THE TIMING OF EMPLOYMENT INTERRUPTIONS AND FUTURE WAGES

by

DAVID PEREZ GUSTAVO

(Under the Direction of Ronald S. Warren Jr.)

ABSTRACT

This thesis formulates and estimates an empirical model of the effect of human capital depreciation on future wages. It permits the identification of human capital depreciation by comparing the different effects that work interruptions have on workers' wages based on the timing of these interruptions during their careers. Recent career interruptions have a negative effect on workers' productivity; as time passes, the negative effects of these interruptions become negligible. The empirical analysis uses the National Longitudinal Survey of Youth 1979. The results show that the rate of human capital depreciation varies according to different types of workers. Depreciation may be lower among women. This may be a result of self-selection among workers who can more easily plan future career interruptions.

INDEX WORDS: Human Capital, Depreciation, Career Interruption, Unemployment Spell, Productivity, Experience

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DAVID PEREZ GUSTAVO

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by

DAVID PEREZ GUSTAVO

Major Professor: Ronald S. Warren, Jr

Committee: David B. Mustard
Scott E. Atkinson

Electronic Version Approved:

Maureen Grasso
Dean of the Graduate School
The University of Georgia
December 2011

DEDICATION

A mi familia.

To Sandy.

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CHAPTER 1

INTRODUCTION

Human capital theory, originally developed by Becker (1964), provides economists with a powerful tool by allowing the systematic analysis of a heterogeneous labor force. The theory explains how workers create this heterogeneity by investing optimally in different skills and knowledge. Through the human capital model, we can group workers with different skills and types of knowledge into a homogeneous labor input.

There are two main ways to invest in human capital: education and experience. Education involves an active investment by the worker, requiring his time and resources to attain knowledge and skills that will increase his productivity once he enters the labor market. Experience is acquired through learning-by-doing, in which workers become more proficient as they become more familiar with the tasks they usually perform at their workplace. Both forms of human capital are complementary and play a vital role in determining workers' productivity. Higher levels of education increase workers' wages from the beginning of their careers and those wages improve during the workers' lifetimes due to the accumulation of work experience. However, workers' productivity typically reaches a maximum before the age of retirement. This can be explained only by the depreciation of human capital. The knowledge acquired by workers becomes obsolete and the value of past experience in the workplace is not a perfect substitute for more recent experience. This imperfect substitutability implies that when the worker leaves the labor market, his human capital depreciates and this depreciation will reduce his future productivity. He gives up not only the forgone income that he would have earned during his absence from the workplace but also experiences the disinvestment of human capital that occurs during the employment gap and this reduces his wage once he returns to the labor market.

Workers anticipate future human capital depreciation when they make decisions about their labor market participation. McDowell (1982) shows how different rates of expected future human capital depreciation affect how women self-select into academic careers with lower depreciation rates. Women are more likely than men to plan career interruptions so they are able to internalize future human capital depreciation more effectively. Gorlich and Grip (2008) support the same hypothesis by showing that traditionally female-dominated occupations have lower rates of human capital depreciation. Human capital depreciation help explain the gender gap in salaries. Women might be subject to higher human capital depreciation due to more frequent interruptions during their work life, and higher depreciation rates are related to lower salaries. Any study of the earnings gap between men and women should take this into account. Different depreciation rates can affect how women make decisions about their labor market participation, fertility, human capital investment and career selection.

Different depreciation rates can also influence labor market participation through different career expectations. Depreciation rates will affect workers' decisions on retirement. Those careers with lower depreciation rates would be more appealing to workers who plan to remain active in the labor market for longer than those who plan to retire. However, this thesis cannot study this effect since most workers in the sample have not reached their retirement age in 2008.

Very few studies introduce human capital depreciation explicitly in their wage equations. Some authors focus on women's life cycle and how the number of career interruptions affects salaries: Mincer and Polachek (1974), Mincer and Ofek (1982), McDowell (1982), Gorlich and Grip (2008). Other authors study how human capital depreciation affects different activities: Weinberg and Galenson (2007) study the work of Nobel laureates in economics, Levin and Stephan (1991) study the productivity of natural scientists, and Kunze (2002) studies the effect of unemployment spells on skilled workers in Germany.

The main point of this thesis is to show how the time distribution of workers´ career interruptions plays a decisive role in the time path of their future earnings. The closer an employment interruption is to the present, the greater the negative impact will be on a worker's productivity. More recent interruptions are likely to have a greater impact since the worker has not had time to recover the lost human capital. If the value of work experience is the same over the life cycle of the worker, any past experience loss would have the same effect on current wages as a more recent loss. However, if the value of work experience decreases over time the most harmful interruption in terms of current salary would be the most recent interruption. My hypothesis is that the negative effect of an employment interruption will diminish as time passes. I focus on this aspect of human capital depreciation. Those occupations or workers with higher depreciation rates will see their productivity reduced more sharply over time. Differences in the reduction of productivity determine what sectors and groups are most harmed by human capital depreciation. To my knowledge, this is the first study to address the importance of the interruption chronology on workers´ productivity and how it can be used to determine the relative severity of different depreciation rates among types of workers and occupations.

Another advantage of this model is that I do not need extremely detailed data. I also need neither very specific information on the worker's output, nor the exact dates of the interruptions, and my sample is not restricted to those workers who just returned to the labor market. All of these data restrictions are common in the literature. To account fully for workers' labor history, however, I use the National Longitudinal Survey of Youth 1979, which follows the careers of a large, stratified sample of individual.

CHAPTER 2

THE MODEL

I will consider two forms of human capital, education and experience. My main focus is how the timing of career interruptions affects future earnings. While the worker is active in the labor force, it is impossible to determine the cost of human capital depreciation because accumulating work experience constantly creates more human capital. The researcher only observes the value of experience once depreciation has taken effect. Only during non-working periods can depreciation be isolated and studied. If there were no depreciation, workers who return to the labor market could restart their professional careers exactly where they left them, and their salaries would be equal to the salaries of comparable individuals with an equivalent level of cumulative experience. If human capital has depreciated during this period, however, the salary of that worker, once he returns, will be lower than the salary he earned before the break, and this will have an impact on lifetime earnings.

Researchers have studied depreciation in the past using career interruptions because it is only during those interruptions that we can isolate human capital depreciation from human capital investment that occurs in the form of experience. However, we should not forget that human capital depreciation is not confined to career interruptions; doing so could lead to some important mistakes. Mincer and Ofek (1982) study human capital depreciation as the difference in women's salaries between the last salary earned in the pre-interruption period and their re-entry salary after the interruption.

They observe a decrease in this salary, which is their evidence of human capital depreciation. This is shown in Figure 1.

Human capital depreciation creates the loss reflected in the distance BD, which is the difference between pre-interruption and re-entry salaries. BC is the loss due to absence from the labor force during the interruption. Mincer and Ofek (1982) find that, immediately after labor market re-entry, workers experience higher wage growth rates than those who never left. They explain this as a "rebound" or restoration period; in Figure 1, this is represented by BE. Their interpretation of this restoration period is that it is easier to repair previously eroded human capital; that is, they infer that the reconstruction of previously acquired skills is more efficient than the acquisition of new human capital. This could be a valid hypothesis but there is no need to make this assumption, as Figure 2 illustrates.

The only difference between Figure 1 and Figure 2 is that in Figure 2 I included depreciation not only during the interruption period but also during the worker's entire life cycle[1]. The negative compounding effect of the depreciation rate creates a curvature in the graph. We do not need to assume a restoration period after the interruption to explain why wage growth is higher immediately after the return to the labor market. The curvature of the *Early Gap* curve at point B is greater than the curvature of the *Nogaps* curve at the same point in time. This explains the difference in wage growth rates between the worker who experiences an interruption and the worker who does not. I will dicuss the implications of this when I introduce the identification strategy.

[1] Both figures have been created using an initial experience of 100 units that increases by 100 per period with a depreciation rate of 10%, and both include a 4 period interruption at the same point in time. In Figure 1 the depreciation rate was applied only during the interruption while in Figure 2 it was applied from the beginning.

There is no reason to assume that human capital depreciation only affects workers during employment interruptions. Researchers use employment interruptions to study human capital depreciation, but this should not lead us to ignore that it is present the rest of the time, even if we cannot distinguish it from human capital investment. Mincer and Ofek also assume linear returns to experience. However, it is commonplace to assume diminishing returns to inputs in production functions. This assumption imposes a stronger curvature on the figure and makes the linear assumption in Figure 1 even less reasonable, as it is shown in Figure 3[2]. Diminishing returns to experience has other implications that I will discuss in subsequent sections.

Accumulated experience contributes to the stock of human capital that depreciates over time. I do not need to assume different depreciation rates during the lifetime to infer that more recent experience is more valuable for the worker than is past experience. In fact, in this model I assume that the depreciation rate remains constant during the worker's lifetime, although it could vary among occupations and other workers' characteristics. At time $t = 0$, suppose that worker A has 1000 units of experience. Assuming a 10% depreciation rate means that during a one-period interruption beginning at time $t = 0$ he loses 100 units of experience. However, at time $t = \tau$ he has accumulated 2000 units of experience, so with the same depreciation rate and the same length of employment interruption he will lose 200 units of experience if he interrupts his career at $t = \tau$. This difference is not driven by a distinction between short-run and long-run depreciation rates but instead arises because depreciation penalizes more severely those workers with higher levels of experience. As long as the worker stays active in the labor

[2] This figure uses the same simulation as Figure1 & 2 but I consider decreasing return of scale of experience by transforming the results using the expression: $L(w) = \text{experiece}^{\alpha}$ where $\alpha = 0.2$.

market, more recent interruptions will have a greater negative impact on productivity than interruptions of the same length that occurred in the more distant past since the worker has accumulated higher levels of experience with the passage of time.

Recent experience is more valuable at any given time since it has not depreciated as much as more distant experience. Therefore, the most recent career interruptions will have the greatest impact on a worker's productivity. For a mature worker, having an unemployment spell late in his career will likely have a more adverse effect on his productivity than an unemployment spell of the same length that happened when he was younger.

If we do not incorporate human capital depreciation, we assume that the negative impact on wages of any career interruption is equivalent throughout the worker's life cycle. The only cost of the interruption is the forgone experience when there is no depreciation. One year out of the labor force during a worker's youth has the same effect as a year out of the labor force during adulthood.

Figure 4 represents a worker with 80 periods of potential experience and linear returns to experience[3]. The "Nogaps" line represents the returns obtained if the worker never leaves the labor force. The red, green and purple lines represent the same worker with different periods out of the labor force but which are experienced differently over time:

A: Red line: The worker stayed out of the labor force five times, four periods each. Interruptions occurred at t = 10, 24, 38, 52 and 66.

[3] Initial experience is 100, it increases 100 units per period .The linear expression is Ln(w) = experience/100

B: Green line: The worker stayed out of the labor market two times, 10 periods each. Interruptions occurred at t = 10 and 52.

C: Purple line: The worker stayed out of the labor market five times, 3 periods each. Interruptions occurred at t = 14, 29, 44, 59 and 74.

In the absence of human capital depreciation, A and B are equivalent at t = 80. This is because the amount of time out of the labor force, 20 periods, is equal for both of them. In C, the worker's return to experience is higher since the amount of time out of the labor force, 15 periods, is smaller. It is clear that, without human capital depreciation, the time pattern of labor force interruptions is irrelevant.

Figure 5 introduces depreciation. The length and timing of employment interruptions are the same as in Figure 4. Returns are also linear, and the curvature is created by the compounding effect of the depreciation rate[4].

The effects of incorporating human capital depreciation are striking. The magnitudes of the effects do not mean anything since this is just a simulation, but the cumulative differences between Figure 5 and Figure 4 are meaningful. Note the importance of the timing of the interruptions:

I: Green and red lines are not equivalent anymore: even if the green line represents the longest career interruptions, the fact that the last interruption under this scenario is the oldest one makes the green line the closest to the maximum potential productivity.

II: Purple line: This scenario represents the shortest interruptions and the lowest cumulative time out of the labor force. However, this line represents the most

[4] Initial worker experience is 100, and increases 100 units per period with a depreciation rate of 10%. Ln(w) = experience/100

recent interruption in the worker's career and, under human capital depreciation, it implies the lowest level of productivity at t = 80.

III: Note that the length of the interruption still plays an important role. For example at t = 67 and t = 68 the green line illustrates the lowest returns even though it incorporates the oldest interruption. Because of the great length of that interruption, a long time is required for the worker to recover after such a lengthy period out of the labor force.

Even when I introduce curvature through diminishing returns to experience, it does not change the dynamics of the model. See Figure 6 and Figure 7[5]:

Any observations from the linear model in Figure 4 are still valid in Figure 6. The only factor that determines which scenario leads to the highest returns to experience is the cumulative length of the interruptions. Lines red and green are equivalent since they both contain 20 periods out of the labor force. The purple line represents the higher returns since it incorporates only 15 periods of interruption.

Figure 7 includes human capital depreciation and diminishing returns to experience. In this case, as in Figure 5, the timing of the interruptions is a major determinant of the worker's reduction in productivity.

Introducing curvature through diminishing returns to experience preserves the order of the productivity reductions but this should not be surprising since it is a monotonic transformation. Yet, curvature affects the magnitude of the depreciation that we can observe in the data. Depreciation makes recent experience more valuable because

[5] Same as footnote 4 and 5. The only difference is that in Figures 5 and 6 L(w) = experience$^{\alpha}$ where α =0.2.

it has depreciated less than past experience. Diminishing returns to experience makes the recent acquisition of experience less valuable because its returns decrease with accumulated experience. The more experience the worker has, the less productive any additional experience will be due to diminishing returns. These two effects act in different directions through different mechanisms: depreciation makes recent experience more valuable through the timing effect and diminishing returns makes it less valuable through the accumulation of additional experience.

The assumption of diminishing returns to experience is not without consequences. When diminishing returns to experience are present, depreciation rates are smoothed. Diminishing returns will not introduce a bias that changes the sign of the effect of depreciation (it preserves the order), but the coefficients will be lower. With diminishing returns to experience, the estimated coefficients will provide a lower bound for the true effect of depreciation[6] because, once the worker returns to the labor force after the interruption, the value of his experience will have eroded substantially. In the linear model, the worker experiences faster wage growth because he now has less experience to be eroded and his net productivity (new experience minus eroded experience) will grow faster. In the diminishing returns scenario, once the worker returns to the labor force there are two factors that increase his productivity. As in the linear model, he has less experience that can eroded but every unit of experience that he acquires will be more productive since he has returned to levels of experience that are more productive. This

[6] Using the data from the previous simulation the worker's reduction on returns of experience under linear returns of experience are -15.54%, -9.90% and -24.87% for the red, green and purple scenarios respectively; however when I introduce decreasing returns of experience the reductions are -3.32%, -2.06% and -5.56%. Of course these figures will change if we vary the functional form of decreasing returns, the value of α, and the depreciation rate.

explains why the wage growth rate is higher in Figures 6 and 7 than in Figures 4 and 5 immediately after the employment interruptions.

Apart from diminishing returns, there is another factor that affects the results. I assume that all workers are equivalent, regardless of how many periods they have not worked in their careers and how long these periods were. My assumption is that the employer does not take this information into account to differentiate more productive workers from less productive workers. Arulampalam (2001) studies this effect; he determines that when employers use unemployment gaps as a signal to determine the quality of workers, the gap that is the most harmful for the worker is the first one. I tried to account for this effect by using the number of non-employment spells each worker experienced over the interval studied, but this did not change my results and that variable was never statistically significant.

CHAPTER 3

DATA

Any analysis of human capital depreciation must include the time line of the subject's work history. Depreciation is, by definition, a chronological phenomenon so we cannot limit our analysis to a mere addition of absences from the labor force (and their durations) without taking into account their time distribution. To account for this timing factor, I use a longitudinal data set to follow how the workers' labor force absences are arrayed over time. Specifically I use data from the National Longitudinal Survey of Youth 1979 (NLSY79), which started in 1979 and was conducted annually from 1979 to 1994 and biannually from 1994 to 2008. I use the most recent year of the survey as my reference period so all my results are relative to 2008 wages.

The survey initially contained data on 12,686 young men and women aged 14 to 22. Because of attrition, the sample was reduced to 7,757 observations by 2008. However, not all of the sample participants answered the survey every single year since 1979. After I eliminate those individuals who missed any interview since 1979 or gave invalid responses to any on the variables I use, I have 3540 observations left. The NLSY79 includes an economically disadvantaged supplemental sample designed to oversample Hispanics, blacks and economically disadvantaged non-black, non-Hispanics. Due to different rates of attrition among these groups, I weight the observations to avoid sample bias.

With these longitudinal data, I can follow the labor force activity of every worker, the length, frequency, and timing of their employment interruptions, and their educational achievements. I can also control for variables that may have an influence on the human capital depreciation rate like sex, marital status, type of worker (blue collar vs white collar) and the presence of children. All of these variables are likely to affect the length and number of employment interruptions.

The NSLY79 collects data on the number and length of employment gaps and their dates. The data provide the number of weeks unemployed and the number of weeks out of the labor force between two consecutive interviews. This means that each period t includes two years (since the survey is collected biannually after 1994) for which I know the length of the employment interruption. The time line of this approach is loose since I am not controlling for the exact date of the breaks and I aggregate all the breaks occurring during the two-year period; the only variable that I have to control for the distribution of gaps within the period is the number of breaks between two consecutive interviews. This is still a very useful approach because it is less burdensome than calculating the exact date of every interruption for every period. Since all employment spells that happen between interviews are aggregated, this approach will allow me to estimate only one effect of all breaks between interviews, regardless of how many employment interruptions occurred during that period.

Table 3 reports how the number of interruptions in the 2006-08 survey is distributed among males and females. The number of interruptions seems to be independent of the sex of the worker. This is counterintuitive if we consider that, typically, only women take maternity leaves and that, traditionally, the male is the main provider for the household. But this information is incomplete, however, without knowing the length of those interruptions.

Table 4 shows the distribution of the interruptions' durations, and here the results are consistent with the hypothesis that women's interruptions are longer than men's. The length of a spell of unemployment is higher for male workers, but this is not enough to overcome the longer period of time that women stay out of the labor force. Men tend to be more active in the labor market, spend more time looking for jobs, and spend less time out of the labor force.

CHAPTER 4

IDENTIFICATION STRATEGY AND ECONOMETRIC SPECIFICATION

Identification Strategy

Because successive interruptions have different impacts on workers' productivity, given their different timing in the worker's career, I am not constrained to analyze only those workers for whom I can observe wages immediately before they left the labor force and immediately after they return. All I need to observe is the current salary, work experience, the number of labor interruptions, their length, and how are they distributed over time. The only additional restriction I impose is that I need to observe more than one interruption during the worker's career, but this is very common in the data.

To my knowledge, this approach has never been used in the estimation of human capital depreciation. It offers me advantages not only because it imposes fewer restrictions on the data, but also because it is sufficiently flexible to allow estimation of human capital depreciation under different scenarios. I can assume linear or diminishing returns to experience, or take the restrictive approach of Mincer and Ofek (1982) and assume that depreciation occurs only during employment interruptions, as shown in Figures 8, 9 and 10.

In all of the possible scenarios shown in Figures 8, 9 and 10, a recent employment interruption is penalized more than a more distant interruption. The green line is above the red line when the later interruption has not happened yet or while the green line is decreasing. Neither of these two possibilities is observed in the data because, in the first case, only one interruption has occurred and in the second case the interruption is still ongoing so the worker is not in the labor market and, hence, will be out of the sample as well. This holds no matter how you place the two interruptions along the worker's career.

Figure 8 shows a very interesting aspect of the model. Even if depreciation occurs only during an employment interruption, the key implication of the model holds. Even if the depreciation rate is the same for both curves, the slope in the graph is not the same for the early and the late interruptions. This is due to the compounding effect of the depreciation rate. Those two decreasing lines are the result of applying the same depreciation rate at different levels of experience and at different times[7].

The NLSY79 has been conducted biannually since 1994. In every period, each worker is asked how many times and for how long he was out of the labor market or unemployed. This provides a way to measure the length of the interruption for every two-year period in which an interview is conducted. I can also control for how those interruptions are distributed within each two-year period by including the number of interruptions, although this variable turns not to be statistically significant. I will estimate separately how different employment interruptions in different periods affect a worker's current productivity. Theoretically, all forgone experience due to such interruptions will have a negative effect on future labor earnings.

[7] See Figure 9 at Appendix for a version of this graph that contains the whole depreciation path of this two interruptions. Path1 represents the levels of aggregated experience that the worker should have at any time to match the depreciation rate during the first break, given the depreciation rate and the level of experience when the interruption started assuming he is out of the labor market during the whole process. Similar for Path2.

In this model, if there is no human capital depreciation all interruptions should have the same effect on productivity regardless of when they occurred. It is possible in that case to aggregate the interruptions of all periods because their timing doesn't have any effect on present or future wages, as I showed in Figures 4 and 6. If this is true, the coefficients on all interruptions in every NLSY79 biannual period should have the same negative magnitude since their effect per unit of time is the same. In my model of human capital depreciation, on the other hand, the timing of the interruptions is relevant; an interruption in the last biannual period will have a greater negative effect per unit of time than an interruption which occurred in previous periods. If this is true, the coefficients on those interruptions recorded in the last NLSY79 interview will have a greater negative effect than those interruptions recorded in previous interviews. In my model of human capital depreciation, interruptions become less and less relevant as time passes, and eventually the effect on today's salary of a distant-past interruption should be negligible.

Econometric Specification:

The basic specification of the estimating equation is:

$$\ln(w_i) = \alpha_0 s_i + \sum_{j=0}^{J} \beta_j g_{i,j} + \lambda_1 e_{1,i} + \gamma X_i + \varepsilon_i \qquad (1)$$

where w_i is worker's *i* wage in 2008, s_i is the highest level of education achieved by worker *i*, $g_{i,j}$ represents the length of the employment gaps created by not working in period jth (this is the variable of principal interest), $e_{1,i}$ is the worker's uninterrupted experience, and X_i is a vector of control variables that includes sex, race, age, marital status, number of children, union and type of worker (blue collar or white collar).

The only direct measure of experience that I include in the model is job tenure; I do not include any experience previous to the last interruption. If I used a total experience variable, the sum of the non-employed spells is perfectly negatively correlated with time spent working. A worker has to be either working or not working, and any additional time spent not working would be, by definition, subtracted from experience and vice versa.

Age is not included among the control variables for the same reason; however, since all workers were born between 1957 and 1964 this is not a big concern.

Identifying Different Depreciation Rates

While negative coefficient estimates on the employment interruption variables in every period are expected, they are not enough evidence to support the presence of human capital depreciation. These coefficients estimate the value of experience lost during the interruption as the sum of the lack of new experience during the interruption plus experience lost due to depreciation during that period. As I showed earlier, smaller negative coefficients on older interruptions is evidence for human capital depreciation. The challenge now is to determine what kind of workers experience higher or lower human capital depreciation.

Those workers subject to a stronger depreciation rate should experience a larger decline over time in the coefficient estimates. As discussed in chapter three, if there is no human capital depreciation the wage effect of an employment interruption should be independent of its timing. If this is true, the coefficient estimates should not change across different periods. However, in the presence of depreciation the coefficients on the most recent non-employment periods should have a more negative effect on the worker's wage; moreover, as the depreciation rate increases the relative change in the coefficients between periods should increase. Figure 11 and Figure 12 show this.

The only difference between Figure 11 and Figure 12 is the depreciation rate. I construct Figures 11 and 12 using 10% and 20% depreciation rates, respectively. A late interruption implies a 13.65% loss in productivity with respect to an early interruption under a 10% depreciation rate. This loss increases to 22.74% under the 20% depreciation rate assumption. A higher depreciation rate makes the slope of the curve more negative during the employment interruption and this is reflected in the final result as a higher impact on workers' productivity.

I use this feature of the model to determine what kind of workers and what kind of occupations are subject to higher depreciation rates. According to the existing literature, we expect women to self-select into occupations with lower depreciation rates; thus, the change in the estimated coefficients should be smaller once I restrict the sample to female workers. I use the same procedure to study blue collar vs. white-collar workers and other factors like the presence of children.

CHAPTER 5

EMPIRICAL RESULTS

I estimated equation (1), using the full sample and different sub-samples of the NLSY to determine if different groups of workers experience different depreciation rates of human capital. This could occur because some workers (e.g. females) sort themselves into occupations with lower depreciation rates or because of the characteristics of the occupation itself (e.g. blue collar workers). The results are shown in Table 2.

The estimated returns to education are consistent with previous literature and are statistically significant in all specifications. The returns to education are always positive and higher for males than females, and are also lower for occupations that usually require less formal education (blue collar workers).

Tenure is my only measure of experience in this model, and it requires further analysis. As expected, tenure is always positive and significant at least at the 10% level in all estimated equations. Returns to tenure are the same for males and females and they are higher for blue-collar workers. The higher returns to tenure for blue-collar workers can play an important role when we consider the depreciation of past work experience. It is likely that blue-collar workers rely more on experience and less on formal education than white-collar workers. Thus, the depreciation of experience will be more harmful for them. The results in Table 2 show that I can assume linear returns to experience in the form of tenure and, therefore, there are no decreasing returns to experience. As I pointed out in Section 2, my identification strategy works both with constant returns and decreasing returns to experience, where experience is measured as job tenure in the empirical work.

Females experience an eighteen percent wage penalty relative to males, and this penalty is smaller for women who hold blue-collar jobs. This reduction in wages is more accentuated for married women or for women who have children younger than fifteen years old as shown in columns 1 and 5 in Table 2. All of this is consistent with the literature.

Black workers earn twelve percent less than white workers once we control for the rest of their characteristics. This earning gap remains constant across occupations, but there is a notable gender difference. Male black workers have a larger earnings gap than female black workers. This is also consistent with previous literature[8]. The results in Table 2 show that there is no wage gap between white and Hispanic workers, except when I restrict the sample to males. This is puzzling since this result is not consistent with other literature.

Workers who are married and/or have children earn higher wages; this result is driven by the positive effect of these two variables on the earnings of male workers. Being a member of an union also has a positive effect on salaries, and this effect is stronger for males and especially for blue collar workers. Working in a blue-collar occupation has a wage penalty that is more severe for males than for females. All of these results are also consistent with previous literature.

[8] This smaller black-white wage inequality among women might be underestimated as shown by Neal (2004). Maybe the difference in inequality between male and female black workers in this paper will be reduced if I could control for all of the variables that Neal considers in his paper.

The coefficients on the interruption variables are the main focus of interest for this thesis. These coefficients are uniformly negative when they are statistically significant. This outcome was expected, but it does not provide enough evidence to support the hypothesis of human capital depreciation. The negative sign on the coefficients reflects not only the effects on today's wages from the human capital depreciation during employment interruptions, but also the forgone wages during a period of non-employment. To determine the presence of depreciation, I take into account the differences in the timing of the interruptions. Under depreciation, as shown in Chapter 2, the negative effect of an employment interruption will decrease as that interruption recedes into the past. Table 2 reveals that this is true in all scenarios; human capital depreciation is present for all of workers and occupations that I considered. The coefficient estimate on the first employment interruption is always higher in absolute value than the coefficient on the second interval. This is an implication of human capital depreciation. After the second interruption, the estimated coefficients are not always statistically significant but, in general, their absolute values decrease with elapsed time.

When I compare the relative decrease in the magnitude of the coefficients on the interruption variables, I can determine what groups or occupations have higher depreciation rates. The basic model uses the entire sample and the relative decrease in this scenario is 5.5%; when I divide the sample between males and females, the relative decrease in the coefficients is 1.8% and 12% respectively. This is consistent with the hypothesis in McDowell (1982) that females tend to sort into occupations with lower human capital depreciation rates. This occurs because women anticipate more time out of the labor force, so they self-select into occupations with lower depreciation rates to minimize the negative effects on their future earnings of spells of non- employment.

The results for blue-collar workers are not as conclusive since the estimated coefficients on their interruptions variables are not statistically significant beyond the first period. However, the absolute values of the point estimates decline more rapidly than they do in the male sub-sample. One reason for this higher depreciation rate of experience among blue-collar workers may be that their experience plays a relatively more important role in wage determination than formal education, compared with the average worker. Thus, the negative effect of the depreciation of experience during the nonworking spells is more harmful for blue-collar workers. Another reason for this difference could be different degrees of worker's adaptability to changes in the labor market that might occur during career interruptions. This adaptability could be an acquired capacity for white-collar workers during their careers or it could simply reflect characteristics that make workers self-select into white-collar occupations. Both of these hypotheses are consistent with the idea that career interruptions are more harmful for blue-collar workers than for white-collar workers.

Fixed Effects Estimation:

The NLSY79 is a panel data set; I can use this feature to control for unobserved heterogeneity. In order to do this I use fixed-effects (FE) estimation. The problem of this technique is that it eliminates any time-invariant regressors in the model along with the unobserved effects. This can be problematic since the main interest of this thesis is the effect of the employment interruptions for specific years, which are time invariant variables. To solve this problem I use a two-step procedure proposed by Hausman and Taylor (1981). To correct the errors obtained in the second step I use the bootstrapping technique proposed by Atkinson and Cornwell (2011).

The results are presented in Table 3. The interruptions variables tend to be not significant much earlier than with the OLS model. One of the reasons that explain this is that for this regression I had to impose the same restrictions from the previous model not only to the 2008 interviews but also to all interviews in the 1996-2008 period. The coefficients on Hispanic and Black and Union were not what I expected. This might be because the FE are capturing the individual unobservable characteristics for which I could not account for with the OLS regression.

Using this procedure I cannot separate blue-collar vs. white-collar workers since classification varies with time and the size of the sub-samples varies in different periods.

CHAPTER 6

CONCLUSION

The results reported in this thesis show how the timing of employment interruptions is important in explaining workers' future wages. Recent interruptions have a greater negative effect on wages than gaps that occurred in the more distant past, but this effect decreases over time. This pattern is due to human capital depreciation. Recent experience is not a perfect substitute for experience acquired in the more distant past. As time passes, the importance for current wages of both past experience and past employment interruptions becomes negligible. This would not occur in the absence of human capital depreciation.

I take advantage of this factor to determine what kind of workers and occupations have greater depreciation rates. I obtain results that are consistent with those in the previous literature; for example, female workers tend to self-select into occupations with lower depreciation rates. Also, for a blue-collar worker human capital depreciation seems to be more harmful than for the average worker, perhaps because a blue-collar worker relies more on experience than the average worker in the sample.

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APPENDICES

Depreciation Paths.

The curvature created by the depreciation rate compounding effect is not limited to working periods. During interruptions, the compounding effect creates a concave curvature. This is especially relevant for a model where there is only depreciation during interruptions since it is the curvature that makes the timing of depreciation relevant to the worker.

Figure 13 shows how this is important. The lines "Path1" and "Path2" reflect two lines with the same depreciation rate, 10%, that is applied at different times and experience values. Path1 represents the levels of experience that a hypothetical worker who never worked during the period would have to obtain the same experience returns that worker *i* obtains during his early interruption. As the time of the interruption gets closer to the present, the "path" line shifts to the right and increases its slope since it is calculated over a higher level of experience. The hypothetical worker will need higher levels of initial experience, that will depreciate faster, to obtain the same returns in order to offset an interruption that happens later in worker's *i* career.

FIGURES

FIGURE 1: Mincer and Ofeck Depreciation.

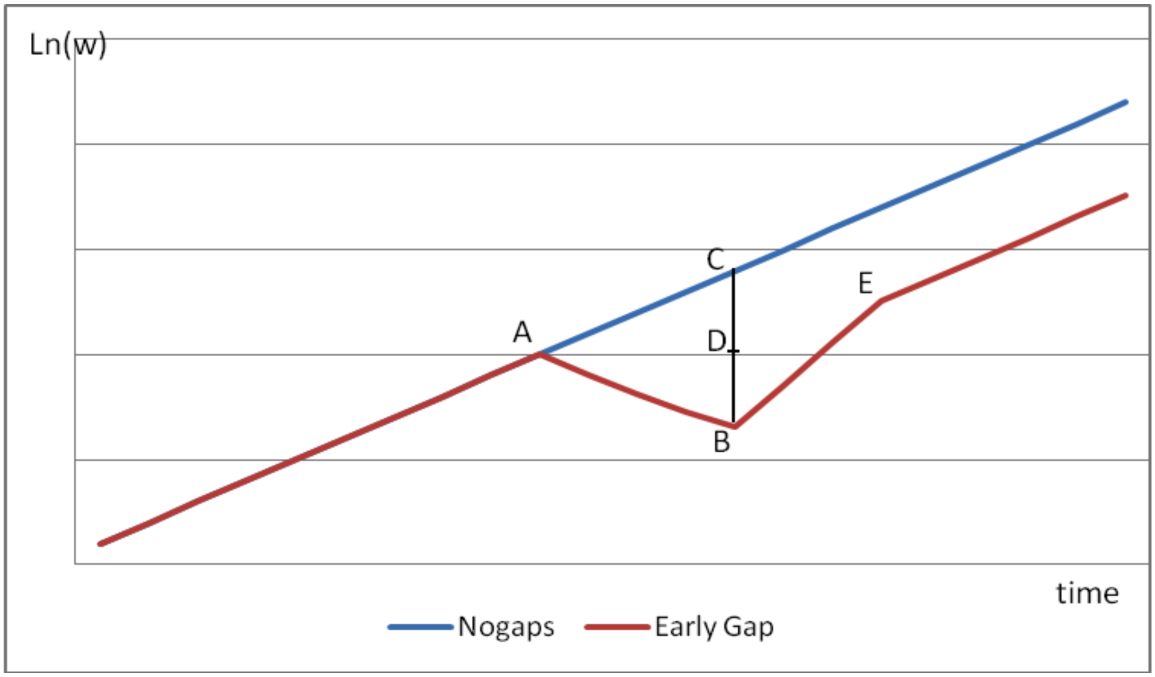


FIGURE 2: Depreciation During the Entire Employment Cycle

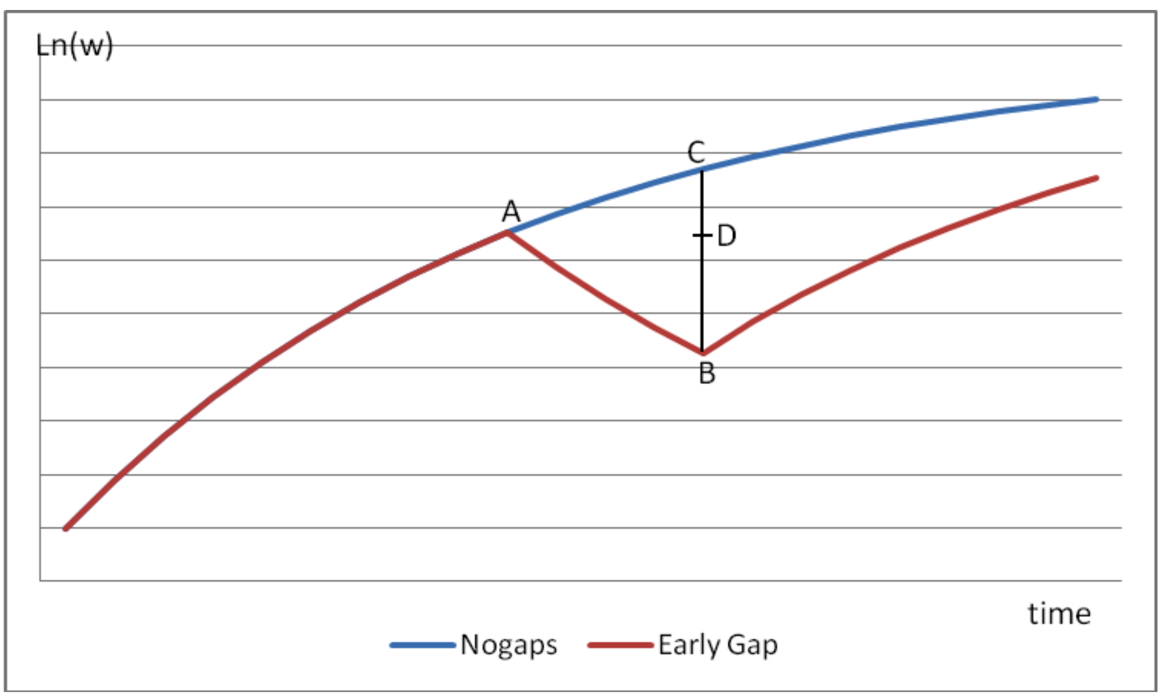


FIGURE 3: Depreciation During Entire Employment Cycle with Diminishing Returns of Experience

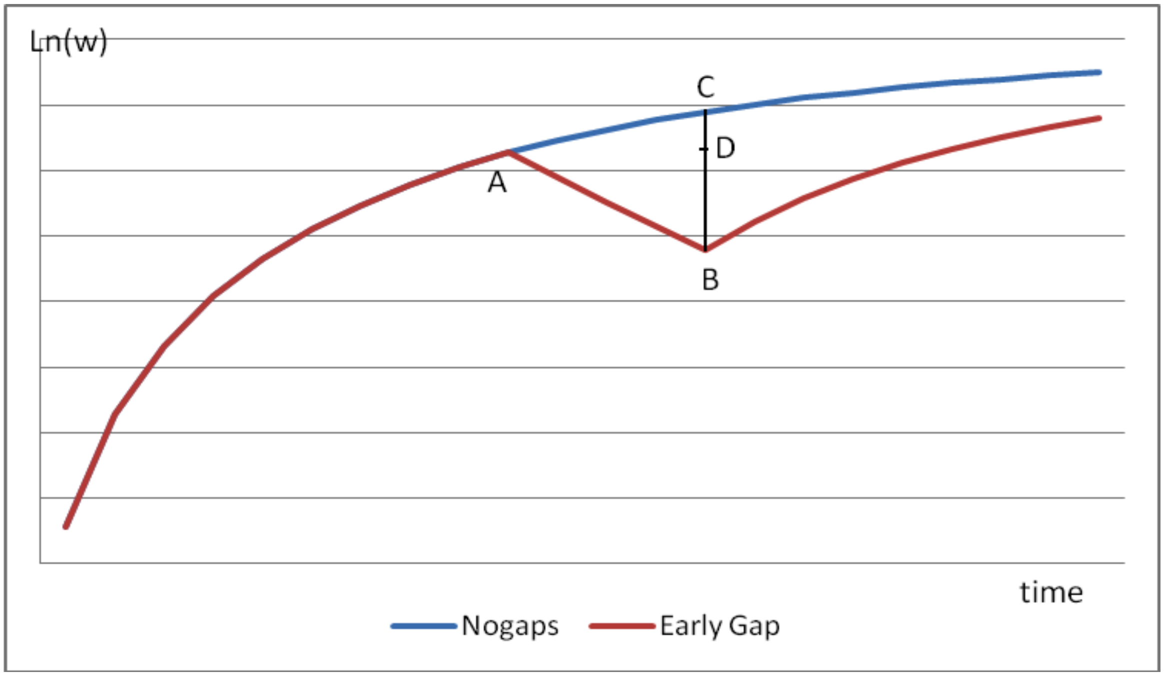


FIGURE 4: Different Interruption Timings with No Depreciation

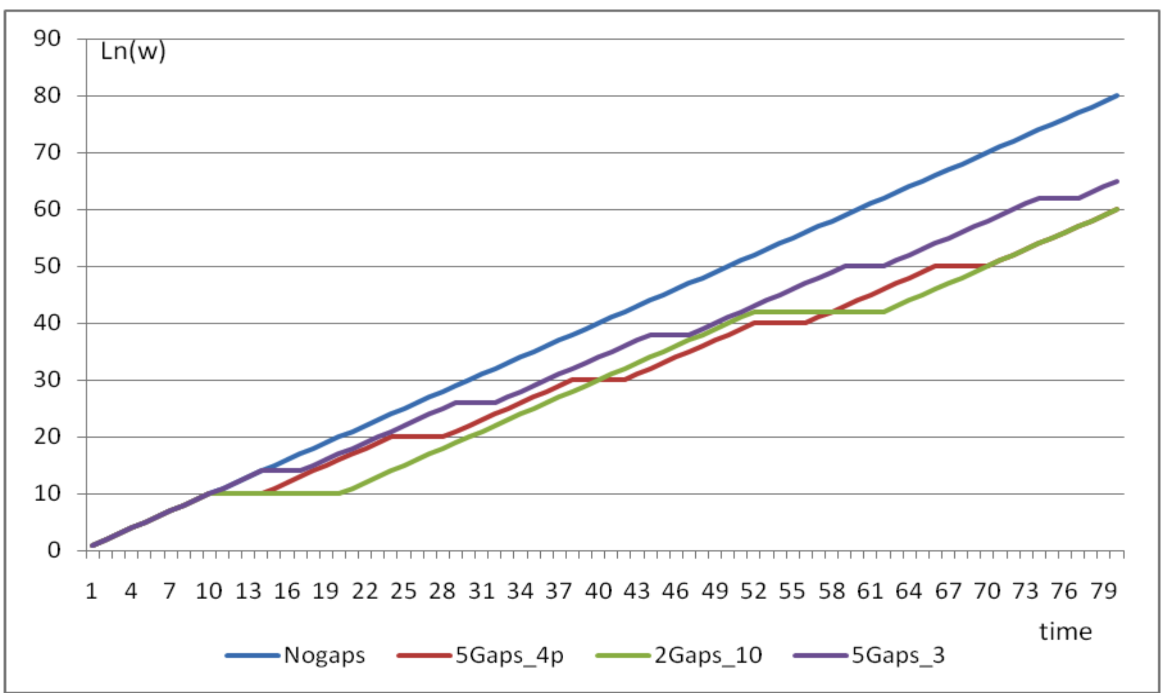


FIGURE 5. Different Interruption Timings with Depreciation

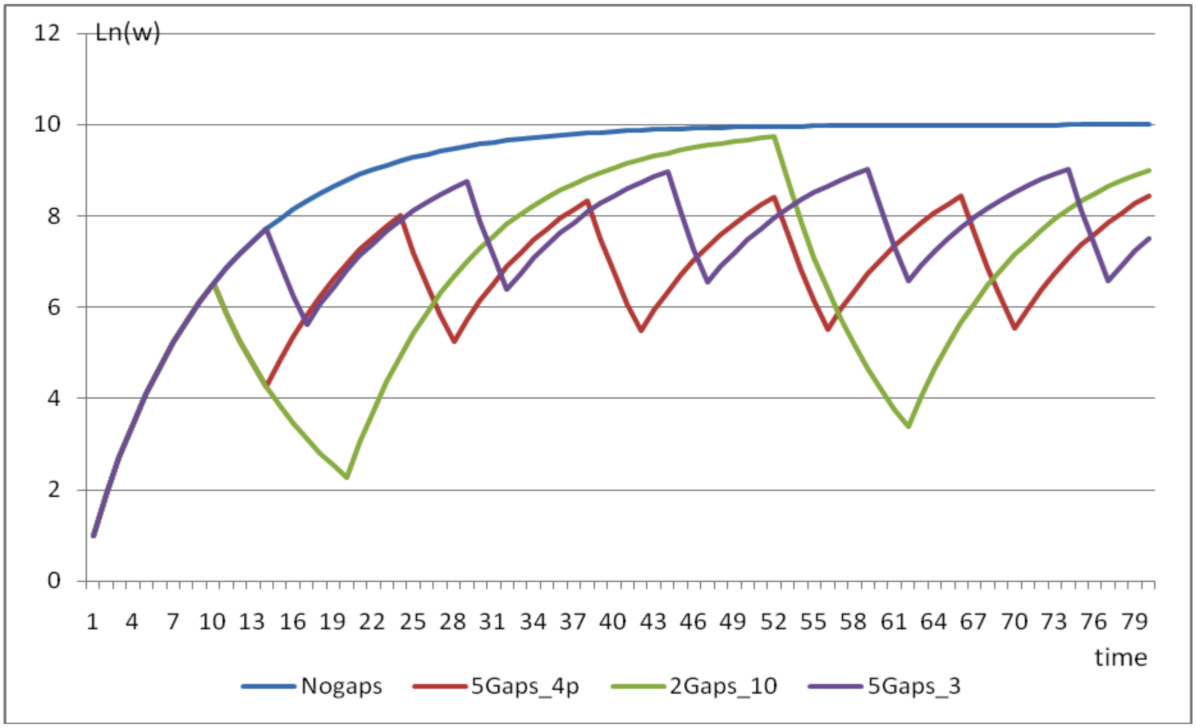


FIGURE 6: No Depreciation and Diminishing Returns to Experience

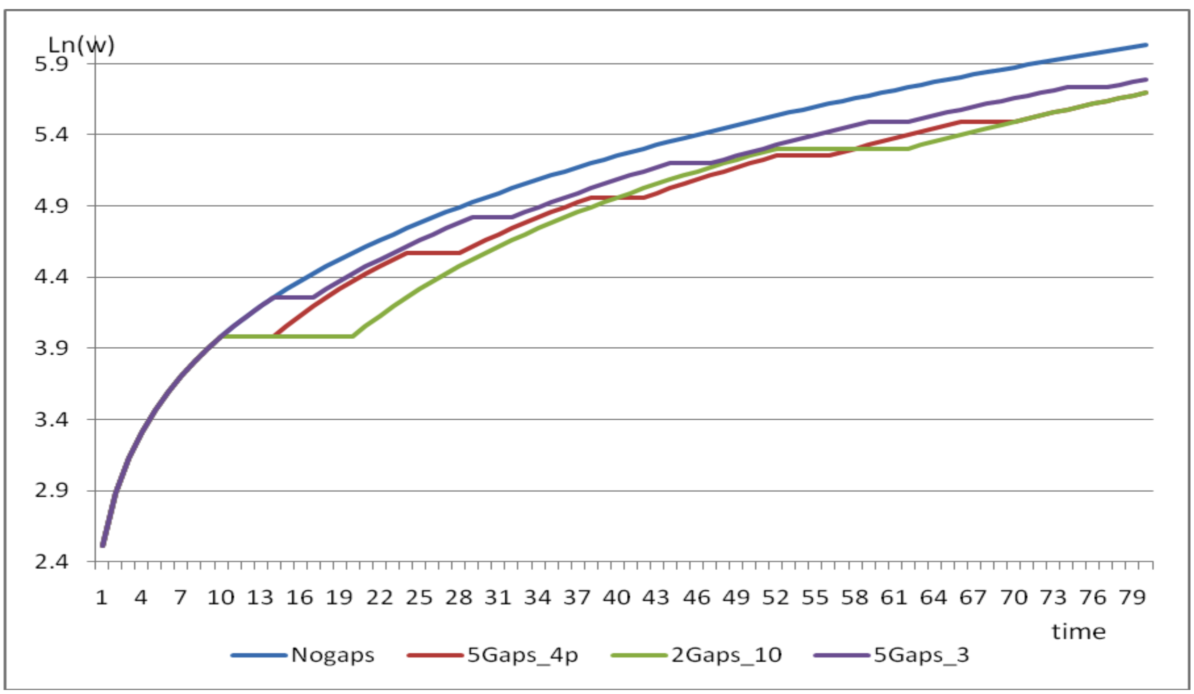


FIGURE 7: : Depreciation and Diminishing Returns to Experience

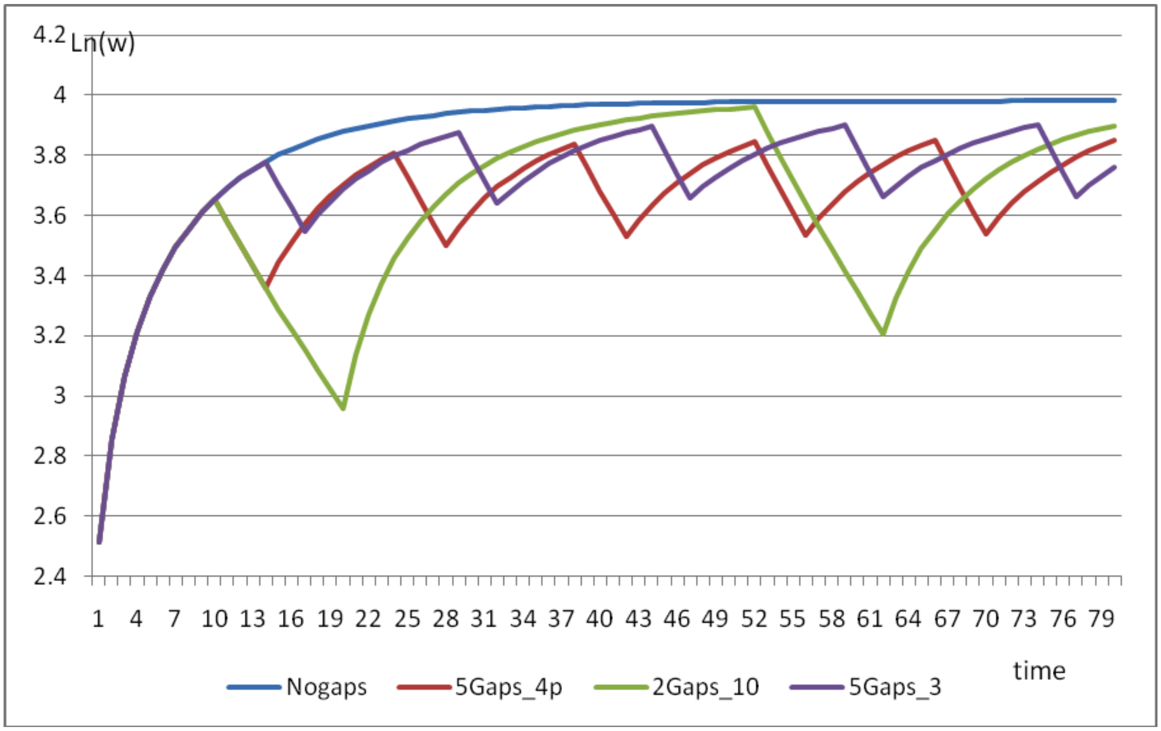


FIGURE 8: Linear Returns of Experience

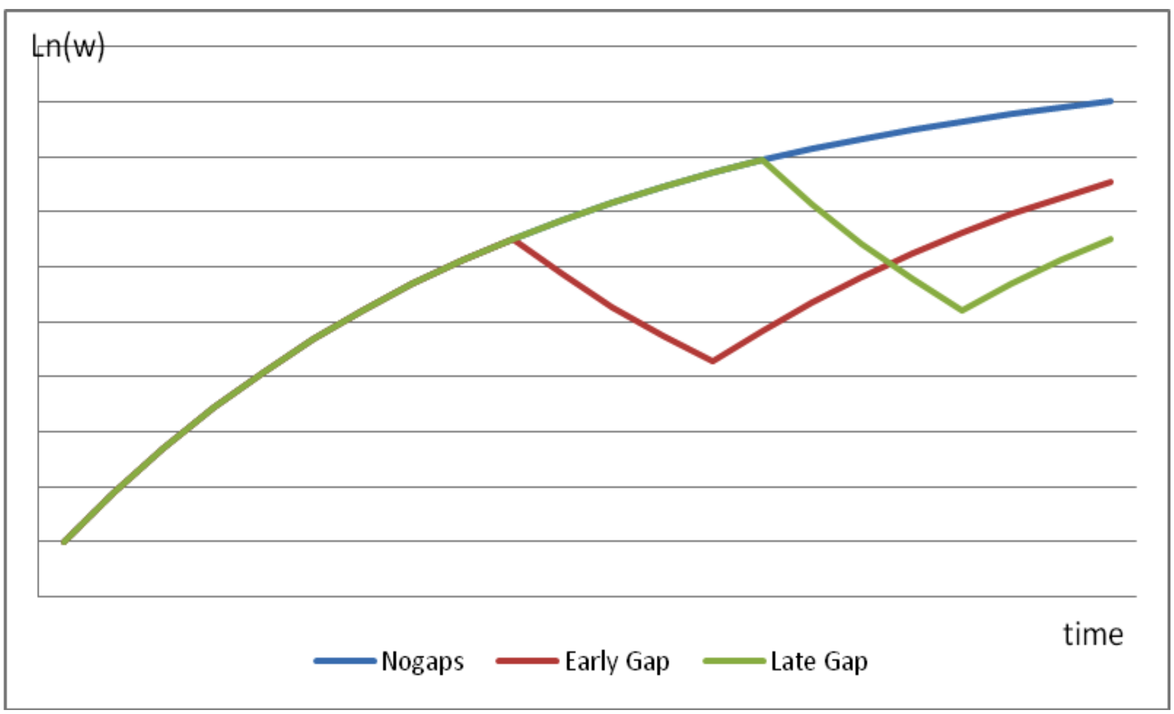


FIGURE 9: Decreasing Returns of Experience:

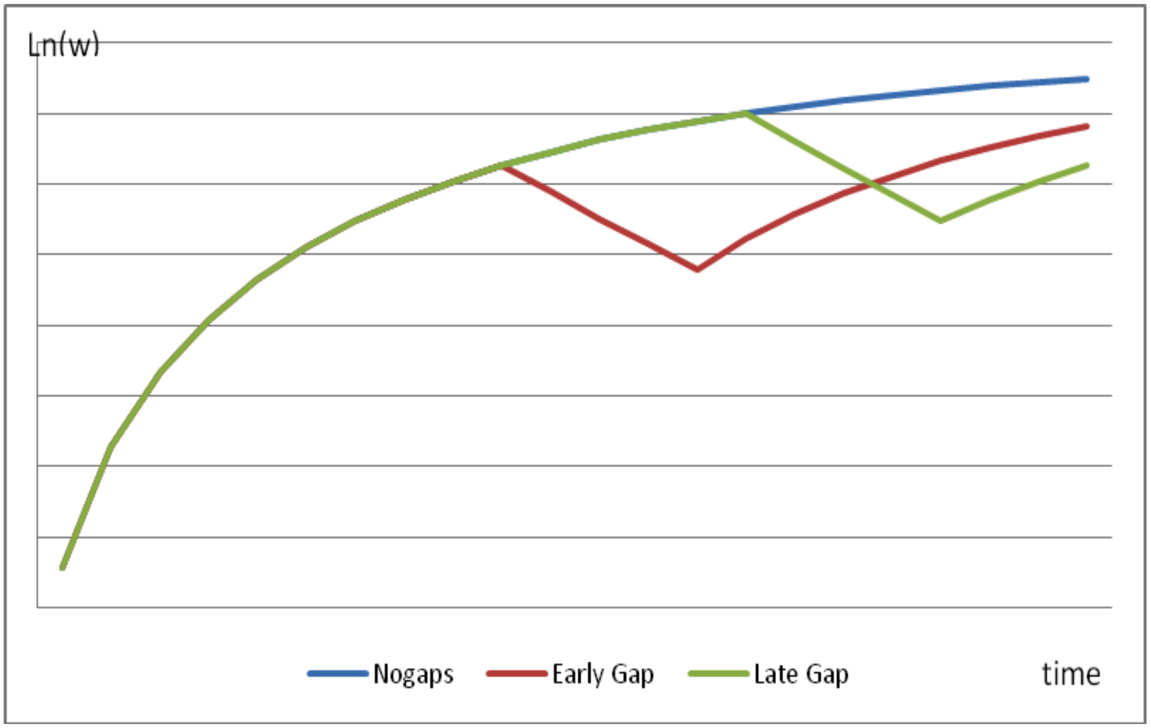


FIGURE 10: Depreciation Only During Interruptions:

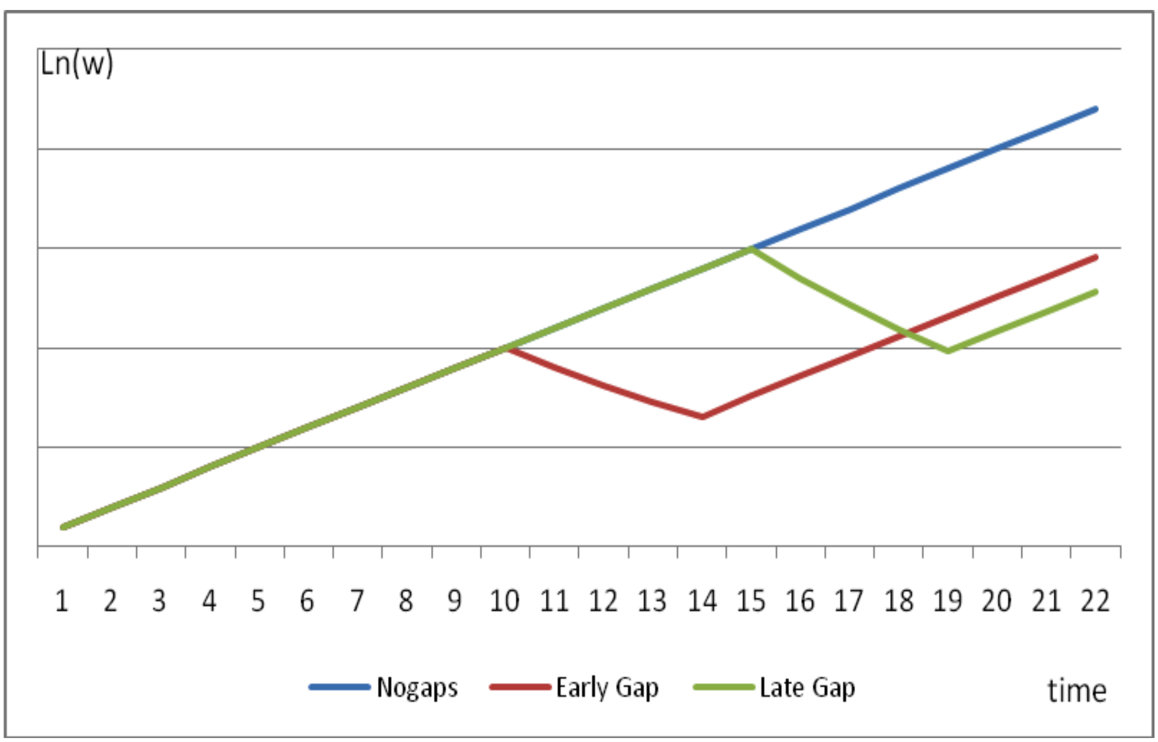


FIGURE 11: Low Depreciation Rate

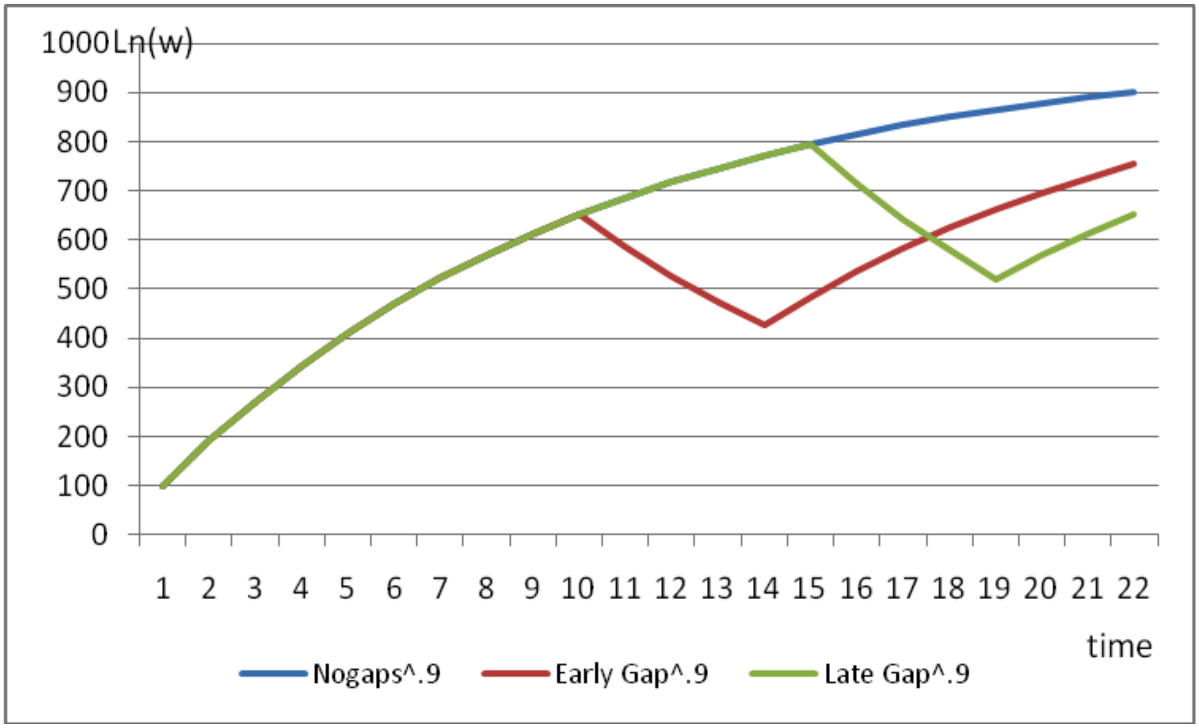


FIGURE 12: High Depreciation Rate

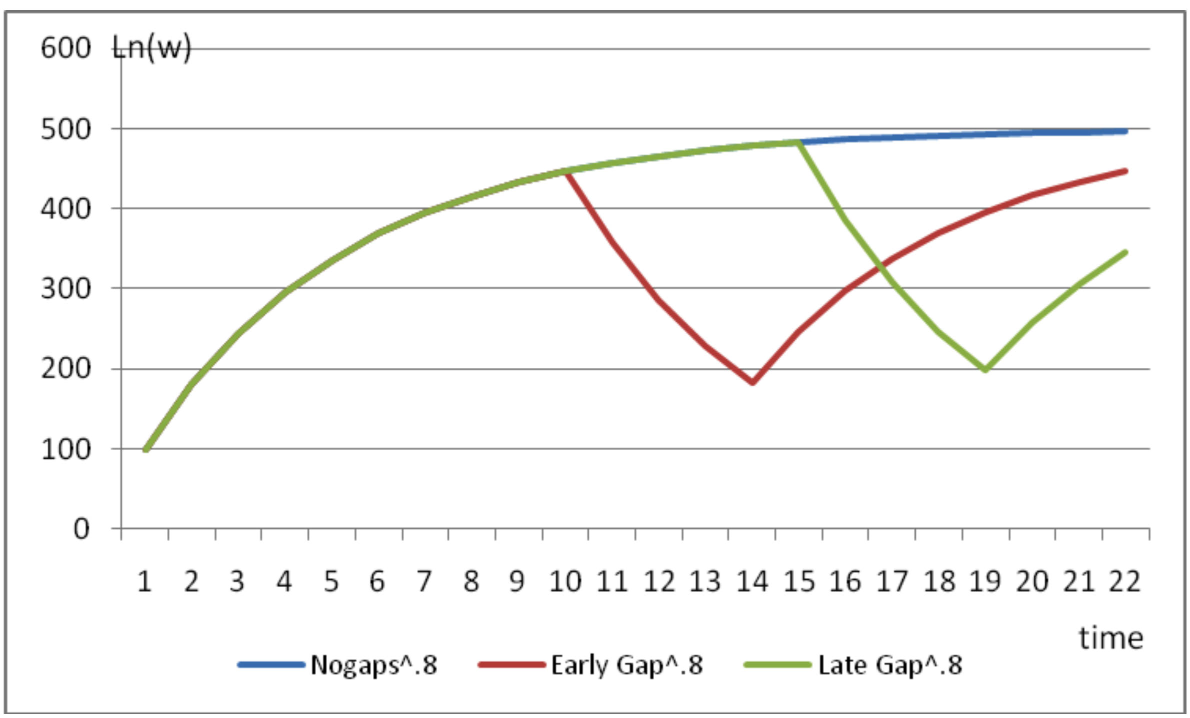
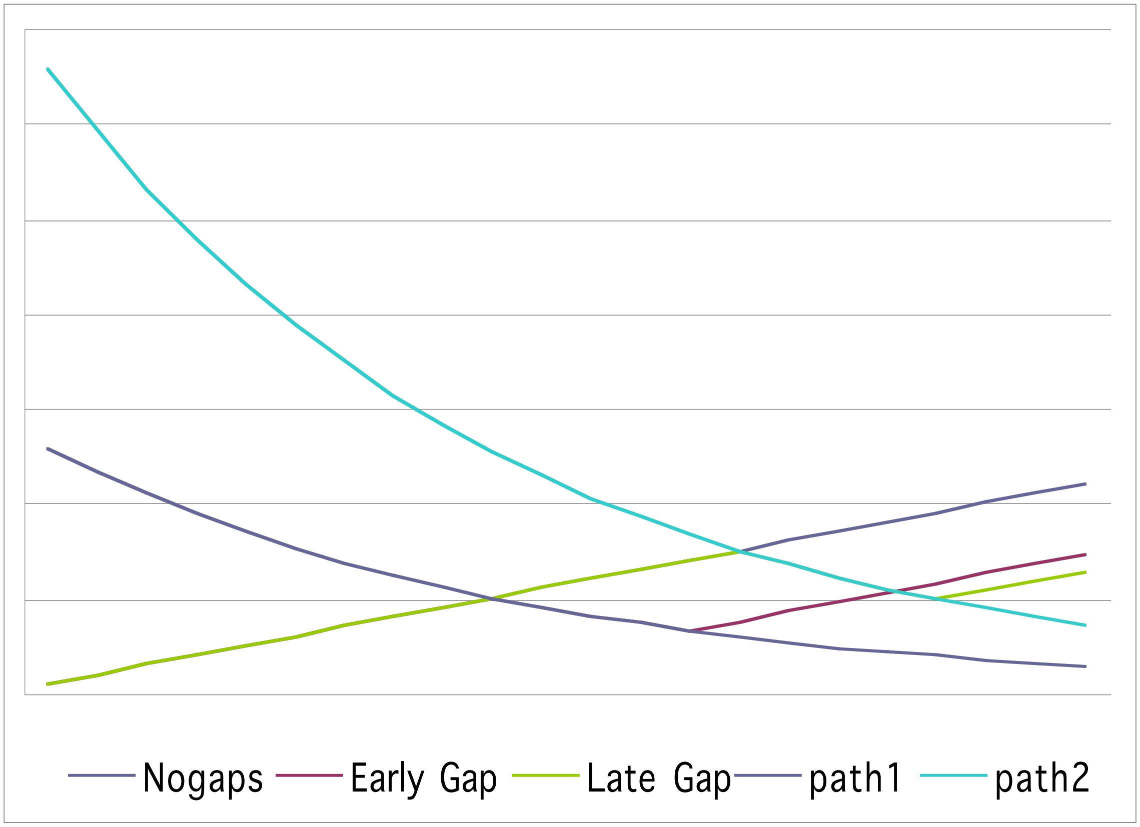


FIGURE 13 Depreciation Paths



TABLES

TABLE 1: Descriptive Statistics

Variable	Mean (Std. Dev)
lwage08	7.531565 (.6361443)
education (years of schooling)	13.82627 (2.527283)
Interruption08 (weeks)	5.888136 (16.97995)
Interruption06 (weeks)	5.747175 (16.36441)
Interruption04 (weeks)	7.560169 (21.49432)
Interruption02 (weeks)	7.834746 (21.38243)
Interruption00 (weeks)	9.664124 (25.49901)
Interruption98 (weeks)	11.49887 (26.47044)
Interruption96 (weeks)	13.17514 (27.46721)
tenure08 (weeks)	527.889 (422.1814)
tenure08sq	456853.5 (588058.4)
female	.500565
female_married	.2841808
female_child15	.1658192
black	.2887006
hispanic	.1646893
married08	.6189266
union08	.1920904
child15	.3819209
blue08	.4141243

TABLE 2: Empirical Results

	Total	Females	Males	Blue Collar
education	.07634** (.00463)	.06706** (.00642)	.08651** (.00668)	.07124** (.00597)
Interruption 2008	-.00241** (.00052)	-.002585** (.00068)	-.00206** (.00077)	-.00145* (.00060)
Interruption 2006	-.00228** (.00075)	-.00254* (.00104)	-.00182** (.00100)	-00049 (.00077)
Interruption 2004	-.00080 (.00049)	-.00089 (.00065)	-.00067 (.00073)	-.00015 (.00056)
Interruption 2002	-.00067 (.00054)	-.00058 (.00064)	-.00068 (.00093)	-.00061 (00061)
Interruption 2000	-.00007 (.00045)	-.00029 (.00054)	.00046 (.00087)	.00083 (.00057)
Interruption 1998	-.00125** (.00054)	-.00043 (.00060)	-.00248 (.00108)	-.00111* (.00061)
Interruption 1996	-.00043 (.00050)	-.00089 (.00064)	.00021 (.00081)	-.00040 (.00059)
tenure	.00019* (.00007)	.00019* (.00010)	.00020* (.00011)	0.00038** (.00009)
tenure squared	-1.54E-8 (5.12E-8)	8.96E--9 (7.03E-8)	-4.05E-8 (7.4E-8)	-1.36E-7** (6.08E-8)
female	-.18751** (.02978)			-.12665** (.03491)
female*married	-.12152** (.03671)			-.12665** (.04485)
female*child	-.08021** (.03877)			-.08790* (.04728)
black	-.12509** (.02010)	-.05314* (.02773)	-.19810** (.03024)	-.12225** (.02342)
Hispanic	-.01150 (.02291)	.03558 (.03402)	-.05392* (.03105)	.00514 (.03117)
married	.13198** (.02560)	.02952 (.02833)	.11761** (.02562)	.18321** (.02743)
child (<15)	.07627** (.02511)	.00019 (.02916)	.06701* (.02481)	.07924** (.02618)
Union	.11777** (.02428)	.05143 (.03691)	.19190** (.03168)	.28157** (.02490)
Blue Collar	-.18202** (.01860)	-.15802** (.02506)	-.19975** (.02752)	
Number of interviews	3540	1772	1768	1466
R-squared	0.3386	.2527	.3559	.3656

** Significant at 5% significance level
* Significant at 10% significance level

TABLE 3: Fixed Effects Results

	Total	Females	Males
education	.05059** (.00264)	.04097** (.00407)	.06192** (.00338)
Interruption 2008	-.00122** (.00040)	-.00157** (.00059)	.00025 (.00074)
Interruption 2006	.00044 (.00054)	-.00197** (.00075)	.00045 (.00098)
Interruption 2004	.00022 (.00043)	.00111* (.00064)	-.00116 (.00079)
Interruption 2002	-.00086* (.00052)	-.00262** (.00055)	-.00458** (.00121)
Interruption 2000	.00310** (.00047)	-.00123** (.00050)	.00355** (.00094)
Interruption 1998	.00125** (.00038)	-.00024 (.00041)	.00507** (.00088)
Interruption 1996	-.00068 (.00043)	-.00022 (.00048)	.00277** (.00089)
tenure	.00042** (.00005)	.00046** (.00008)	.00043** (.00007)
tenure squared	-1.41E-7** (4.44E-8)	-1.29E-7* (6.95E-8)	-1.78E-7** (5.55E-8)
female	-.04773** (.01134)		
female*married	-.12152** (.03671)		
female*child	-.21180** (.02234)		
black	-.03034** (.01301)	.00716 (.01814)	-.00194 (.02561)
Hispanic	.15943** (.01436)	.20520 (.01845)	.25512** (.02921)
married	.11225** (.01861)	-.01614 (.01968)	.08952** (.01781)
child (<15)	.08357** (.02511)	-.08554** (.02641)	.05723** (.02001)
Union	.01632 (.01559)	-.05667** (.02521)	.08216** (.01905)
Blue Collar	-.12856** (.01463)	-.10680** (.02452)	-.13369** (.01774)
N	11850	5765	6085

** Significant at 5% significance level
* Significant at 10% significance level

TABLE 4: Distribution of the number of interruptions by gender.

	0	1	2	3	>3
Male	64.12	29.28	5.33	.89	.37
Female	64.99	29.62	4.29	.81	.30
Total	64.53	29.44	4.83	.86	.33

TABLE 5: Length of Interruptions: Weeks

	Unemployment		Out of The Labor Force	
	Mean	Std Deviation	Mean	Std Deviation
Male	4.91	20.91	15.49	47.38
Female	3.64	15.31	23.63	46.10
Total	4.26	18.24	19..68	46.90