Effects of age, period and cohort effects on wage trajectory: An application of Panel Study of Family Dynamics (PSFD)

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中文摘要

本研究旨在透過縱貫資料與多層次模型的整合，檢驗年齡、時代及世代變數的效果，以及性別、教育程度與工時等薪資溢酬變數對薪資軌跡的影響。過去這類型的研究多半是由橫斷面資料及相對應的統計方法來完成，因此年齡、時代與世代變數兩兩之間會有完全線性相依的問題；然而，透過兩階層的多層次模型，即可將這三個變數分成兩個層次來處理，亦即時代效果在組內、世代效果在組間，而年齡效果則可以同時作用在組內和組間層次，如此一來，三個變數便可以一起納入模型，解決年齡、時代與世代變數所存在的共線性問題。本研究運用「華人家庭動態資料庫」自 1999 年至 2016 年長達 18 年共 16 波的追縱調查資料，以多層次模型分析 5,800 位受訪者的薪資軌跡與其他變數的變動關係。

研究結果顯示，年齡效果的薪資軌跡不論是組內或組間，都是顯著的二次曲線模型，且在 50 歲左右的時候會有最高點；其次，發生在組內的時代效果也同樣對薪資軌跡有顯著影響，然而隨著其他共變數(控制變數)的加入，該二次曲線的最低點會從原本的 2009 年遞延到 2014 年。再來，世代效果對薪資軌跡的二次曲線則說明了，1966 年到 1970 年出生的人的薪資水準最高，可是一旦把年齡、時代和其他溢酬變數控制住之後，世代效果就會變成不顯著。最後，性別、教育年數和工時的溢酬效果則再次證明，隨著人力資本的累積，薪資水準會跟著增加。本研究運用高階統計方法進行年齡、時代與世代效果分析，除了具備學術意涵，也提供人力資源管理實務的決策性參考。

關鍵字：薪資軌跡、年齡-時代-世代分析、人力資本理論、縱貫資料、多層次模型
Abstract

This study is aimed to combine longitudinal data analysis with multilevel models to examine effects of age, cohort and periods on wage trajectory. With an extension of those, premium effects of human capital factors on wage, such as gender, education and working hours, are also included. In the past, examination of such effects had relied on cross-sectional data and methodology, thus confounding any two of the three variables—age, period and cohort. However, by adapting a two-leveled multilevel modeling, relationships among these three variables are able to be decomposed into within- and between-effects, where period is counted as within-variable in level one, cohort is a between-variable in level two, and age is viewed as both within- and between-variable in level one and level two, so that all three variables are simultaneously analyzed. In this study, a longitudinal data with 16 waves spanning 18 years of over 5,800 individuals in a Panel Study of Family Dynamics (PSFD) database was used to conduct wage trajectory research, and a series of multilevel models were proposed.

It is found that age effect is a curvilinear trajectory across life span, with the highest level around 50s, and it is steadily significant both within an individual and among individuals. Period effects also bring about significant variations in one’s wage trajectory; moreover, the lowest points of this effect defer from the year 2009 to the year 2014, when other covariates are controlled. Lastly, cohort effect reveals that people born in 1966 to 1970 earn most in each month; however, this effect becomes insignificant as the other two temporal effects are simultaneously included. Three premium effects (i.e. gender, years of education and working hours) are also examined and thus verify the fact that the accumulation of human capital can result in an increase in wage. In all, this study not only successfully demonstrates effects of age, period and cohort with improved methodology, but also generate useful implications and empirical solutions to classical human resource practices.

*Keywords*: wage trajectory, age-period-cohort analysis, human capital theory, panel data, multilevel modeling
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Chapter I. INTRODUCTION

1.1 Research Background and Motivation

1.1.1 Current Salary issues in Taiwan

Salary issues had been widely discussed in management and social sciences fields throughout the years, because it could draw dramatic impacts on micro and macro levels. One of the popular research fields in micro perspectives, such as organizational behavior, deals with organizational performance, job satisfaction, quit intention of employees, and other issues. Salary is a very popular factor for discussing the causal effects among these issues, thus identifying mechanism behind. On the other hand, salary in a macro scale influences every individual from a broader perspective. For example, new entrants to the workplace in Taiwan have been troubled with 22k (Taiwanese legal minimum wage) for many years. Additionally, people nowadays have been arguing about the amendment of the law of minimum wage, which not only associates with labor rights but also draws implications on the competitiveness of a country. Overall, salary issues are so complicated but crucial to many fields that corporate leaders, policy makers, employees, and household members tend to bring them up from time to time, urging researchers to incessantly conduct analysis on various topics.

1.1.2 Past and current research on salary issues

When coping with issues about impacts of salary, lots of research compare the amount of salary among different people based on several demographic variables, such as job categories, gender, educational levels, and other sociodemographic. For instance, human capital theory talks a lot about the impacts of several variables—formal education years, experiences, working hours, on the level of salary. Human capital is a term popularized by Gary Becker (1964) and Jacob Mincer (1958) which refers to the stock of knowledge, habits, social and personality attributes embodied in labors so as to produce economic value. A series of human capital variables, such as formal education, working hours, seniority, marital status, were taken into the examination of wage premium and/or wage penalty (e.g. Gupta & Shaw, 2014; Blaug, 1972; Becker, 1993; Card, 1995). In addition, issues about salary changes as a result of changes in marital status in terms of women and men, termed as “wage penalty” and “wage premium”, respectively, have been popular research topics.
these years (Hsu & Chiou, 2015). Consequently, research on salary comparisons among people has been developed for many years, and mostly has been done by cross-sectional analytical techniques.

Nevertheless, discussions about salary nowadays are not only limited to between-subject analysis, but are expanded to areas which are suitable for using temporal variables, such as age, period and cohort variables (Hsu & Chiou, 2015; Fienberg & Mason, 1985). This kind of research requires more advanced statistical tools; therefore, traditional analytical models, such as cross-sectional models, are still inadequate. Nowadays, more advanced models driven by more comprehensive data—data obtained from individuals of a representative sample being measured across numbers of years—enable researchers to observe individual’s wage profile throughout his/her life span, and compare wage levels among different cohort groups at the same time. Compared to traditional techniques, it is more likely for modern advanced analytical tools to complete wage trajectory research from more perspectives.

1.1.3 Relevant Issues on Age, Period, and Cohort (APC) Analysis

One of the systematic studies of temporal issues is called age-period-cohort (APC) analysis, which deals with the influence of age, period and cohort variables on certain dependent variable (Jaspers & Peters, 2016; Chernyavskiy, Little, & Rosenberg, 2017; Sun & Chen, 2017). In following sections, in order to make it more clearer, some past research as well as modern applications on age, period and cohort variables are introduced.

Age effects are variations associated with age groups chronologically. They can result from physiological changes, accumulation of social experience, social role changes, or a combination of these. Age effects therefore represent biological and social processes of aging to individuals and also reflect developmental changes across the life span. This can be seen in considerable variations across time and space in many outcomes, such as fertility, schooling, employment, marriage, disease prevalence, mortality, and other socioeconomic issues.

Due to the limitation of statistical tools and database, past researchers had difficulties tracking down and analyzing the wage profile across one’s lifespan. Most research collected cross-sectional data and compared and drew conclusions on the relationship between salary and age. For example, a prior research confirmed that there is a quadratic relationship between age and salary, indicating a downward concave of the relationship (Hsu & Chiou,
2015). Nonetheless, due to the nature of age, we should focus more on the changing trajectory within subjects as they get older when doing research on salary trajectory.

Period effects are variations over time periods or calendar years that influence all age groups simultaneously. Shifts in social, cultural, economic, or physical environments may in turn induce similar changes in the lives of all individuals at a point in time. Period effects subsume a complex set of historical events and environmental factors, such as world wars, economic expansions and contractions, famine and pandemics of infectious diseases, public health interventions, and technology breakthroughs. For example, the financial crisis occurred in 2007-2008 or even Taiwan's reform to labor policy and annuity implemented in 2017 are such variations that influence people of all age groups at the same time.

Cohort effects are changes across groups of individuals who experience an initial event such as birth or marriage in the same year or years. A birth cohort moves through life together and encounters the same historical and social events at the same ages. Birth cohorts that experience different historical and social conditions at various stages of their life course therefore have diverse exposures to socioeconomic, behavioral and environmental risk factors. For instance, in the 1940s, it was the starting point of economic development in Taiwan, so people born before 1940s experienced those years of low wage level. In the 1950s, Taiwanese people encountered the painful Post-Martial Law Period together. Whereas in 1960s and 1970s, they went through the prosperous periods of economic take-off, and the wage level had peaked in those 20 years. However, in the 1980s, Taiwan saw an economic downturn again, with people experiencing the falling wage level (Directorate General of Budget, Accounting and Statistics, Executive Yuan, R.O.C, 2013). That is to say, cohort effect means that people of different birth cohorts went through different social or economic events as a whole.

1.1.4 The importance, the main problems and solutions of APC analysis

APC analysis has the extraordinary ability to depict the whole complex of social, historical and environmental factors that affect individuals and populations of individuals in the meantime. Many research topics emphasize trajectory, such as the studies of social change, etiology of diseases, aging, and population processes and dynamics, often show that age, period and cohort effects exist in both longitudinal and cross-sectional data. That is to say, age, period and cohort effects exist in the lifespan of different people simultaneously. Researchers from all kinds of fields are interested in separating them to find out the
mechanism behind those time-related issues.

However, the challenges posed by APC analysis are also well-known because the three variables are completely collinear. Whether time-related changes can be sorted out and separated into age effect, period effect, and cohort effect is viewed as conceptually important but practically difficult. If we know the age of an individual and what year he/she is measured, we can also know his/her cohort, that is, the year he/she was born, which making it impossible to separate linear age, period and cohort effects from one another. It also means that if we get one of these trends wrong, we will get the others wrong as well. Data produced by just a linear period effect would look identical to data produced by a combination of age and cohort effects of the same size, but telling them apart is impossible. And this is the identification problem that lies in solving the APC issues:

\[
\text{Age} = \text{Period} - \text{Cohort}, \quad \text{or} \\
\text{Period} = \text{Age} + \text{Cohort}
\]

There have been many attempts to figure out solutions to identification problem. Thanks to the evolution of advanced statistical tools, research on APC issues has gradually increased over the last few years. Compared to cross-sectional data which mostly applied in prior studies on APC issues, when longitudinal data is adapted, we have to not only focus on the theoretical and practical implications of the issue itself, but also apply rigorous methodological design with more complex statistical models. Therefore, the rise of high-level statistical models, such as hierarchical linear modeling (HLM), structural equation model (SEM), and latent growth model (LGM) can provide better analytical solutions for processing temporal variables.

1.1.5 Applying an appropriate database to trajectory research

When dealing with broad topics like salary issues, both between-person differences in development and the development of individuals as they age are concerned. As mentioned in the previous section, age-period-cohort analysis can be used to deal with such differences across genders, races, socioeconomic classes and other characteristics, where birth cohort to which an individual belongs and period events (i.e. economic downturn) play important roles in shaping development. And this is one kind of so called “trajectory research”.

Trajectory methods have emerged over the last several decades as important tools for investigating life course dynamics, including between-person differences in development (George, 2009). Trajectories are simply patterns of variable values over time. For example, one may be interested in trajectories of unemployment rates, stock market closing values, or other macro-level phenomena; on the other hand, one may have interests in trajectories of income or health at an individual level. In addition, trajectories can also be referred as the ordered timing of life events, such as school completion, employment, marriage, childbearing, retirement, and death (Lynch & Taylor, 2016). In this study, models of such trajectory issues would be restricted to repeated measures (i.e. levels) of the same phenomenon, not the timing of multiple qualitative events.

For the purpose of illustrating trajectory methods, we rely on a subset data from Panel Study of Family Dynamics (PSFD), a panel study of adults in Chinese families. It not only contains demographic information and human capital variables but also a long-term collection of household dynamics and income information. Therefore, this study combines the use of this database with high-end statistical methods (i.e. multilevel modeling) to make salary comparisons in both between- and within-perspectives. When measuring variables within subjects, it is more difficult but at the same time more meaningful because such research is able to detect internal variations which couldn’t be achieved in most prior research. For example, when processing age and period variables in this study, it is crucial to note that they are synchronized along the trajectory. Namely, variations along a trajectory can sometimes be counted as the aging process of individuals but other times be referred to as the shifting of time. To deal with such confusing concepts and inseparable relationships between variables in trajectory research, research on age-period-cohort analysis therefore thrives and becomes more and more important.

1.1.6 How to incorporate the Human Capital Theory

Results reveal that human capital is the primary factor that explains wage differences between and within subjects. One of the most popular theories credited to it is human capital theory (Mincer, 1958; Becker, 1964; Blaug, 1976). Economist Mincer constructs an earning function that describes individuals’ wage trajectory across lifespan, and Becker (1964) proposed the word “human capital” to explain that labors’ techniques and abilities can have positive impacts on their level of production and wage. They both talked about some basic
human capital factors, such as job experiences, personal techniques, and abilities, and their contribution to the enhancement of personal production value and wage premium. Blaug (1976) later elaborated that the enhancement of human capital can be seen as a kind of personal investment, including accumulating years of formal education and work experiences, finding a better job, as well as looking for better medical and health supports, and the overall purpose is to exchange for monetary and non-monetary compensation. Of all the above discussions about human capital theory, we will select some critical factors that benefit our study the most on wage trajectory.

1.2 Research Problems and Purposes

The purpose of this study is to investigate APC issues by applying an evidence-based database with an incorporation of human capital factors, age, period and cohort variables as well as the wage variable. We hope to conduct a longitudinal research by expanding our discussions about salary issues to the influences of age, period and cohort effects on wage trajectory. Accordingly, we will incorporate A, P and C respectively, or simultaneously in our study, and our research purposes are listed as follows:

1. The relationship between age effects and wage trajectory
2. The relationship between period effects and wage trajectory
3. The relationship between cohort effects and wage trajectory
4. Discussions about an incorporation of the combination of age, period and cohort effects to wage trajectory
5. Examination on the relationship between human capital factors and wage premium
Chapter II. Literature Review

2.1 Salary Issues

From personal aspects to industrial aspects, from microeconomic discussions to macroeconomic discussions, and from within-subjects’ analysis to between-subjects’ analysis, salary issues are just so critical and relevant to our lives that we can see them leading various discussions everywhere. Some people care about the organizational design of salary structure in a micro-level, while some people put more emphasis on the national wage structure in a macro perspective.

Many terms like wage or earnings are the alternatives to salary; therefore, it is important to define in this paper the terms that would be used to describe such concept. And it is their different managerial implications that needs to be clarified before being further interpreted in this paper. Normally, "wages" are accumulated on the basis of working hours, and paid by employers every day or every week, while "salary" typically defines a fixed amount paid by employers, not necessarily for specific hours worked but for completing the duties of job. On the other hand, "earnings" can indicate a variety of income. It can include wages and salary, but it also describes funds received from nonworking income, such as interests and dividends (Gupta & Shaw, 2014; Merriman, 2014; Hsu & Chen, 2011; Carliner, G., 1980; Mincer, 1974). By definition, salary and wage issues are both parts of studies of earnings, or we can say, compensation. In order to make the terms we use in our study as consistent as possible, we will use “wage” as we address our main discussions in this research, for it fits our research objectives the best and it is the most suitable term to conduct analysis on the wage trajectory across lifespan.

Different from what we expected, in 2014, there was an article published in Human Resource Management Review pointing out that employee compensation had been a neglected area of HRM research. Therefore, Gupta and Shaw offered a plea for more research on compensation. Among many reasons mentioned in the article for the neglect of compensation research, we think the most important one is that compensation can arguably make critical influences on the quality and effectiveness of human capital (Gupta & Shaw, 2014). It implies that the variation and accumulation of one’s salary are highly associated with the organizational design. Unless the compensation system is done appropriately, other organizational policies and procedure cannot have their desired effects (Gupta & Shaw, 2014). Downes and Choi (2014) quoted the taxonomy of Gupta et al (2012) for horizontal
versus vertical pay variation, and they illustrated the positive and negative influence mechanisms of pay dispersion on employees' performance. Therefore, since compensation remains probably the most influential tool for executing successful human capital management and enhancing organizational effectiveness, such questions are in critical need of more comprehensive answers.

Recently in Taiwan, there have been lots of conflicts between different parties. In 2017, the implementation of the reform to annuity and the amendment of minimum wage legislation resulted in not only political opposition and disputes but also the changes in operation, especially the wage level and welfare system, of the entire industry in Taiwan. Take the impacts of minimum wage legislation for example: research found out that such legislation influenced mainly the employment of youths, and results showed that a 10% jump in the minimum wage would increase the youth employment rate and the youth labor participation rate by 0.47% (Chuang, 2006). In a short summary, labor problems recently in Taiwan had not only aroused organizational pay structure and pay distribution issues (which corresponds to the minimum wage issue), but affected some human resource practices and operational costs of corporations; last but not the least, it even influenced the structure of the whole labor industry. Obviously, salary issues have two-sided effects: one with individual and microeconomic impacts, and the other one with labor-sided and macroeconomic impacts.

Throughout history the most comprehensive and clearest function view of earnings is Mincer Earnings Function. Mincer, father of modern labor economics, proposed the Mincer Earnings Function in 1974, which was the first empirical formulation of earnings over one’s lifecycle. It is a model that illustrates wage as a function of schooling and experience, with the logarithm of earnings modelled as the sum of years of schooling and a quadratic function of years of labor market experience (Mincer, 1974).

\[ Y_i(T) = \ln(wage)_i = \beta_0 + \beta_1 T_i + \beta_2 T_i^2 + \beta_s S_i + \epsilon_i \]

The function construct and the selection of variables above are based on human capital theory, and the t and t square reflect that Mincer believed the accumulation of years of experience make the most critical contributions to organizational performance. S is a collective concept in the function, which is associated with the schooling phase of human capital, such as education and employee trainings. The total investment of schooling is a kind of investment that we define as a fixed element of human capital, while tenure on the other hand, develops and increases as we age. Thanks to Mincer’s pioneering work,
variables such as schooling and work experience are now the most commonly used in human capital research.

2.2 Critical Factors of Human Capital Theory on Wage Issues

Wage level can reflect the outcome of production and the value of human capital. Among factors that cause variations and distinctions of wage levels, the most critical element is the investment and accumulation of human capital factors, namely factors of wage premium. In this study, we are going to incorporate some most widely studied variables in the human capital theory (Mincer, 1958; Becker, 1964) to our statistical models to test their interpretation of variations in wage.

2.2.1 Formal Education

The influence of formal education on rising levels of labor production had been a classical topic discussed since human capitalist like Adam Smith. They assumed that such mechanism is the same as physical capital investments (such as machines or equipment), which have direct impacts on improving the efficiency of labor production. In more recent years, Mincer (1974), Becker (1975) and Blaug (1976) also suggested that accumulation of schooling years can lift up one’s knowledge level and his/her capabilities; subsequently, level of production and returns on jobs increased. Education is the main human capital factors that causes wage premium: if human capitals are invested and level of production and capacity are enhanced, the individual capabilities of employees as well as their investments on themselves define the wage differences accordingly. Comparing to tenure that is beyond one’s control, people can actively invest in their education and get higher returns on job. The wage premium effect of formal education plays an indispensable role in wage differentiation individually.

2.2.2 Tenure

Because of the influence of job supply, accumulation of tenure is impossible to be decided by individuals. Despite of this, tenure is still a crucial wage premium factor in human capital theory. The longer employees stay in the same company, they are more likely to accumulate knowledge in that field and achieve higher proficiency of that job. In the end,
they will contribute to the enhancement of their production levels as well as their wages (Ang et al., 2002; Johnston, 2002; McKnight & Tomkins, 2004). In addition, according to the job match theory, employees’ production levels depend on how they’re matched to their jobs. If they match their jobs well, it means that they are likely to perform higher production on jobs, resulting in higher salary (Topel, 1991). Otherwise, if they match their jobs poorly, they tend to leave their jobs in the end. Therefore, the longer employees stay (higher tenure), the better they fit their jobs—a positive effect on wage premium.

However, due to its high collinearity with age variable, eventually tenure variable is not considered as the research variable.

2.2.3 Job Involvement

Another important human capital factor is job involvement. In addition to the vertical competition in an organization, which makes employees actively invest in education and work harder to pursue higher positions and higher salary returns, employees in the same job level or in the same position may create horizontal pay dispersion via pay-for-performance pay structures or seniority pay structures (Gupta et al., 2012; Shaw & Gupta, 2007). Downes and Choi (2014) pointed out that vertical variations can be explained by competitive theory; however, horizontal differences should refer to traditional theories such as social comparative theory and equity theory.

When discussing wage premium, working-hour variable is another important explanatory variable. In a recent study, Merriman (2014) examined the relationships among working mode, working hours and wage, and he argued that the increase of working hours not only contributes to objective benefits, but also generates subjectively perceptual differences and cognitive variations. He pointed out that overwork in most cases results in the reduction of productivity instead. Therefore, Merriman (2014) argued that if more working hours generate higher wage premium, it is based on vertical competitiveness. However, when examined in another perspective from the research, benefits of working hours to wage are defined as a quadratic polynomial, with an existence of an optimal level. Whether to adopt a linear premium perspective or an optimal level perspective is to be tested in the future. All in all, different working hours can not only create wage differences between individuals but create wage variations within individuals at different periods of time.
2.3 Other Factors of Wage Issues

Besides human capital theory, there are many other demographic factors, such as genders, marital status, motherhood penalty, and health conditions, and some accidental factors that might have impacts on earnings.

2.3.1 Demographic factors

In terms of industrialized countries in Europe and America, some relevant studies pointed out that the gender wage gap has gradually narrowed, but the shrinking rate has gradually slowed or stagnated (Blau and Kahn 1981; Eurostat 2013; Weichselbaumer and Winter-Ebmer 2005). Other researchers paid attention to the impacts of motherhood on gender wage gap, called “motherhood wage penalty”. Hsu and Chiou (2015), have proved that human capital is the primary factor that explains motherhood wage penalty.

2.3.2 Accidental impacts

Above are some research reviews about impacts on individuals; however, some factors may influence earnings from a broader environmental context: economic cycle, industry structure, and financial crisis. In years 2007-2008, global financial crisis began with a crisis in the subprime mortgage market in the United States, and developed into a full-blown international banking crisis with the collapse of the investment bank Lehman Brothers. Subsequently, Taiwan’s economy was affected most seriously in the year 2009, and it caused several negative impacts of all kinds. As we can see from Figure 1, Taiwanese GDP declined significantly in the year 2009, and it could cause a rise in unemployment rate. Another interesting discovery is in Figure 2 that while there was a drop in monthly salary in 2009, there were decreasing working hours in 2009 as well. We can infer that it was resulted from the “unpaid leave” policy proposed that year in Taiwan, which made people go on holidays without being fired.
Figure 1 Changes in Taiwan’s GDP and Consumer Price Index in the past 15 years

Figure 2 Changes of salary and working hours of Taiwan industrial and service industry in the past 15 years
Source: Directorate-General of Budget, Accounting and Statistics, Executive Yuan, R.O.C., Salary and Production Statistics

It showed that factors with regard to age which variates individually, such as some human capital factors and working hours, as well as factors concerning period effect which impacts people in the same period as a whole, can both contribute to wage differences among people, or even different wage trajectory across one’s lifespan.
2.4 Earning function with temporal perspective

Researchers have been paying attention to the relationships between wage differences and organization’s fairness, justice, and performance. In human resource field, when researchers discuss issues of wage differences, they basically take a cross-sectional between-individual dispersion perspective. Nevertheless, if we pay attention to the forming mechanism and process of wages, wage difference is not a static result. It is a longitudinal result of cross-time accumulation. That is to say, wage issues should be discussed not only in an individual differences perspective, but in a within-individual change view, namely conducting analysis in the form of earning profile or wage profile.

Basically, wage profile is an essential point of view to human capital theory, and it’s also a fundamental basis for human capitalists to build earning function. The most classical wage profile econometric model is Mincer’s earning function, with quadratic polynomial temporal factors. Different from our previous discussions about this function, we are going to elaborate it in a more temporal way; therefore, we have to demonstrate it once more:

\[
Y_t(T) = \ln(\text{wage})_{it} = \beta_0 + \beta_1 T_{it} + \beta_2 T_{it}^2 + \beta_s S_{it} + \epsilon_{it}
\]

The outcome variable is the logarithm of wages as a function of time, and the intercept reflects the starting point of wage, while the slope associated with T is a temporal effect with quadratic function. \( \beta_1 \) is the first-order term of temporal effect, and \( \beta_2 \) is the second-order term of temporal effect, showing a downward opening when the latter one is negative. \( S_{it} \) represents schooling phase of investment. This earning function indicates that as the time goes by, wage profile is a parabolic shifting from positive to negative. Because time usually increases with age, the time term is mostly substituted with age, becoming an invert-U-shaped of concave age-earning profile (Becker, 1993; Ben-Porath, 1967). Literally, Mincer Earning Function only depicts time as one of the explanatory variables of wage; therefore, observations in empirical models are cross-sectional continuous spectrum obtained by different individuals at different points of time or ages. And that’s the reasons that the equation 1 has no time coding in subscript. Late scholars used panel data, which is collected repeatedly across many years on a fixed sample, to conduct wage profile analysis both between- and within- individuals. Taking a motherhood penalty research done by Staff and Mortimer (2012) as an example, its earning function is illustrated as follows:

\[
Y_{it} = \ln(\text{wage})_{it} = \beta_{0i} + \beta_{1i} T_{it} + \beta_{2i} T_{it}^2 + \beta_{si} S_{it} + \epsilon_{it}
\]
In the equation 2, each variable contains $t$ in subscript, indicating that the same individual would be measured or surveyed $t$ times, while the $i$ in subscript representing different individuals. Such function enables researchers to test premium effects of cross-time and cross-sample simultaneously. In other words, panel data here could be regarded as a two-leveled multilevel modeling (MLM), with $t$ in the first level in subscript representing variation of time, and $i$ in the second level in subscript depicting individual differences. In the first level, wages at different points of time were taken as the outcome variables, and the regression equation is called level-one equation. Additionally, the intercept and the slope in level-one equation can be used as the outcome variables in level-two equation, and explained by the level-two regression equation. It is called the hierarchical linear modeling (HLM).
2.5 Statistical Issues with Age, Period and Cohorts

Because earning function is associated with time-series issues, time related variables are regarded as the main focus of these studies. Age, period and cohort variables are among them the most representative variables.

2.5.1 Age Effect

Basically, wage increases as we age, and this is called an age effect. In terms of wage-related research, age variable is the most fundamental explanatory variables that variates with time. Based on human capital theory, productivity increases as we age, hence a wage premium effect of age. According to Hsu & Chiou (2015) and Hsu & Chen (2011), they affirmed that there is a quadratic relationship between age and wage in the wage trajectory study, namely, age is an explanatory variable with downward concave characteristics.

2.5.2 Period Effect

As for people living in a specific period, their wage levels are easily influenced by some specific social and economic events, and we refer this as period effect. For instance, 2008 to 2009 global financial crisis and the adjustments to Taiwanese labor policies and annuity policy have impacted everyone during those periods of time. In a recent research, Jaspers and Pieters (2016) conducted an APC analysis on the development of materialism across the life span of American people. Over 4,200 individuals were examined through 8 waves spanning 9 years, and divided into 13 birth cohorts with 5-year interval. They were measured repeatedly by their thoughts about materialism, monetary values, and health conditions. Additionally, during the measurement period of this study, a global economic downturn took place; therefore, to capture the economic downturn, a period dummy variable (1= years before 2008, and 0= years after 2008) was put into the model in addition to age and cohort variables. The results showed three ways that respondents’ material values and desires are influenced. Acquisition as the pursuit of happiness (the belief that possessions are essential to satisfaction in life) was lower after the economic downturn. Moreover, Age×Period interaction effects were also significant: younger adults, who were threatened more by the economic downturn, were higher on acquisition centrality (the extent to which one places possessions and acquisition at the center of their lives) and possession-defined success (using possessions as indicators of success) after the economic downturn. Especially when the outcome variable is possession-defined success, the quadratic coefficient is
negative and significant. It indicates that before the economic downturn, the significant and positive quadratic effect on age would slow down, which means that from young to older age, quadratic effect on materialism gradually becomes a linear effect. However, after the economic downturn, age effect on acquisition centrality accelerated instead. Overall, this research emphasizes the importance of period effect on trajectory research.

2.5.3 Cohort Effect

Nevertheless, despite every measurement period, different people with different birth cohorts have distinct life experiences, while people in the same cohort experience life together and encounter similar historical and social events at the same ages. It is called the cohort effect. Hsu and Chen (2011) compared the wage differences between the second-generation immigrants from China to Taiwan after 1949 and natives (Hokkien and Hakka) in Taiwan, by using cross-sectional data from Taiwan Social Change Survey for six years 1992, 1993, 1995, 2000, 2003, and 2005. This research found out that there are significant wage differences between different generations in Taiwan, and the major cause of differences in wages among ethnic groups is the difference in productivity. However, the influence of other factors, such as discrimination, is minimal. Furthermore, the difference between ethnic groups gradually shrink as more and more younger generations enter. In other words, if research subjects are across different generations, especially in wage research, cohort variables become the essential focus of such research. Unfortunately, the study of Hsu and Chen is not a panel study but an analysis of cross-sectional data, so it is impossible to investigate the interaction effects between age and cohort variables in this study. As a result, to examine the cohort effects on wage trajectory, accelerated longitudinal data is adopted in our study.

2.5.4 Data Structure in APC models

In social studies, such as social demography, epidemiology, education development and production economy, which focus on vicissitudes, age, period and cohort effects often co-exist in those panel data, and because of this, it is called an APC issue (Bell & Jones, 2016; Feinberg & Mason 1985; Yang & Land, 2008, 2013). Because A, P, and C are all related to time, their collectively shared experiences are taken as contextual factors (Robertson, Gandini, & Boyle 1999; Glenn 2003). When A, P, and C are discussed in the form of some
data structures, they are often called an APC model (Feinberg & Mason 1985; Yang & Land, 2008, 2013).

When coping with the data structure of APC analysis, we have to pay attention that in terms of individual observations, period variable increases with time, but everyone’s beginning and ending periods of time are the same, thus resulting in the same mean value and variance. Period variable only has within-subject variance, but it does not have between-subject variance. On the contrary, age variable regarding individual observations also changes with time, but the age variable of every respondent varies in beginning, end points and mean values, except for variance remaining the same. Even though both age and period are variables that change with time, they are constrained to a linear equation that period minus age is equal to cohort.

Assuming that from 2010 to 2019, we repeatedly measured respondents who were born in 1980 to 1989 for ten times, and developed a 10×10 cells of age, as demonstrated in Table 1. In each cell, age equals to period minus cohort. For instances, in the 2010 survey, people born in 1980 aged 30, while people born in 1989 was at the age of 21. By the year 2019, people born in 1980 to 1989, they are going to be 30- to 39-year-old.

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Although people of different cohorts are measured in diverse periods, they are simultaneously aging, making the relationships among age, period and cohort become inseparable and completely dependent. Besides, if researchers would like to explore issues of a specific age range, take juvenile years 21-29 for example, only the first measurement period (2010) has the complete samples of 21- to 29-year-old. As time passes, fewer samples are of that age range; therefore, we have to increase our sampling cohorts in order to obtain sufficient samples.

In general, social science studies take age variable as the most fundamental demographic variable, so it needs adequate range and sample size. Secondly, we have to compare cohort differences with sufficient numbers of cohorts. As a consequence, when a study involves issues of age, period and cohort variables simultaneously, the key to the design of sampling is how to obtain ample observations of certain ages and cohorts within a limited time of collection. It is referred to as an issue of cohort design.

2.5.5 Recent Analytical Techniques for APC Issues

Thanks to the improvement of statistical analytical techniques, in recent years age-period-cohort analysis has gradually increased (for example: Chernyavskiy, Little, & Rosenberg, 2017; Jaspers & Pieters, 2016; Mehrotra & Carter, 2017; Huang, Keyes, & Li, 2018; Sun & Chen, 2017; Schomerus, Auwera, Matschinger, Baumeister, & Angermeyer, 2015). It revealed that in longitudinal research design, besides the practical meanings of the issue itself, the more important thing is the way of dealing with these three critical time variables. Especially for the rise of some advanced statistical models, such as multilevel modeling and structural equation modeling, it provides more ideal analytical tools for APC analysis.

The value of conducting research on the issues of age, period and cohort is the existence of an identification problem among these three variables. That is, these three variables are completely linearly dependent, making them impossible to coexist in a statistical model:

\[ \text{Period} = \text{Age} + \text{Cohort}, \text{ or,} \]
\[ \text{Age} = \text{Period} - \text{Cohort} \]
Some researchers have approached this problem by cross-classified model in the multilevel modeling (MLM) to analyze APC issues of non-panel study (Jou & Chu, 2008; Yang & Land, 2006, 2008, 2013). In single-cohort longitudinal data, where people of the same initial age are observed over a longer time period, cohort effects fail to be estimated, and age confounds with period. As illustrated in Table 2 (a), if we repeatedly measure people born in a single cohort 1980 from the year 2003 to 2017, for 15 years, and then we are able to analyze their age changes.

Nevertheless, if a single cohort from 23 to 37 years old is examined, then the same groups of people need to be repeatedly measured for 15 times, and then the research has to be suspended for 15 years. However, if we repeatedly measure respondents who are born in 1980(23-year-old), 1975(28-year-old), and 1970(33-year-old) simultaneously in 2003, and we are able to obtain a complete age-spectrum data from 23 years old to 37 years old in five years. This kind of repeated longitudinal design targeting at multiple-cohort respondents is called a “multiple cohort design”, as we can see in the Table 2 (b) and (c).

Table 2

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In the multiple cohort design, age data obtained from different birth cohorts and in different periods, gradually increases in the data structure showing above, thus called “accelerated longitudinal design” (Bell, 1953). This kind of data can not only conduct research on changing trajectory between different cohorts, but also separate age effect from period effect. Most importantly, it can save researchers’ time to keep track of respondents and reduce sample loss. Furthermore, accelerated longitudinal designs combined with multilevel models have been gradually developed to identify age, period and cohort effects (Fienberg, 1985; Yang & Land, 2013), which would be elaborated in the following chapters.

2.6 Inference about research hypothesis

In this research, three human capital factors—gender, years of education and working hours, are selected as wage premium factors. Considering the effect of gender, an inference that men earn more than women is still proposed as our hypothesis. In terms of years of education variable, it does not change with time; therefore, it is supposed to have positive premium effects on between-subject wage levels. Regarding working-hour variable, it differs with time, thus resulting in positive premium effects at both within- and between-subject levels. In all, the following is a set of hypothesis regarding premium effects of human capital variables.

**Hypothesis 1:**
Human capital factors have different effects on wage levels.

**Hypothesis 1a:**
Gender difference is positively associated with wage difference.

**Hypothesis 1b:**
More years of education are relevant to higher wage levels.

**Hypothesis 1c:**
More working hours are associated with higher wage levels.

In addition to hypothesis about human capital factors’ impacts on wage premium effects, in this study the most important discussions about wage trajectory are the temporal effects, namely identifying the issue of APC effects. According to our previous discussions, many precedent research had drawn some inferences about relationships between wage and
age, period and cohort variables. Therefore, in this section regarding temporal effects on wage levels, some hypothesis is developed as follows.

**Hypothesis 2:**
Age, period and cohort variables have different effects on wage levels.

**Hypothesis 2a:**
Age variable influences within- and between-subject wage levels.

**Hypothesis 2b:**
Period variable influences within-subject wage levels.

**Hypothesis 2c:**
Cohort variable influences between-subject wage levels.

It is particularly worth mentioning that these three variables draw impacts on wage at different levels. Both age and period are variables that change with time, which means that they may influence the wage level on the within-individual level (L1). However, the influence of age effect may not only occur across one’s lifespan but among individuals. That is to say, as people age, their own wage level might change (L1 age effect), and levels of wage among people might diverse as well (L2 age effect). Lastly, one’s birth cohort does not change with time, so this variable only impacts between-individual comparisons (L2) on wage levels.

Among the hypothesis made in the previous two sections, some are further investigated to test whether wage premium effects differ when APC factors are incorporated. Based on the hierarchical regression analysis, A, P and C variables belong to demographic variables, and their effects on wage are prior to the human capital variables. To discuss the covariate effects of these variables, because A, P and C provide temporal effects of history context, they would be firstly examined in the models, and after that, the human capital factors are subsequently examined. Namely, the integration effect of APC variables on premium effects is acted as a role of controlling variable which derives the APC controlling effect hypothesis as below.

**Hypothesis 3:**
Age, period and cohort effects are significant with human capital premium variables. (Controlling effect hypothesis)
Chapter III. Methods

To begin the APC analysis on wage trajectory, in this chapter the longitudinal database—Panel Study of Family Dynamics (PSFD) database as well as the corresponding methodologies would be introduced. To illustrate, firstly detailed information of the PSFD database are presented, and then characteristics and processing of research variables are elaborated. Subsequently, the research procedure would be listed; last but not the least, some methodologies adapted in this study would also be summarized.

3.1 Database and Research Sample

“Panel Study of Family Dynamics” is a long-term fixed-sample panel design initiated in 1999, targeting the adult population in Chinese families. It covers different birth cohorts, and in the Taiwan survey, children of the main respondents have been added into the sample since 2000. It is currently administrated by the Project for the Study of Family in Chinese Societies (PSFCS) under the Research Center for Humanities and Social Sciences (RCHSS). The latest data has been released on 16th, Jan, 2018.

The PSFD project aims to undertake a comprehensive research on economic, social, psychological and institutional aspects of Chinese families. It originates from the belief that the types, structures, and patterns of interaction of families in Chinese societies are more complicated than those in Western societies. Correspondently, the theoretical models embodied in the values and practices of Chinese families should be more complex than those set up from Western ones. The PSFD project is therefore intended to examine whether existing western theories of the family can be applied to Chinese society. On the other hand, based on the empirical findings from PSFD, new theoretical frameworks different from Western ones are expected to be abstracted and developed.
**Figure 3** Data structure of survey years

*Note:* * means that the data has not been publicly released. Birth cohorts are denoted by the Republic Era. Blue area (RR) is the main sample; yellow area (CV) is the child sample; green area (RCI) is the main samples of either newly sampling ones or children who aged over 25 and being tracked for the first time. The same box represents the same questionnaire. RI-2009 questionnaire consists of newly nationally sampling representative and those who aged 25 and being tracked as the main sample for the first time.

Source: [http://psfd.sinica.edu.tw/web/check.htm](http://psfd.sinica.edu.tw/web/check.htm)
As demonstrated in Figure 3, in 1999, the first face-to-face interview of PSFD was conducted to collect 1,000 randomly sampled individuals born in 1953-1964. Refreshment samples of adult respondents born in 1935-54, 1964-76, and 1977-83 were first interviewed in 2000, 2003, and 2009, respectively. These follow-up surveys for these four groups of main respondents were conducted annually. The core contents of the follow-up questionnaire (Questionnaire R) include the respondent’s demographic traits, work status and job information, marital status and spousal information, demographic traits of parents and parents-in-law, interaction with family members, housing and living arrangement, income and expenditure, and childbearing and rearing information.

The parent-child relationship is one of the most important intra-family relationships. In the questionnaire of the main respondent, there are many question items regarding his or her children. To establish more comprehensive two-generational data, the surveyed sample has been extended to the young children of the main respondents since 2000. When the children were aged between 16 and 24, they were re-interviewed biennially using Questionnaire C. When the children reach the age of 25, they are treated as main respondents and interviewed using the first-wave questionnaire of the main respondents (Questionnaire RCI). After that, the children are traced annually using the same questionnaire as the main respondents (Questionnaire R). To lessen the interviewing burden, since 2012 the follow-up survey of the main respondents (Questionnaire R) is conducted on a biennial basis, in the mean while as Questionnaire C and Questionnaire RCI. Please refer to SRDA website (https://psfd.sinica.edu.tw/web/plan_01en.htm).

In our study, we focus on the discussions about salary issues and corresponding issues of APC; therefore, only some research variables would be extracted from PSFD. We dropped question items regarding parent-child relationship, marital status, spousal information, childbearing and rearing information, and those that are unnecessary to the study, which accounts for a large proportion of PSFD database. Moreover, other great proportion of detailed information of work status and job description: daily commuting hours, reasons for leaving the last job, reasons for not having a job, reasons for not looking for jobs, and so on, are also excluded. Although these items are invaluably important to this database, only some variables based on our research purposes would be used and further elaborated in the following sections.

Of the four groups of main respondents born in 1953-64, 1935-54, 1964-76, and 1977-83, the numbers of complete interviews of the first-wave survey conducted in 1999, 2000,
2003, and 2009 were 999, 1,960, 1,152, and 2,182, respectively. In a previous study (Chiou, 2014-2016), the data from 1999 to 2011 were used for analysis (The survey data from 2012 to 2016 were under verification then). In 2012, their corresponding numbers of complete interviews were 545, 1,066, 652, and 1,649. In the same year, the number of complete interviews for the sample of children was 1,836 in total, of which 1,064 cases were interviewed by Questionnaire R, and the rest (752 cases) by Questionnaire C. Our study will be expanded to 2016 (4774 cases) with the latest data released on 25th Jan, 2018. From 1999 to 2016, an average cluster size of 5.598 indicates the average number of years to which participants had given their answers is 5.598, less than half of the overall measuring years.

3.2 Research Variables

This research aims to explore the impacts of human capital premium factors on wage level in different periods and different cohorts. Consequently, we not only extract variables with wage information, but include data about formal education, tenure, and working hours.

3.2.1 Wage Variables

Total amount of wage is derived from monthly returns of jobs that states in the question: “How much do you receive from the total of your job in one month (sources ranging from salary, bonuses, overtime pay, year-end bonuses, executive business income, and self-employment income)?” Normally the data obtained is nominal and positively skewed; therefore, in order to reduce skewness, eliminate the impact of prices, and align the scale with other variables, wage variable used in this model is the logarithm of actual monthly income, adjusted by Consumer Price Index updated from the website (https://www.dgbas.gov.tw/ct.asp?xItem=760&ctNode=3091), and then all multiplied by 100.

3.2.2 Age, Period and Cohort Variables

(1) Age:

It is obtained from the interview year minus the year in which subjects were born. Since there might be a diminishing effect of the positive linear relationship between age and wage variables (Waldfogel 1997; Budig and England 2001), we also use the square of age variable as a quadratic form, testing the non-linear effect of age by incorporating both of them into the polynomial regression.
(2) Period:
During the measurement period (1999-2016) of our study, a global economic downturn took place. In order to capture the incidence, a period dummy variable indicating whether measurement took place before or after (during) the economic downturn (1 = 1999 to 2009, and 0 = 2010 to 2016) is inserted (Jaspers and Pieters, 2016).

(3) Cohort:

3.2.3 Human Capital Variables
In this category, this study focuses on schooling years and working hours:

(1) Years of schooling (eduyear):
This number is obtained from the question, “What is your highest educational level?”, and it is originally coded as ordinal variable; however, in this study, we recode it into continuous one.

Continuous variables, on the other hand, are years of formal education converted by the educational levels, such as 0 year for none-educated or self-study, 6 years for graduation from primary schools, 9 years for graduation from junior high schools (or any degrees that take 9 years to graduate), 12 years for graduation from senior high schools (or any degrees that take 12 years to graduate), 14 years for graduation from institutes of technology (or any degrees that take 14 years to graduate), 15 years for graduation from three-year junior colleges, 16 years for graduation from universities, 18 years for graduation from graduate schools, and 22 years for graduation from doctoral degrees.

(2) Working hours (WH):
Working hours of every participant is obtained from the question, “On average, how many hours do you work each week?”. 
3.3 Research Procedure

In this section, some critical procedures of data preparation and data analysis are introduced.

Firstly, we have to register the member of SRDA website and get the permissions to download the latest data without any restrictions.

Secondly, researchers have to thoroughly inspect the dataset, and refer it the code book, which is also provided on SRDA website.

Third, we extract some of the research variables that we need from the data, and try to keep them consistent every year.

Fourth, data concatenation proceeds. It is essential that we get the logarithm of variables after data concatenation.

Fifth, we prepare and create variables forms that are needed for doing analysis, such as continuous schooling variables.

Later on, we will keep examining our observations, and filter unqualified observations from our dataset. For example, observations with two-year information, or those who aged above 65, would be filtered.
3.4 Analytical methods

In this study, we are going to apply MPLUS8 (Chiou, 2017) to conduct a two-level analysis on wage among employed people. To better normalize and standardize the data and the model structure, an MLR (maximum likelihood parameter estimates with standard errors) estimation approach was used in MPLUS 8 (Muthen & Muthen, 1998-2012), as well as a Bayesian measure of model fit (BIC). Models with smaller BIC values are preferred to models with larger values. Wage comparisons among individual differences and the analysis with some related factors belong to the level-two model, and the variations within individuals during periods of study, namely the wage changes within-subjects, belong to level-one model.

3.4.1 Multilevel Modeling (MLM)

In a hierarchical linear modeling, explanatory variables that change with time are separated into level-one variables, such as age (quadratic polynomial), tenure (quadratic polynomial), working hours, and other continuous variables. In order to maintain the same design as a fixed coefficient model, explanatory variables or control variables in level-one function need to enter the equation in the form of group-meaning centering, and then we can get some within-subject information of variables changing with time (Staff and Mortimer 2012; Wen and Chiou 2015). Except that the dependent variable does not need to do the mean deviation process, other features of variables are the same as the fixed effect regression model.

Explanatory variables that do not change with time in a hierarchical linear model are some fixed information of individuals, and they are treated as level-two variables. These variables include levels of cohorts, levels of education, and the mean value of level-one variables, namely age (quadratic polynomial), tenure (quadratic polynomial), and working hours (the mean value of repeated measures). In addition, such variables that both applied in level-one and level-two functions: individual numbers applied in level one function representing within-subjects’ variance and mean value applied in level two function reflecting between-subjects’ variance, can be regarded as the contextual effects of individuals; therefore, they are called “contextual variables” (Duncan, Jones and Moon 1996). Explanatory variables in level-two function need to enter the equation in the form of grand-meaning centering, so that we can keep the overall intercept of the entire equation fixed.
Looking at the terms used by MLM, panel data for the design of a fixed-sample longitudinal study can be illustrated by a two-leveled model, which separates the outcome variable $y_{ti}$ that changes with time (observed from n observations) into within-subject variation(level-1; L1) and between-subject variation(level-2; L2), as demonstrated in the equations (3) and (4):

L1 \hspace{1cm} (3) \hspace{1cm} y_{i} = \pi_{0i} + \epsilon_{ti} \\
L2 \hspace{1cm} (4) \hspace{1cm} \pi_{0i} = \beta_{00} + u_{0i} \\
Mixed \hspace{1cm} (5) \hspace{1cm} y_{i} = \beta_{00} + u_{0i} + \epsilon_{ti}

After substituting equation L2 into equation L1, we can reach the mixed equation as shown in the equation (5). In these equations, there are no explanatory variables; therefore, it is called a null model (Raudenbush & Bryk, 2002). Because $y_{ti}$ is a random variable, in equation (3) there are no explanatory variables, with only one constant term ($\pi_{0i}$) and one random term ($\epsilon_{ti}$). $\pi_{0i}$ reflects the mean $y_{ti}$ of different individuals across different periods of time (the subscript $i$ of $\pi_{0i}$ indicates that each respondent has a different average number), and $\epsilon_{ti}$ shows the (within-individual) variations of each respondent across T-wave measurement, which follows a normal distribution with a mean of zero and a variance of $\sigma^2$: $\epsilon_{ti} \sim N(0, \sigma^2)$.

On the contrary, L2 equation deals with between-subject variations, which indicates that the outcome variable of equation L2 is an average number $\pi_{0i}$ of different individuals, and $\beta_{00}$ is the grand mean of total observations, reflecting the mean of $y_{ti}$ (the average number of n respondents). $u_{0i}$ demonstrates the variations of the mean $y_{ti}$ of n respondents, and it follows a normal distribution with a mean of zero and a variance of $\tau_{00}^2$: $u_{0i} \sim N(0, \tau_{00}^2)$.

Variances $\sigma^2$ and $\tau_{00}^2$ both follow random normal distribution, so they are called the random effect; however, $\beta_{00}$ is a constant number, so it is called the fixed effect. By using these two variances ($\sigma^2$ and $\tau_{00}^2$), we can estimate the level of variations between subjects, which can be called as intra-class correlation (ICC), illustrated in the equation (6) (Hox, 2010; Raudenbush & Bryk, 2002). Higher ICC indicates higher ratio of between-subject variance to total variance, and lower within-subject variance, and vice versa.

\begin{equation} \label{6} 
ICC = \frac{\tau_{00}^2}{\tau_{00}^2 + \sigma^2}
\end{equation}
The purpose of a null model is separating the variance of an outcome variable $y_{ti}$ into within- and between-subject variances, but it cannot show the trajectory of $y_{ti}$ changing with time. If $y_{ti}$ is a wage variable, we have to incorporate a time variable ($T_{ti}$) into the model, and then we can estimate the linear trend of wage changing with time, namely, the linear growth model. If we incorporate another variable which is the square of a time variable ($T_{ti}^2$), we can estimate the concave trajectory of wage changing with time, namely, the quadratic growth model showed in the equations (7) to (11).

\[
\begin{align*}
L1 & \quad (7) y_{ii} = \pi_{0i} + \pi_{1i} T_{ti} + \pi_{2i} T_{ti}^2 + \varepsilon_{ii} \\
L2 & \quad (8) \pi_{0i} = \beta_{00} + u_{0i} \\
& \quad (9) \pi_{1i} = \beta_{10} + u_{1i} \\
& \quad (10) \pi_{2i} = \beta_{20} + u_{2i} \\
\text{Mixed} & \quad (11) y_{ii} = \beta_{00} + \beta_{10} T_{ti} + \beta_{20} T_{ti}^2 + u_{0i} + u_{1i} T_{ti} + u_{2i} T_{ti}^2 + \varepsilon_{ii}
\end{align*}
\]

In the equation (7), $\pi_{0i}$, $\pi_{1i}$, and $\pi_{2i}$ are the trajectory of an individual’s quadratic curve, and in equations (8) to (10), $\pi_{0i}$, $\pi_{1i}$, and $\pi_{2i}$ are outcome variables, which is disintegrated into respective fixed effects $\beta_{00}$, $\beta_{10}$, and $\beta_{20}$, as well as respective random effects $u_{0i}$, and $u_{1i}$, and $u_{2i}$. Among them, $\beta_{00}$, $\beta_{10}$, and $\beta_{20}$ are the constant, the first-order, and the second-order terms of the total trajectory, respectively, while $u_{0i}$, and $u_{1i}$, and $u_{2i}$ are individual differences showed in the variance-covariance matrix in the equation (12).

\[
\begin{bmatrix}
  u_{0i} \\
  u_{1i} \\
  u_{2i}
\end{bmatrix} =
\begin{bmatrix}
  \tau_{00}^2 \\
  \tau_{01}^2 \\
  \tau_{02} \\
  \tau_{11}^2 \\
  \tau_{12} \\
  \tau_{22}^2 \\
  \tau_{03} \\
  \tau_{13} \\
  \tau_{23} \\
  \tau_{33}^2
\end{bmatrix}
\]

From equations (7) to (11), these trajectories imply variations between individuals, and they are called random coefficient models (Raudenbush & Bryk, 2002) or mixed effects model (Fitzmaurice, Laird, & Ware, 2011) in MLM. In this study, the outcome variable is wage; therefore, the whole model is a wage trajectory model. If other explanatory variables are included in the equations as covariates or control variables, such as tenure, schooling years, working hours, or other human capital factors, the within- or between- individual wage variances can be explained. And it is the earning function of equation (2).
3.4.2 MLM of APC variables in the panel data

If age, period and cohort variables are included simultaneously, the simplest way is to substitute the time variable T in the equation (9) with age variable, which means that we conduct a MLM analysis of age-changing trajectory of wage. Moreover, we take period variable as a covariate, and cohort variable as an explanatory variable in the L2, which shows individual differences that do not variate with time. Our study is going to be divided into two parts: part one is an APC/ MLM without covariates, focusing on the influence of age, period and cohort variables on wage variations; whereas, part two includes human capital factors, examining their influences and APC variables at the same time.

Multilevel data analysis with nested structures has to be firstly tested the effectiveness of its dependent variable (the logarithm of wages), by separating it into between- and within- subject levels, namely conducting a null model analysis.

3.4.2.1 APC/MLM model without covariates

Samples of different cohorts are measured repeatedly and continuously, making each sample represents multiple measurement data. Here, age effect arouses when different individuals are measured repeatedly; therefore, age effect and period effect are both level one variables (within-individuals) that change with time, and they both have a time-series subscript t, representing the effect of repeated measurements. On the other hand, cohort effects exist in making comparisons between individuals in a macro-level, making it a level-two variable. If we assume that age variable (A) and wage trajectory have a quadratic curve relationship, and we incorporate period variable into level-one equation to explain the variations of wages, as demonstrated in the equation (13). Similarly, cohort variable that does not change with time is likely to have a quadratic curve relationship with wage trajectory as well; therefore, when being included in the L2 equation, we also make it be a second-order term, which is shown in the equation (14). Since there are no interaction effects among age, period and cohort variables here, we call this model an APC model without interaction effects (M1).

\[
\begin{align*}
\text{M1} & \quad \text{L1 (13)} \quad y_{ni} = \pi_{0i} + \pi_{1i}A_{ni} + \pi_{2i}A_{ni}^2 + \text{Period}_{ni} + \varepsilon_{ni} \\
\text{L2 (14)} & \quad \pi_{0i} = \beta_{00} + \beta_{01}\text{Cohort}_{i} + \beta_{02}\text{Cohort}_{i}^2 + u_{0i} \\
\text{(15)} & \quad \pi_{1i} = \beta_{10} + u_{1i}
\end{align*}
\]
3.4.2.2 APC/MLM model with covariates

In the previous model, relationships of time-related variables and wage trajectory are examined, but effects of human capital factors are excluded. Once the relationships of APC and wage are ensured, human capital variables could subsequently be incorporated into the equations to examine the wage premium effects. If we take the model without interaction effects (M1) as the example, and incorporating human capital variables that change with time into L1 equation (e.g. the influence of working hours WH on wages), and human capital variables that do not change with time into L2 equation (e.g. the influence of schooling ears Edu on wages), we can derive a MLM model (M2) in equations 18 to 23:

\( M_2 \)

\[ L_1 (18) \ y_{i} = \pi_{0i} + \pi_{1i} A_{i} + \pi_{2i} A_{i}^2 + \pi_{3i} Period_{i} + \pi_{4i} WH_{i} + \epsilon_{i} \]

\[ L_2 (19) \ \pi_{0i} = \beta_{00} + \beta_{01} Cohort_{i} + \beta_{02} Cohort_{i}^2 + \beta_{03} Edu_{i} + u_{0i} \]

\[ (20) \ \pi_{1i} = \beta_{10} + u_{1i} \]

\[ (21) \ \pi_{2i} = \beta_{20} + u_{2i} \]

\[ (22) \ \pi_{3i} = \beta_{30} + u_{3i} \]

\[ (23) \ \pi_{4i} = \beta_{40} + u_{4i} \]

We can see from the six equations in M2 that with more explanatory variables in L1, more random effects to be estimated in L2. At the same time, both variance and covariates of error terms in L2 are needed to be estimated, resulting in a difficulty of model convergence. Therefore, when executing analysis, researchers would make reference to ordinary approaches of MLM analysis. Depending on the degree of model convergence, they will make L1 explanatory variables a fixed effect and eliminate the estimations of \( u_{1i} \) to \( u_{4i} \), in order to enhance the effectiveness and efficiency of conducting an analysis (Hox, 2010, 2018; Raudenbush & Bryk, 2002).
### 3.4.3 Overall research models applied

Based on the research purposes and some framework of multilevel modeling, in this study twenty research models are carefully developed and listed as follows.

Table 3

<table>
<thead>
<tr>
<th>Research models</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Model Code</strong></td>
</tr>
<tr>
<td>M0</td>
</tr>
<tr>
<td>M1</td>
</tr>
<tr>
<td>Ma1</td>
</tr>
<tr>
<td>Ma2</td>
</tr>
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<td>Ma3</td>
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<tr>
<td>Ma7</td>
</tr>
<tr>
<td>Map</td>
</tr>
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<td>Mp1</td>
</tr>
<tr>
<td>Mp2</td>
</tr>
<tr>
<td>Mp3</td>
</tr>
<tr>
<td>Mp4</td>
</tr>
<tr>
<td>Mpp</td>
</tr>
<tr>
<td>Mc1</td>
</tr>
<tr>
<td>Mc2</td>
</tr>
<tr>
<td>Mcp</td>
</tr>
<tr>
<td>Mapc</td>
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<tr>
<td>MM`</td>
</tr>
</tbody>
</table>

*Note. ‘y’ equals to the logarithm form of real wage which is the nominal wage divided by yearly CPI index and multiplied by 100. ‘age1’ and ‘age2’ respectively denotes the within effects of the linear and quadratic forms of age, while ‘mage1’ and ‘mage2’ respectively means the between effects of the linear and quadratic forms of age. ‘period1’ and ‘period2’ are in respective orders of the linear and quadratic forms of period. ‘cohort1’ and ‘cohort2’ respectively represents the within effects of linear and quadratic forms of cohort. ‘sex’ means gender, ‘eduyear’ represents years of education and ‘wh’ equals to working hours.*
Chapter IV. Results

In this chapter, firstly the null model and some table and figures of descriptive statistics for our sample structure are introduced. Subsequently, results of age, period, and cohort are provided respectively, each along with a short summary of premium effects. Lastly, an aggregated result is presented to illustrate the total effects of age, period and cohort on wage.

4.1 Sample Structure

The data for the study were obtained from the Panel Study of Family Dynamics maintained by the Research Center for Humanities and Social Sciences. The panel is based on the adult population of Chinese families in Taiwan over 18 years. All data collected in the panel including those for the current database are available for academic research purposes (https://psfd.sinica.edu.tw/web/plan_02en.htm). Panel drop-outs were replaced to retain representativeness. An average cluster size equals to 5.598, indicating that average participants complete 5.598 periods during the measurement years.

The average age of participants is 37.68 years (SD=14.04, min=18.5, max=72.5), and the average cohort size is 6.37 (SD=2.823, min=0, max=10), as shown in Table 3.

Table 4
Descriptive statistics of research variable

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>Min.</th>
<th>Max.</th>
<th>Mode</th>
<th>Std.</th>
<th>Skewness</th>
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<tbody>
<tr>
<td>cpiwage</td>
<td>41432.85</td>
<td>5053.06</td>
<td>1224410.56</td>
<td>--</td>
<td>34042.81</td>
<td>--</td>
</tr>
<tr>
<td>lgciwage</td>
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<td>3.70</td>
<td>6.02</td>
<td>--</td>
<td>0.24</td>
<td>--</td>
</tr>
<tr>
<td>age</td>
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<td>72.50</td>
<td>26.50a</td>
<td>14.04</td>
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<td>period</td>
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<td>17</td>
<td>--</td>
<td>5.19</td>
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</tr>
<tr>
<td>cohort</td>
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<td>8.00</td>
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</tr>
<tr>
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<tr>
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<td>3.84</td>
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<td>wh</td>
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<td>152</td>
<td>40.00</td>
<td>12.09</td>
<td>0.93</td>
</tr>
</tbody>
</table>

Note. ‘cpiwage’ denotes the real wage which is the nominal wage divided by yearly CPI index and multiplied by 100. ‘lgciwage’ denotes the logarithm form of real wage which is the nominal wage divided by yearly CPI index and multiplied by 100. ‘sex’ means gender, ‘eduyear’ represents years of education, and ‘wh’ denotes working hours.
Table 5

Frequencies of gender, years of education and cohorts

<table>
<thead>
<tr>
<th>Variables</th>
<th>Values</th>
<th>Counts</th>
<th>Percentage (%)</th>
<th>Cumulative Percentage(%)</th>
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</thead>
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<td>sex</td>
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<td>43.58</td>
<td>43.58</td>
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<tr>
<td></td>
<td>1 (male)</td>
<td>3324</td>
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<td>0.03</td>
<td>100.00</td>
</tr>
<tr>
<td>Total</td>
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<td></td>
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<td>6</td>
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<td>3 (1951-1955)</td>
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<td></td>
<td>4 (1956-1960)</td>
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<td></td>
<td>5 (1961-1965)</td>
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</tr>
<tr>
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<td>6 (1966-1970)</td>
<td>339</td>
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</tr>
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<td></td>
<td>7 (1971-1975)</td>
<td>372</td>
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<td>46.75</td>
</tr>
<tr>
<td></td>
<td>8 (1976-1980)</td>
<td>1508</td>
<td>25.58</td>
<td>72.33</td>
</tr>
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<td>9 (1981-1985)</td>
<td>1343</td>
<td>22.78</td>
<td>95.12</td>
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<td>Total</td>
<td></td>
<td>5895</td>
<td>100</td>
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</tr>
</tbody>
</table>

*Note.* 'sex' means gender, and 'eduyear' represents years of education.
As listed in Table 4, cohort sizes based on people who participated at least once in the measurement period were, respectively, 187 for Cohort 0 (1935-1940), 266 for Cohort 1 (1941-1945), 246 for Cohort 2 (1946-1950), 630 for Cohort 3 (1951-1955), 335 for Cohort 4 (1956-1960), 381 for Cohort 5 (1961-1965), 339 for Cohort 6 (1966-1970), 372 for Cohort 7 (1971-1975), 1,508 for Cohort 8 (1976-1980), 1,343 for Cohort 9 (1981-1985), and 286 for Cohort 10 (1986-1989). And of all the birth cohorts of participants, most are in cohort 8 (25.6%) and cohort 9 (22.8%), which are born in 1976 to 1985.

The total sample size of our study is 5,895, in which 2,569 (43.6%) are male and 3,324 (56.4%) are female (female=0, male=1). Average educational level was 12.71 years, and average working-hour is 46.84 hours (SD=12.086). Of all the categories defining years of education, most participants complete 12-16 years of education, which in total represent 67.6%. And average net monthly income is 41,433 NTD (SD=34,043), that is 4.53 NTD (SD=0.241) in logarithm.
Table 6

*Average income in categories of periods, cohorts, and years of education*

<table>
<thead>
<tr>
<th>Variables</th>
<th>Values</th>
<th>Counts</th>
<th>Mean</th>
<th>Std.</th>
</tr>
</thead>
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<td>.28</td>
</tr>
<tr>
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<td>.31</td>
</tr>
<tr>
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<td>4.56</td>
<td>.32</td>
</tr>
<tr>
<td></td>
<td>3 (2002)</td>
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</tr>
<tr>
<td></td>
<td>4 (2003)</td>
<td>829</td>
<td>4.58</td>
<td>.22</td>
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<td>6 (2005)</td>
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<td>9 (2008)</td>
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<tr>
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<td>11 (2010)</td>
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<td>15 (2014)</td>
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<td>17 (2016)</td>
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<td>.27</td>
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<td>.32</td>
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<tr>
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<td>3 (1951-1955)</td>
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<td>.30</td>
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<td>4 (1956-1960)</td>
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<td>.28</td>
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<td>5 (1961-1965)</td>
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<td>.25</td>
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<td></td>
<td>6 (1966-1970)</td>
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<td>.25</td>
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<tr>
<td></td>
<td>7 (1971-1975)</td>
<td>371</td>
<td>4.59</td>
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<td>8 (1976-1980)</td>
<td>1507</td>
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<tr>
<td></td>
<td>9 (1981-1985)</td>
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<td>4.53</td>
<td>.17</td>
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<td>10 (1986-1989)</td>
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<td></td>
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<td>.24</td>
</tr>
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<td>82</td>
<td>4.15</td>
<td>.20</td>
</tr>
<tr>
<td></td>
<td>6</td>
<td>660</td>
<td>4.29</td>
<td>.25</td>
</tr>
<tr>
<td></td>
<td>9</td>
<td>540</td>
<td>4.44</td>
<td>.23</td>
</tr>
<tr>
<td></td>
<td>12</td>
<td>1530</td>
<td>4.51</td>
<td>.20</td>
</tr>
<tr>
<td></td>
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</tr>
<tr>
<td></td>
<td>15</td>
<td>51</td>
<td>4.65</td>
<td>.23</td>
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<td></td>
<td>16</td>
<td>1061</td>
<td>4.63</td>
<td>.21</td>
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<td>544</td>
<td>4.71</td>
<td>.21</td>
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<tr>
<td></td>
<td>22</td>
<td>56</td>
<td>4.68</td>
<td>.37</td>
</tr>
<tr>
<td></td>
<td>Total</td>
<td>5851</td>
<td>4.53</td>
<td>.24</td>
</tr>
</tbody>
</table>

*Note: ‘eduyear’ represents years of education.*
Table 5 depicts the average income in every category of periods, cohorts, and years of education, respectively. And Figure 4 to Figure 7 below illustrate the logarithm of the adjusted wage in average lines by years of education, age, period, and cohort.

Figure 4 Wage by age

Figure 5 Wage by period
Figure 6 Wage by cohort

Figure 7 Wage by years of education
4.2 Age Effects on the Trajectory of Wage

In this section, null model of this research is firstly proposed and models of age effects are presented as follows.

4.2.1 Null Model

As mentioned in the previous chapter, the simplest model is a null model without any explanatory variables, with only a grand mean ($\gamma_{00}$) and two variations: intercept variations among groups [$u_{0j}$] and within group variations [$\varepsilon_{ij}$].

The results show that the grand mean ($\gamma_{00} = 453.03, p<.001$), intercept variations among groups ($\tau_{00}^2 = 520.79, p<.001$), and within-group variations ($\sigma_{\varepsilon}^2 = 204.96, p<.001$) are all significantly different from zero. Intra-class correlation coefficient (ICC) is calculated by:

$$\text{ICC}_y = \frac{\tau^2}{\tau^2 + \sigma^2} = \frac{520.79}{520.79 + 204.96} = 0.718$$

As demonstrated in the calculation of ICC, variance among groups explain 71.8% of total variance, a percentage that reminds us in our research to observe variance among individuals.

4.2.2 Age Effects on the Trajectory of Wage without Covariates

To begin our discussion on the APC effects on the trajectory of wage, the age effect is the most primary and widely studied one. As a result, our models for the wage variable include not only age but its contextual variables (the mean value of age), displayed in both the linear growth model and the quadratic growth model in Table 6. All models estimated the fixed effects—in Ma1, Ma3, Ma5 and Ma6—as well as the random effects—in Ma2, Ma4 and Ma7; as a whole, there are 7 models. (Syntax of Mplus of Ma6 and Ma7 are listed in Appendix I and II, respectively)

Table 6 summarizes the estimated age effects and contextual effects for the wage. The results of Ma1 indicate that when only fixed effects are considered, the linear effect of age for the wage was positive but insignificant (age1 = 0.005, p>.05), suggesting that the mean wage for everyone remains quite the same as they age. However, if random effects (tau1 = 4.165, p<.001) were taken into account, it reveals that linear effects of age are actually significantly different among individuals, but overall, average wage rises as people age.
Table 7

Results of age effects on wage

<table>
<thead>
<tr>
<th>Fixed effect</th>
<th>M0</th>
<th>Ma1</th>
<th>Ma2</th>
<th>Ma3</th>
<th>Ma4</th>
<th>Ma5</th>
<th>Ma6</th>
<th>Ma7</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept(b00)</td>
<td>453.03**</td>
<td>453.03**</td>
<td>453.00**</td>
<td>453.01**</td>
<td>452.99**</td>
<td>458.52**</td>
<td>453.19**</td>
<td>453.29**</td>
</tr>
<tr>
<td>age1(b10)</td>
<td>--</td>
<td>0.005</td>
<td>0.257**</td>
<td>3.736**</td>
<td>3.920**</td>
<td>--</td>
<td>3.736**</td>
<td>3.990**</td>
</tr>
<tr>
<td>age2(b20)</td>
<td>--</td>
<td>--</td>
<td>--</td>
<td>-0.042**</td>
<td>-0.046**</td>
<td>--</td>
<td>-0.042**</td>
<td>-0.046**</td>
</tr>
<tr>
<td>mage1(b01)</td>
<td>--</td>
<td>--</td>
<td>--</td>
<td>--</td>
<td>0.108*</td>
<td>3.768**</td>
<td>4.328**</td>
<td></td>
</tr>
<tr>
<td>mage2(b02)</td>
<td>--</td>
<td>--</td>
<td>--</td>
<td>--</td>
<td>--</td>
<td>-0.047**</td>
<td>-0.047**</td>
<td>-0.053**</td>
</tr>
</tbody>
</table>

Random effect

| Epsilon      | 204.96** | 204.96** | 158.41** | 194.95** | 157.12** | 204.91** | 194.94** | 157.17** |
| Tau0         | 520.79** | 520.79** | 533.80** | 523.47** | 533.78** | 472.84** | 476.07** | 484.23** |
| Tau1         | --      | --      | 4.165**  | --      | 19.45**  | --      | --      | 18.80**  |
| Tau2         | --      | --      | --      | --      | 0.003**  | --      | --      | 0.003**  |

Model Fit

| BIC       | 263502 | 263513 | 260519 | 262176 | 259825 | 263004 | 261684 | 259300 |

Note. *p<.05, **p<.01. ‘age1’ and ‘age2’ respectively represents the within effects of linear and quadratic forms of age. ‘mage1’ and ‘mage2’ respectively denotes the between effects of linear and quadratic forms of age.

Moreover, when considering the quadratic growth model of age on the trajectory of wage, both Ma3 (age2=-0.042, p<.001) and Ma4 (age2=-0.046, p<.001) still show significantly negative results, and indicating an increase from young to middle age but a decrease toward older age. Ma4 has an estimation on random effects of the curvature, which is significant at p<.001, meaning that the rate of people’s wage going upward and then going downward is again significantly different.

Contextual variables are the mean value of age and age square, labeled as mage1 and mage2, variables that are transformed from level one variables to explain the individual differences of intercepts in level two equation.

In Ma5, only level two variables, mage1 and mage2, are included, without any variations within individuals. The square term of this quadratic growth model is also significantly negative (mage2=-0.047, p<.001). Adding the age and age square variables in Ma6 and Ma7, respectively, did not affect the results. Both the square of age (Ma6: age2=-0.042, p<.001; Ma7: age2=-0.046, p<.001) and of the mean age (Ma6: mage2=-0.047,
p<.001; Ma7: mage2=-0.053, p<.001) remain significantly negative, and they didn’t differ much in estimates, either. As a whole, there is a quite robust curvilinear relationship between age and wage, where wage rises from young to middle age but declines toward older age.

Additionally, after taking random effects into considerations in Ma7, both slope variance and curvature variance are significant at p<.001, revealing individual differences in these coefficients. In other variances, variances among individuals (Tao0) were significant in all models at p<.001—from Ma1 to Ma7—as well as variances within individuals (Epson), indicating significant differences in comparing individually and tracking personally. With the lowest BIC, Ma7 is the best to fit the data; therefore, in the next discussions of premium effects, the research is going to base on this model.

4.2.3 Age Effects on the Trajectory of Wage with Covariates

As shown in Table 7 model Map, adding human capital factors to Ma7 did not affect the estimates for age effects considerably. However, when those are controlled, the estimates for both age and age square variables dropped a little but still remained significant, inferring that part of the age effects actually come from the effects of those premium factors. Moreover, compared from model M1, the model of pure human capital premium effects, the effect of education year is stronger in Map than in M1. It revealed the fact that controlling the effects of age would magnify the effect of education, that the rise of wage is not only because of aging but because of the accumulation of education.
### Table 8
**Premium effects of age on wage**

<table>
<thead>
<tr>
<th></th>
<th>M0</th>
<th>Ma7</th>
<th>M1</th>
<th>Map</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Fixed effect</strong></td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Intercept(b00)</td>
<td>453.03**</td>
<td>453.29**</td>
<td>389.37**</td>
<td>353.77**</td>
</tr>
<tr>
<td>age1(b10)</td>
<td>--</td>
<td>3.99**</td>
<td>--</td>
<td>3.79**</td>
</tr>
<tr>
<td>age2(b20)</td>
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<td>-0.046**</td>
<td>--</td>
<td>-0.042**</td>
</tr>
<tr>
<td>mage1(b01)</td>
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<td>4.328**</td>
<td>--</td>
<td>4.542**</td>
</tr>
<tr>
<td>mage2(b02)</td>
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<td>--</td>
<td>-0.047**</td>
</tr>
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<td>sex</td>
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<td>11.197**</td>
<td>11.089**</td>
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<td>3.135**</td>
<td>3.626**</td>
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<td>--</td>
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<td>0.256**</td>
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<td></td>
</tr>
<tr>
<td>Epson</td>
<td>204.96**</td>
<td>157.17**</td>
<td>195.34**</td>
<td>131.04**</td>
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<td>484.23**</td>
<td>324.17**</td>
<td>266.65**</td>
</tr>
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<td>18.80**</td>
<td>--</td>
<td>14.231**</td>
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<td>--</td>
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<td>0.233**</td>
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<td>263502</td>
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<td>256801</td>
<td>251091</td>
</tr>
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</table>

*Note.* *p*<.05. **p**<.01. ‘age1’ and ‘age2’ respectively represents the within effects of linear and quadratic forms of age. ‘mage1’ and ‘mage2’ respectively denotes the between effects of linear and quadratic forms of age. ‘sex’ means gender, ‘eduyear’ represents years of education and ‘wh’ equals to working hours.
4.3 Period Effect on the Trajectory of Wage

Different from age, everyone goes through the same periods, from 1999 to 2016; therefore, period effects only involve within-subject discussions, without any discussions about contextual effects.

4.3.1 Period Effect on the Trajectory of Wage without Covariates

Table 8 demonstrates five models which include linear growth models (Mp1 and Mp2) and quadratic growth models (Mp3 and Mp4), with estimation merely on fixed effects in Mp1 and Mp3 and on both fixed and random effects in Mp2 and Mp4.

Table 9

<table>
<thead>
<tr>
<th></th>
<th>M0</th>
<th>Mp1</th>
<th>Mp2</th>
<th>Mp3</th>
<th>Mp4</th>
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</tr>
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<td>Intercept(b00)</td>
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<td>452.75**</td>
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<td>458.62**</td>
<td>456.03**</td>
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<td>0.028</td>
<td>0.252**</td>
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<td>-1.434**</td>
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<td>--</td>
<td>0.097**</td>
<td>0.087**</td>
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<tr>
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<td>204.96**</td>
<td>161.14**</td>
<td>199.92**</td>
<td>146.67**</td>
</tr>
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<td>520.56**</td>
<td>704.76**</td>
<td>523.12**</td>
<td>731.435**</td>
</tr>
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<td>--</td>
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<td>--</td>
<td>17.971**</td>
</tr>
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<td>260951</td>
<td>262863</td>
<td>259854</td>
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</tbody>
</table>

Note. *p<.05. **p<.01. ‘period1’ and ‘period2’ respectively represents the within effects of linear and quadratic forms of period.

The estimated period effects for the wage are reported in Table 8. In the result of Mp1, it reveals that when only fixed effects are considered, the linear effect of period was positive but insignificant (period1=0.028, p>.05), indicating that the mean wage for everyone remains about the same as they age. Nevertheless, if random effects (tau1=3.335, p<.001) were taken into account, the linear effect of period becomes significantly positive (period1=0.252, p<.001), confirming that our average wage rises as time goes on. Comparing these two models, BIC decreases in Mp2 but increases in Mp1, an indicator that suggests Mp2 be a better model for fitting the data than Mp1.
As the quadratic growth model of period is estimated on the trajectory of wage, both Mp3 (period2=0.097, p<.001) and Mp4 (period2=0.087, <.001) exhibit significantly positive results. These suggest that as the time goes by the average wage did not always go up, but rather it went down in a period of time, and then it rose again. Mp4 demonstrates the random effects of the curvature, which is significant at p<.001, inferring that the rate of people’s wage going downward and then going upward is significantly different.

Moreover, from Mp1 to Mp4, variances among individuals (tao0) were significant in all models at p<.001, as well as variances within individuals (Epsilon), indicating significant effects for comparing among individuals and within subjects. Adjusting for all covariates in Mp4 decreased the BIC the most and hence best improved the model fit; therefore, the discussion of premium effects in the next section will base on this model.

4.3.2 Period Effect on the Trajectory of Wage with Covariates

In Table 9, the quadratic function of period is significant and intensified after including some premium effects into the model, meaning that period effects stand out a little after controlling the effects of other human capital factors. On the other hand, when comparing model Mpp to model M1, effects of all premium factors remain significant and even get magnified. It implies that part of the period effect results from not only itself but also the influence of gender, educational levels and working hours.
Table 10

*Premium effects of period on wage*

<table>
<thead>
<tr>
<th></th>
<th>M0</th>
<th>Mp4</th>
<th>M1</th>
<th>Mpp</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Fixed effect</strong></td>
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<td>3.284**</td>
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<td>wh</td>
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<td>0.254**</td>
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<tr>
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<td></td>
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<td></td>
</tr>
<tr>
<td>Epsilon</td>
<td>204.96**</td>
<td>146.67**</td>
<td>195.34**</td>
<td>122.77**</td>
</tr>
<tr>
<td>Tau0</td>
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<td>324.17**</td>
<td>467.74**</td>
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<td>0.035**</td>
</tr>
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<td>Tau3</td>
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<td></td>
<td></td>
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<tr>
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<td>259854</td>
<td>256801</td>
<td>251475</td>
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</tbody>
</table>

*Note.* *p<.05, **p<.01. ‘period1’ and ‘period2’ respectively represents the within effects of linear and quadratic forms of period. ‘sex’ means gender, ‘eduyear’ represents years of education and ‘wh’ equals to working hours.
4.4 Cohort Effect on the Trajectory of Wage

In this section, only cohort effect, a between-subject comparison, would be discussed first, so level one explanatory variables are not included in the models. As the model equation is explained by the differences between individuals, regardless of any variations within individuals, the mean value of wage was adapted as the dependent variable.

4.4.1 Cohort Effect on the Trajectory of Wage without Covariates

Based on the above description, fixed effects of the variables are demonstrated in Mc1 and Mc2 models in Table 10. Both of them are models of intercept-as-outcome, but in respective order they are linear growth model and quadratic growth model.

Table 11

\textit{Results of cohort effect on wage}

<table>
<thead>
<tr>
<th></th>
<th>M0</th>
<th>Mc1</th>
<th>Mc2</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Fixed effect</strong></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>Intercept(b00)</td>
<td>453.03**</td>
<td>445.18**</td>
<td>428.98**</td>
</tr>
<tr>
<td>cohort 1(b01)</td>
<td>--</td>
<td>1.23**</td>
<td>9.86**</td>
</tr>
<tr>
<td>cohort 2(b02)</td>
<td>--</td>
<td>--</td>
<td>-.801**</td>
</tr>
<tr>
<td><strong>Random effect</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Epsilon</td>
<td>204.96**</td>
<td>204.90**</td>
<td>204.90**</td>
</tr>
<tr>
<td>Tau0</td>
<td>520.79**</td>
<td>509.67**</td>
<td>481.26**</td>
</tr>
<tr>
<td>Tau1</td>
<td>--</td>
<td>--</td>
<td>--</td>
</tr>
<tr>
<td>Tau2</td>
<td>--</td>
<td>--</td>
<td>--</td>
</tr>
<tr>
<td><strong>Model Fit</strong></td>
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<td></td>
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<tr>
<td>BIC</td>
<td>263502</td>
<td>263369</td>
<td>263075</td>
</tr>
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</table>

\textit{Note.} *p<.05. **p<.01. ‘cohort1’ and ‘cohort2’ respectively represents the within effects of linear and quadratic forms of cohort.

Table 10 reports the model estimates for the mean value of wage by cohorts. The results of Mc1 indicate that the linear effect of cohort was positive and significant for the mean wage (cohort1 =1.23, p<.001). This shows that mean wage increased as the value of cohort increased. To move a step further, the quadratic growth model (Mc2) also revealed a significant curvilinear relationship between cohort and the mean wage (cohort2=-0.801, p<.001), all linear and quadratic effects significant at p<.001. Variances among individuals were significant in both models (Mc1: Tau0=509.67, p<.001; Mc2: Tau0=481.26, p<.001), suggesting that there be a significant difference in comparing the wage level among cohorts.
Jointly, in a quadratic equation it is not only a model with lower BIC but a higher order growth model with significant results; consequently, a quadratic growth model is best to fit the data and to be the baseline model testing premium effects.

4.4.2 Cohort Effect on the Trajectory of Wage with Covariates

Similarly, after including premium effects in the model, cohort effect drops a little but remains significant at p<.001, suggesting that part of the effect is controlled by some demographic factors. Next, when model Mpp and model M1 are compared, premium effects except for gender are more significant. And it has an implication that controlling the effect of cohort could let the effect of educational years and working hours stand out, thus more profoundly differentiating individuals.

Table 12

<table>
<thead>
<tr>
<th>Premium effects of cohort on wage</th>
<th>M0</th>
<th>Mc2</th>
<th>M1</th>
<th>Mcp</th>
</tr>
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<tbody>
<tr>
<td><strong>Fixed effect</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Intercept (b00)</td>
<td>453.03**</td>
<td>428.98**</td>
<td>389.37**</td>
<td>456.30**</td>
</tr>
<tr>
<td>cohort 1 (b01)</td>
<td>--</td>
<td>9.86**</td>
<td>--</td>
<td>4.13**</td>
</tr>
<tr>
<td>cohort 2 (b02)</td>
<td>--</td>
<td>-0.80**</td>
<td>--</td>
<td>-0.58**</td>
</tr>
<tr>
<td>sex</td>
<td>--</td>
<td>--</td>
<td>11.20**</td>
<td>11.15**</td>
</tr>
<tr>
<td>eduyear</td>
<td>--</td>
<td>--</td>
<td>3.135**</td>
<td>3.96**</td>
</tr>
<tr>
<td>wh</td>
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<td>--</td>
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<td>0.27**</td>
</tr>
<tr>
<td><strong>Random effect</strong></td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Epsilon</td>
<td>204.96**</td>
<td>204.90**</td>
<td>195.34**</td>
<td>163.22**</td>
</tr>
<tr>
<td>Tau0</td>
<td>520.79**</td>
<td>481.26**</td>
<td>324.17**</td>
<td>258.20**</td>
</tr>
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<td>Tau1</td>
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<td>0.283**</td>
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<td>BIC</td>
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<td>263075</td>
<td>256801</td>
<td>253944</td>
</tr>
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</table>

Note. *p<.05. **p<.01. ‘cohort1’ and ‘cohort2’ respectively represents the within effects of linear and quadratic forms of cohort. ‘sex’ means gender, ‘eduyear’ represents years of education and ‘wh’ equals to working hours.
4.5 Results of APC Effects on Wage

Compared to previous discussions in sections 4.2 to 4.4, which examines single age effect, single period effect, and single cohort effect, respectively, this section is demonstrated by a combination of those three effects in one model. The combination effects are shown in respective order of without and with covariates in the first and the second section.

4.5.1 The Results of APC on Wage without Covariates

As demonstrated in the model Mapc of Table 12, effects of both age and period remain statistically significant, and they are quadratic curves with downward opening (age$^2$=-0.04, $p<.001$) and upward opening (period$^2$=0.061, $p<.001$), respectively. Taking a closer look at age effects, not only within-subject results but also between-individual comparisons (mage$^2$=-0.039, $p<.001$) are significant. However, the effects of cohort become insignificant (cohort$^2$=-0.226, $p>.05$) when age and period effects are controlled.  

(Syntax of Mplus of Mapc and MM are listed in Appendix III and IV, respectively)
Table 13

**Results of APC effects on wage**

<table>
<thead>
<tr>
<th>Fixed effect</th>
<th>Ma7</th>
<th>Mp4</th>
<th>Mc2</th>
<th>Mapc</th>
<th>MM</th>
</tr>
</thead>
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<tr>
<td>Intercept(b00)</td>
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<td>456.03**</td>
<td>428.98**</td>
<td>397.33**</td>
<td>409.11**</td>
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<td>3.607**</td>
<td>3.687**</td>
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<td>age2(b20)</td>
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<td>-0.04**</td>
<td>-0.035**</td>
</tr>
<tr>
<td>mage1(b01)</td>
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<td>--</td>
<td>3.071**</td>
<td>3.112**</td>
</tr>
<tr>
<td>mage2(b02)</td>
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<td>-0.039**</td>
<td>-0.036**</td>
</tr>
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<td>-1.333**</td>
<td>-1.689**</td>
</tr>
<tr>
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<td>0.061**</td>
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<td>9.86**</td>
<td>2.673</td>
<td>-0.873</td>
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<tr>
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<td>--</td>
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<td>-0.226</td>
<td>-0.043</td>
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<td>--</td>
<td>--</td>
<td>0.225**</td>
</tr>
</tbody>
</table>

| Random effect | | | | | |
| Epison | 157.17** | 146.67** | 204.90** | 144.24** | 120.26** |
| Tau0  | 484.23** | 731.44** | 481.26** | 1089.9** | 502.86** |
| Tau1  | 18.80** | --    | --    | 34.237** | 23.903** |
| Tau2  | 0.003** | --    | --    | 0.003** | 0.002** |
| Tau3  | --    | 17.971** | --    | 11.127** | 7.899** |
| Tau4  | --    | 0.037** | --    | 0.039** | 0.033** |
| Tau5  | --    | --    | --    | --    | 0.225** |

| Model Fit | | | | | |
| BIC | 259300 | 259854 | 263075 | 258105 | 249969 |

Note: *p<.05, **p<.01. ‘age1’ and ‘age2’ respectively denotes the within effects of the linear and quadratic forms of age, while ‘mage1’ and ‘mage2’ respectively means the between effects of the linear and quadratic forms of age. ‘period1’ and ‘period2’ are in respective orders of the linear and quadratic forms of period. ‘cohort1’ and ‘cohort2’ respectively represents the within effects of linear and quadratic forms of cohort. ‘sex’ means gender, ‘eduyear’ represents years of education and ‘wh’ equals to working hours.

4.5.2 The Results of APC on Wage with Covariates

As demonstrated in the full model MM, human capital factors are subsequently added as the covariates of the previous Mapc model. When those premium effects are controlled, with only slight differences in estimates, the effects of age (within- and between-effects) and period effects remain significant as in the results of any other models. Nevertheless, cohort effects are still insignificant, with even more trivial lower estimates (cohort2=-0.043, p>.05). This model, with the combination of age, period and cohort effects, as well as the covariates considered, reaches the lowest BIC; as a consequence, to fit our data it is the best one among all models.
Chapter V. Discussions and Conclusion

The purpose of this study is to examine the impacts of three critical temporal variables as age, period and cohort on wage. Due to the nested structure of our data, which is composed of both longitudinal and cross-sectional parts, it is decomposed into within- and between-subject effects. Based on this feature, variables that change with time, like age, period and working hours, are tested as level-one effects; on the other hand, demographic variables like birth cohort, gender and years of education that differentiate individuals are treated as level-two effects.

5.1 An Overall Discussions on Age, Period and Cohort Effects

5.1.1 Age Effects

In social science studies, age effects have long been a widely discussed topic. Among several discussions in human capital theory, relationships between age and any dependent variables that involve performance, rewards, or pay are likely to be illustrated in a downward quadratic function, a function that is also validated in our research. In this research, the highest level of wage across one’s lifespan occurs at the age of 42.61 (without any covariates), 45.09 (with cohort and period as covariates), and 52.67 (with all covariates), while the highest counterpart between individuals are at the age of 40.83 (without any covariates), 39.37 (with cohort and period as covariates), and 43.22 (with all covariates), as illustrated in Figure 8 in respective order of model Ma4, Mapc, and MM. No matter comparing within one’s lifespan or comparing between different people, the results are all consistent with the fact that wage level is highest in one’s middle ages (40s to 50s). On the other hand, in our discussions about age-period-cohort analysis, the effects of age are fairly significant and the results in all models are quite stable. As can be seen in the comparison of models Ma7 and Mapc, whether to control the effects of period and cohort has little influence on the estimates and the significance level of age.

Moreover, age effects can be observed both on the wage levels of individuals within and on the wage comparisons of person to person. These outcomes are significant in all models, indicating a downward quadratic curve of wage in not only the aging process of individuals but the development of between-person. Furthermore, there is substantial
variation in the intercepts, the slopes and the curvature, presenting the fact that both the beginning and the degree of change in wage, even the rate of change would differ from people to people.

(a1) age effects (within) without covariates

Max y at age = 42.61

(b1) age effects (within) with period and cohort as covariates

Max y at age = 45.09

(c1) age effects (within) with period, cohort and premium effects as covariates

Max y at age = 52.67
Figure 8 Anchor points of quadratic function of wage by ages
5.1.2 Period Effects

During 1999 and 2016 (the measurement period), every participant would simultaneously experience the same events, such as the global financial crisis; therefore, without considering random effects, period effects only cause wage differences in an individual’s lifespan. In all models period effects are all upward quadratic function with significant estimates. It reveals that even with the control of covariates, period effects still result in notable fluctuations on the wage trajectory, a result that reminds us the importance of environmental factors to the wage dynamics.

Moreover, when the lowest points of those quadratic functions are observed, Mp4, Mapc, and MM models depict diverse outcomes in respective order: 8.24 (year 2009.24), 10.93 (year 2011.93), and 13.84 (year 2014.84), which are illustrated in Figure 9 (a), (b), and (c). It shows that the more covariates are added to the models, the more profound period effects are postponed.

In model Mp4, without any covariates, the lowest wage level occurred in the year 2009.24, a time that the global financial crisis generally causes the overall wage level to drop. After controlling age effects in model Mapc, the lowest level of wage was deferred to the year 2011. This indicates that after considering the effect of a certain age group of people, whose reaction to the financial crisis was vehement, the economic impacts about which financial crisis bring would be postponed to the year 2011. Last but not the least, adding human capital factors as covariates into the model MM can further control the period effect, suggesting that people with higher educational level, or higher socioeconomic status, contribute stability to the economy. It also corresponds to the perspective of human capital theory that one of the most important factors to defend environmental impacts (period effects) is the accumulation of human capital.
Figure 9 Anchor points of quadratic function of wage by periods
5.1.3 Cohort Effects

Everyone is born in a certain year, so that each person belongs to a certain generation, suggesting that in age-period-cohort analysis, cohort effect is the only level-two variable. An effect that would differentiate the wage level between person to person.

In the model without any covariates, Mc2, cohort is another downward quadratic curve with statistically significant effect. After the calculation of estimates, the highest wage level is at 6.15, as shown in Figure 10 (a), presenting that people born in year 1966-1970 yield the most earnings each month.

Nevertheless, in Mapc and MM models, the controlling effects of covariates make cohort effects insignificant, as demonstrated in Figure 10 (b) and (c). It can be illustrated by a statistical concept that when age, period and cohort variables are simultaneously incorporated into a model, the cohort effect would be largely explained by the effect of period or age, thereby becoming insignificant. Therefore, when conducting age-period-cohort analysis, it is crucial to note that cohort effect may be credited to period or age effects, that cohort effect alone may not have significant implications on temporal issues.
Figure 10 Anchor points of quadratic function of wage by cohorts

(a) cohort effects without covariates (significant)

Max y at cohort = 6.15

(b) cohort effects with age and period as covariates (insignificant)

Max y at cohort = 5.91

(c) cohort effects with age, cohorts and other premium effects as covariates (insignificant)
5.2 An Overall Discussions on the Premium Effects

In the preceding models, premium effects are mainly regarded as the covariates of age, period and cohort effects. However, in human capital theory, such factors as gender, years of education and working hours are fairly representative when issues of premium effects are investigated.

Table 14

<table>
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<th></th>
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<th>age</th>
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<th>cohort</th>
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<td>10.63**</td>
</tr>
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<td>3.66**</td>
</tr>
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<td>-1.69**</td>
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<tr>
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<td>-0.043</td>
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<td></td>
</tr>
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</table>

Model Fit

BIC 256801 251091 251475 253944 249969

Note. *p<.05. **p<.01. The above age discussions are represented by the combination of the square terms of age in both levels, period represents the square term of period, and cohort is the square term of cohort. And the APC part stands for a combination of age, period and cohort effects which are all in their square term.

As shown in Table 13, overall these human capital factors are significant at p<.001 in whatever models, but each of them generate different implications to our wage study. Firstly, since the gender variable is coded as 0 (female) and 1 (male) in this research, it can be inferred from the table that the wage of male is significantly and consistently higher than the wage of female. Secondly, no matter which temporal effect is controlled, the effect of education is then magnified, comparing to the premium-only model. Especially when cohort
effects are the covariates, the effect of the accumulation of educational years is at most intensified. Lastly, working-hour is another stable and significant factor of premium effect, indicating that longer working hours generally result in higher wage levels.

As explained in the previous section, in different models the effects of age, period and cohort vary; nonetheless, the results of premium effects are stable in all models, which again confirm the value of human capital theory. To make a brief summary, age-period-cohort analysis in this study does not affect human capital theory; more importantly, it is the methodology of the general discussion of these common variables to which it wants to contribute.

5.3 Methodological Discussions

The most significant contribution of age-period-cohort analysis is that with the increasing availability of large-scale longitudinal data, it opens up new possibilities to investigate the different effects of age, period and cohort on wage trajectory and relevant constructs. Even though many multilevel models have been used to estimate age and cohort effects with longitudinal data, period effects are usually excluded. This is because the effects of age and period are typically confounded in longitudinal studies (Yang & Land, 2013). However, the global financial crisis during the period of this study (1999-2016) was such a relevant shock for the level of wage, an event that made it possible to separate age effects from the effect of the economic downturn period. Additionally, other demographic factors that are also human capital factors are included in some of the models, enabling us to generate a comprehensive analysis of wage trajectory. As a result, not only the pure effects of age, period and cohort variables are examined but their relationships among human capital factors are included.

Among longitudinal studies of multilevel modeling, ‘centering’ has always been a critical issue. If certain independent variable has not been moved to a proper location, say, the original point, its interpretation of the intercept would be distorted. Therefore, it is indispensable to center variables in multilevel modeling (Raudenbush, 1989).

Furthermore, data in this longitudinal study carries the information of time, so that centering becomes even more essential. For example, in terms of the characteristics of variables, as the beginning (year 1999) and ending (year 2016) periods are the same for every participant, the group mean, 8.5, does not vary from person to person. This shows little difference on whether or not to do the centering. Nonetheless, it is the age variable that
presents such difference. Since the beginning and the ending ages of all participants are not the same, the group means of age variable are endowed with individual differences. Consequently, age variable is centered, so that the average wages for each average age are obtained and then the intercept acquired at this time reflects the average salary spanning 18 years for everyone. In addition, in a recent research of Fur-Hsing Wen (2015) it claims that the optimal approach to coping with repeated cross-sectional dataset is to use group-mean centered in a level-one equation and place group means in the level-two intercept equation. With regard to the age variable in our study, it is a quadratic growth equation, so both age and age square are centered by group-mean in the level-one equation, a procedure that is able to measure the within-subject impacts of age on the wage. At the same time, group means of age and age square (mage and mage2) are centered by grand-mean and placed in the level-two intercept equation, being considered as explanatory variables of the intercept (average age). By doing this, the mean wage differences between individuals are able to be restored.

Generally speaking, a linear model is always the beginning of an analysis, for it is the most intuitive one. However, the slope of a linear model can sometimes be significant, but at times it can be insignificant. Especially temporal effects in this research, they may not be linear but parabolic, a parabolic perspective is usually considered important when conducting longitudinal data analysis. Besides, as can be seen from the human capital theory that some human capital factors are square terms. In this study, the estimation results are different in the linear and the quadratic terms. Normally if we do not have the concept of a quadratic item in mind, we tend to think that the linear model is correct; therefore, it is highly recommended to bear the quadratic term in mind in a longitudinal study. Due to the model complexity, in our study only quadratic items are achieved. As for the possibility of cubic or higher order terms, future research is expected to find it.

In multilevel modeling, shrinkage of the coefficients is not easy to determine the goodness-of-fit, while the Bayesian Information Criterion (BIC) is better adopted to make model comparisons. The BIC, developed in a 1978 paper by Gideon E. Schwarz, is a criterion for model selection among a set of models: models with smaller BIC values are preferred to models with larger values. If more variables with significant effects are included in the models, a better model with less BIC value is obtained. Therefore, it is such criterion that could utilize the process of model selection for multilevel modeling.
5.4 Conclusion

The study demonstrates how the integration of longitudinal data and multilevel models can be used to separate effects of age, cohort, and periods on wage, and how these methodologies can be extended to examining premium effects of gender, education and working hours. Results are subsequently summarized. Firstly, age is a downward quadratic function with stable and significant effects, and the highest level of wage occurs at forties to fifties. Even more, age effects are significant not only at a within-individual level, but also at between-level comparisons. Next, period effects are significant across one’s lifespan, which means that this effect can bring about notable variations on one’s wage trajectory. However, the lowest point of this upward quadratic function is likely to defer from the year 2009 to the year 2014, as other covariates are controlled. Lastly, cohort effect is a level-two variable, generating an outcome that people born in the year 1966 to 1970 earn most per month. But this effect becomes insignificant when the other two effects are also included in a model. In addition, premium effects, such as the investments of educational years and working hours, verify the fact that with the accumulation of important human capital factors and without being affected by temporal variables, more salary would be generated. Results above are all supported by several methodologies chosen in this study—the adoption of BIC, centering of variables, and the use of both linear and quadratic terms—enabling our models to better fit the data and produce more accurate estimates.

5.5 Managerial Implications

An observation on wage trajectory as well as the premium effects can not only contribute to academic research but bring about several managerial implications. Phenomena that have been advocated in economics, such as gender, education, and other labor factors, provide so long-standing meanings and durable values that would not be challenged by the effects of age, period and cohort. This discovery is in line with the established confidence in human capital, a theory that has long been practiced in many fields. For example, the idea that the accumulation of education can promote salary level and that longer working hours can usually result in higher salary are essential to both applicants and the firm.

Additionally, based on the discovery of this research, people aged 40 to 50 yield most income in their lives, which is consistent with our general understanding, and it be related to the policies of recent Taiwan’s annuity reform. On the other hand, it is advised that
managers care less about cohort differences, because of their insignificant effects. Lastly, inferred from the deferment of period effects, with the increasing inputs of human capital and some rearrangement of related policies, it is possible for managers of a company to withstand and postpone the impacts of exogenous shocks. In sum, besides academic realization, information that is indicated by human capital practices and findings of temporal effects are the facets of practical application of this research.

5.6 Limitations and Suggestions

Some potential limitations have to be proposed to provide opportunities for further research and theorizing. One limitation is that even though it uses a large representative sample followed over 18 years, the number of average periods answered by every participant is actually 5.6 years. It may due to a large quantity of missing values in this study, which may generate invalid results for the corresponding. A second limitation concerns the generalizability of the discoveries to other societies. The data set used in this study only covers Chinese families, and it could thus be that the changes and variations of the wage trajectory are specific to the Chinese population. Therefore, it is suggested that other cross-national research could construct the influence of socioeconomic and other cultural conditions in future studies. Third, higher order (three- or four-way) of variables, such as age, period and cohorts, were not examined. Moreover, although our model allowed sociodemographic such as gender, educational level, and working hours to influence the trajectory of wage across the lifespan, other relevant factors could have important effects, too. To sum up, in age-period-cohort analysis, future research using such data and models is hoped to have the potential to find more phenomena with solutions and more implications for other variables, such as well-being, over time.
Reference


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Appendix I. Syntax of Mplus of Ma6

TITLE: Longitudinal APC unconditional model
DATA: FILE= apc4.csv;
VARIABLE: NAMES=bid id sex birth edu cohort period age1 cpiwage lgcpiwage wh eduyear cohort0 cohort1 cohort2 cohort3 cohort4 cohort5 cohort6 cohort7 cohort8 cohort9 cohort10;
USEV=lgcpiwage age1 age2 mage1 mage2 y;
CLUSTER= id;
WITHIN= age1 age2;
BETWEEN= mage1 mage2;
MISSING IS sex birth edu cohort eduyear cpiwage lgcpiwage (-9);
DEFINE: age2=age1*age1;
!IF (P LT 4) THEN Period=0;
!IF (P GE 4) THEN Period=1;
mage1 = CLUSTER_MEAN (age1);
mage2 = CLUSTER_MEAN (age2);
y=100*lgcpiwage;
CENTER age1 age2 (GROUPMEAN);
CENTER mage1 mage2 (GRANDMEAN);
!CENTER wh (grandmean);
ANALYSIS: TYPE= TWOLEVEL;
!ESTIMATOR=BAYES; PROCESSORS=2; BITER=(5000);
MODEL: %WITHIN%
y ON age1 age2;

%BETWEEN%
y ON mage1 mage2;
Appendix II. Syntax of Mplus of Ma7

TITLE: Longitudinal APC unconditional model
DATA: FILE= apc4.csv;
VARIABLE: NAMES=bid id sex birth edu cohort period age1 cpiwage lgcpiwage wh eduyear
cohort0 cohort1 cohort2 cohort3 cohort4 cohort5 cohort6 cohort7
cohort8 cohort9 cohort10;
USEV= lgcpiwage age1 y age2 mage1 mage2;
WITHIN= age1 age2;
BETWEEN= mage1 mage2;
CLUSTER= id;
MISSING IS age1 lgcpiwage (-9);

ANALYSIS: TYPE= TWOLEVEL random;
!ESTIMATOR=BAYES; PROCESSORS=2; BITER=(5000);

DEFINE: !period2=period*period;
y=lgcpiwage*100;
age2=age1*age1;
mage1=CLUSTER_MEAN(age1);
mage2=CLUSTER_MEAN(age2);
CENTER age1 age2 (GROUPMEAN);
CENTER mage1 mage2 (GRANDMEAN);

MODEL: %WITHIN%
s1 | y ON age1;
s2 | y ON age2;
%BETWEEN%
y  on mage1 mage2;
! s1 s2 on mage1 mage2;
y WITH s1;y WITH s2; s1 WITH s2;

Output: sampstat;
  stdyx;
Appendix III. Syntax of Mplus of Mapc

TITLE:      Longitudinal APC unconditional model
DATA:       FILE= apc4.csv;
VARIABLE:   NAMES=bid id sex birth edu cohort period age1 cpiwage lgcpiwage wh eduyear
cohort0 cohort1 cohort2 cohort3 cohort4 cohort5 cohort6 cohort7
cohort8 cohort9 cohort10;

USEV= lgcpiwage age1 cohort period y period2 c2 age2 mage1 mage2;
    WITHIN= age1 period period2 age2;
    BETWEEN= cohort c2 mage1 mage2;
    CLUSTER= id;
    MISSING IS eduyear sex age1 cohort lgcpiwage (-9);

ANALYSIS:   TYPE= TWOLEVEL random;
    !ESTIMATOR=BAYES; PROCESSORS=2; BITER=(5000);

DEFINE:     y=lgcpiwage*100;
            period2=period*period;
            c2=cohort*cohort;
            age2=age1*age1;
            mage1=CLUSTER_MEAN(age1);
            mage2=CLUSTER_MEAN(age2);
            CENTER age1 age2(GROUPMEAN);
    !CENTER eduyear sex wh(GRANDMEAN);

MODEL:      %WITHIN%
            s1 | y ON age1;
            s2 | y ON age2;
    !s3 | y ON wh;
            s4 | y ON period;
            s5 | y ON period2;
    %BETWEEN%
            y on cohort c2 mage1 mage2;
    !s1 on eduyear sex mage1 mage2;
    !s2 on eduyear sex mage1 mage2;
            y WITH s1; y WITH s2; s1 WITH s2;
            y WITH s4; y WITH s5; s1 WITH s4;
            s2 WITH s4; s1 WITH s5;
            s2 WITH s5; s4 WITH s5;

Output: sampstat;
      stdyx;
Appendix IV. Syntax of Mplus of MM

TITLE: Longitudinal APC unconditional model
DATA: FILE= apc4.csv;
VARIABLE: NAMES=bid id sex birth edu cohort period age1 cpiwage lgcpiwage wh eduyear cohort0 cohort1 cohort2 cohort3 cohort4 cohort5 cohort6 cohort7 cohort8 cohort9 cohort10;
USEV= lgcpiwage age1 eduyear cohort period sex wh y period2 c2 age2 mage1 mage2;
WITHIN= age1 period wh period2 age2;
BETWEEN= eduyear sex cohort c2 mage1 mage2;
CLUSTER= id;
MISSING IS eduyear sex wh age1 cohort lgcpiwage (-9);

ANALYSIS: TYPE= TOWLEVEL random;
!ESTIMATOR=BAYES; PROCESSORS=2; BITER={(5000)};

DEFINE: y=lgcpiwage*100;
period2=period*period;
c2=cohort*cohort;
age2=age1*age1;
mage1=CLUSTER_MEAN(age1);
mage2=CLUSTER_MEAN(age2);
CENTER age1 age2(GROUPMEAN);
CENTER eduyear sex wh(GRANDMEAN);

MODEL: %WITHIN%
s1 | y ON age1;
s2 | y ON age2;
s3 | y ON wh;
s4 | y ON period;
s5 | y ON period2;
%BETWEEN%
y on eduyear sex cohort c2 mage1 mage2;
l s1 on eduyear sex mage1 mage2;
l s2 on eduyear sex mage1 mage2;
y WITH s1;y WITH s2; s1 WITH s2;
y WITH s3;s1 WITH s3; s2 WITH s3;
y WITH s4; y WITH s5; s1 WITH s4;
s2 WITH s4; s3 WITH s4; s1 WITH s5;
s2 WITH s5; s3 WITH s5; s4 WITH s5;

Output: sampstat;
stdyx;