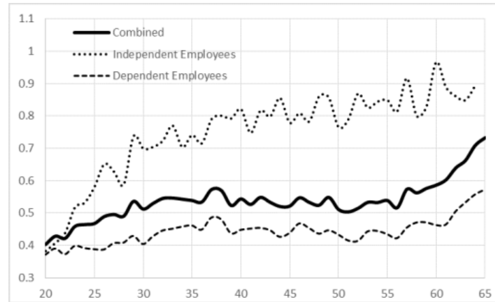
Appendices

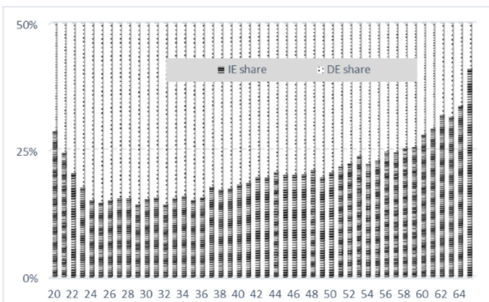
A1 Log earning variance profiles by types of employees in the Unites States and Taiwan



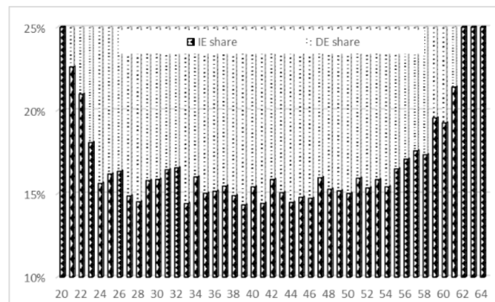
United States male workers



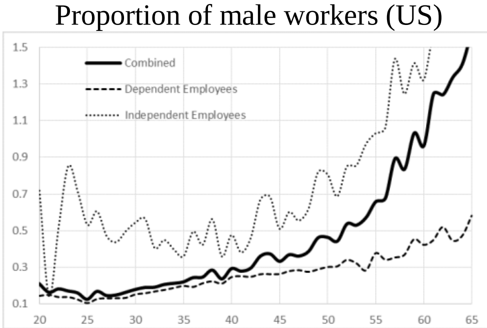
United States female workers



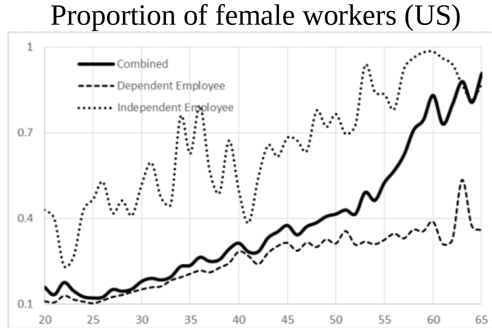
Proportion of male workers (US)



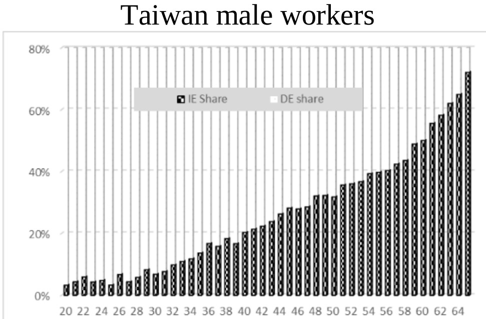
Proportion of female workers (US)



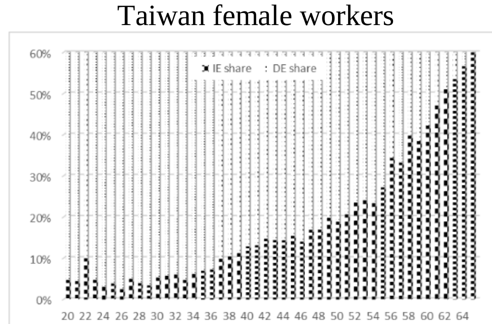
Taiwan male workers



Taiwan female workers



Proportion of male workers (Taiwan)



Proportion of female workers (Taiwan)

Note. This figure has been replicated from Rahman (2017). Following this paper in this study we also compare between U.S. and Taiwan. In many other related literature a comparison between U.S. and Taiwan is often observed (Deaton & Paxson, 1994; Deaton & Paxson, 1995; Deaton & Paxson, 1997).

A2 Sample Code to use data from LIS database for United States male workers

```
append using $us04p $us07p $us10p $us13p
keep if sex==1 & age>19
sum  hid pid year wave relation pil  oddjob_c  status1 status2 sector1 fyft ptime
tab sex  * Check if only male or not
gen worker=0
replace worker=1 if pil>0 & pil<.
tab year if worker==1 , sum(pil)
tab year  status1 if worker==1
gen labinc= .
replace labinc=pil if worker==1
gen y04=0
replace y04=1 if year==2004
gen y07=0
replace y07=1 if year==2007
gen y10=0
replace y10=1 if year==2010
gen y13=0
replace y13=1 if year==2013
reg labinc y04 y07 y10
gen norminc=.
replace norminc=labinc + 8658.355 if year==2004
replace norminc=labinc + 4067.524 if year==2007
replace norminc=labinc + 3902.875 if year==2010
replace norminc=labinc  if year==2013
sum norminc, det
replace norminc= 4514.5 if norminc<4514.5
replace norminc=293902.9 if norminc>293902.9 & norminc<.
gen loginc=.
replace loginc= log(norminc)
gen regwork=.
replace regwork=0 if worker==1
replace regwork=1 if worker==1 & status1<200
tab year regwork
tab age if regwork<. , sum(loginc)
tab age if regwork==0 , sum(loginc)
tab age if regwork==1 , sum(loginc)
```

A3 Transitory component (η_t) with individual fixed effect (α_t)

In fixed effect models with richer specification, one way to eliminate individual – specific fixed is to take first – difference. We take first – difference assuming that individual – specific fixed effect does not change from one period to another. Now when you use a parsimonious model (with one or two regressors) the method of first – difference may give us bias estimates for the model in this paper.

Why? Assume that we study a life-cycle model. Where the earning equation has only one regressor *age*. That implies the effects of all other possible regressors are explained by *age* only. Now consider the model of this paper. We segregate the earnings by types of employments, - that is, we partial out the effect of employment status. Then if we take first – difference the consequences leads to a bias estimate of fixed effect. Because – though individual fixed effect does not vary across time, it its highly likely to vary across employment status. Let us give an example: a university lecturer takes a leave for child care and during the leave period she works independently as a consultant. However, after the leave when she returns she gets her usual salary. Now if we take the first – difference between her working period and leave period, it gives a biased estimate of fixed effect.

Therefore, in this model, we assume that individual – fixed effects produce differential earning profile depending on employment status. In this case Deaton (1985) provides the arguments of unbiased and consistent estimates. We assume that the cohort population is constant conditional on employment status. Though the fixed effects, and transitory components cannot be estimated separately, they can be estimated together given that the sample size is sufficiently large.

A4 Dependent and Independent Employees

Dependent Employees – or simply employees: According to ILO classification for status in employment ‘employees’ constitute the first major group of ICSE (International Classification of Status in Employment). It is defined as (ICSE – 21) *Employees are defined as ‘all those workers who hold the type of job defined as paid employment jobs.’ Whilst more detailed categories of employees are not provided as a formal part of the classification, the definition of this group provides guidance on the definition of employees on stable contracts and of ‘regular employees’.*

Independent Employees – workers other than Dependent Employees called independent employees in this paper. Which includes the rest four major groups: Employers, Own – account workers, Members of producers cooperatives, and Contributing family workers (see ICSE 23 – 25).