

An Empirical Examination of Annual Wage Variation:  
Expanding Beyond Mincer to Human Capital Portfolios

Laura L. Coogan  
Department of Economics  
University of Kentucky  
laura.coogan<at>uky.edu

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## *Abstract*

Using data from the 1960 and 2000 U.S. Census for white male workers, two econometric models, and the standard deviation of the natural log of wages as the variation measure, I find that education has a multi-faceted role in predicting the variance of annual wages over the work life. Investment in education through college reduces annual wage variation, and this implies that investment in human capital can increase mean earnings while reducing the variation of those earnings. This result implies that education has a diversification effect. When education is interacted with age (or potential experience), education increases the variation of wages as the worker ages. Past research, including the seminal works of Becker (1993) and Mincer (1974), has focused more on the education-age interaction term while being close to silent on the impact of education when separated from age. A second result indicates that the impact of education on annual wage variation (both in isolation and when interacted with age) is smaller for full-time full-year workers than for all workers in the labor force. In addition to these results, this paper contributes to the literature by using portfolio theory to explain education's complex contribution to wage variation.

## ***I. Introduction and Motivation***

While it may seem intuitive that workers consider both the expected mean and the expected variation of earnings over their lifetime when making human capital investment decisions, research has tended to focus on the former over the latter. When compared to the volume of work on human capital and average earnings (or wages), the research on human capital's impact on the variance of wages appears to be less plentiful. While the reasons for this relative silence are not readily apparent, it may be that the discussion that was provided by Mincer (1974) was persuasive and additional research was of little interest. Alternatively, the lack of research may indicate a failure to clearly answer the basic question of what is the ideal level of variation for wages. While most individuals (and economists) would agree that greater earnings are favorable, the optimal level of variation is ambiguous. Greater variance may imply more occupational opportunity while lower variance may mean more employment and earnings stability, but which level of variation is preferred? Additionally, it may be that these preferences change over an individual's work life.

Another possible explanation for the smaller volume of research on the variation of earnings may be the lack of an established, easy-to-understand earnings' variation model. While the Becker-Mincer human capital earnings equation has consistently predicted a positive return to human capital investment (as well as positive return to experience that diminishes over time), there does not appear to be a similar model that consistently predicts the variation of earnings.<sup>1</sup> Complicating this situation is the fact that variance estimates are very sensitive to data conditions including the nature of the labor market (e.g. level of regulation and diversity of occupations)

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<sup>1</sup> The Becker-Mincer human capital equation is often generalized as:

$$\ln(\text{earnings}) = B_0 + B_1 \text{education} + B_2 \text{experience} + B_3 \text{experience-squared} + u$$

It should be noted that Heckman, Lochner, and Todd (2006) provide a recent update of work associated with this model and provide an alternative approach to analyzing this relationship.

and the type of worker of worker is observed (e.g. full-time full-year worker or any participant in the labor market). Still another possible explanation for this apparent gap in the literature is a combination of the above. Without a clear notion of what level of wage variation is ideal for a worker within a specific labor market, it is not completely obvious what form the model should take or what variables will provide a causal explanation.

In this work, I will address these questions by proposing a simple model that explains some of the wage variation of annual earnings. Using U.S. Census data from 1960 and 2000 for white males (age 18 to 66), I will estimate the impact human capital accumulation has on the variance of annual earnings over the work life. In this model, annual earnings variation is assumed to be heterogeneous, and the goal of this analysis is to identify some of the causes of this heterogeneity. Annual wages, which are reported in the Census as income from salary and wages, are used as the earnings measure of interest since they include all of the fluctuation from periods of employment and unemployment, overtime and bonus pay, and seasonal and slack cycles. Due to all of these factors, it is reasonable to assume that annual wage variation could differ from analyses that have measured income variation based on hourly or weekly earnings.<sup>2</sup> That the empirical results presented here contrast with work on hourly wages should therefore not be a cause for concern, nor should these divergent results be a surprise.

My most important result is that education through college (16 years of schooling) reduces annual wage variation. Based on this result, it appears that human capital investment can contribute to a worker's earnings stream by both increasing the mean of wages and reducing the variation of those wages. I propose that the economic intuition for this result is that education has a diversification effect, and I use portfolio theory to support this intuition. This result is separate and distinct from the traditional observation (also confirmed here) that when

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<sup>2</sup> For a detailed analysis of hourly wage variation, see Lemieux (2006)

education is interacted with age (or potential experience), education increases the variation of wages. Additional results indicate that the impact of education (both in isolation and when interacted with age) lessens when the data only includes observations of full-time full-year workers. Combined, these results indicate that education may provide for steadier employment for those seeking to be in the labor force while also increasing opportunities for those who have already obtained employment.

As mentioned above, it is not clear what level of wage variation is optimal. In the case of annual earnings from employment, variation arises from many sources including, but are not limited to, such factors as the worker's choices (employer selection, self-employment, and labor/leisure trade-offs (family, location)); payment calculation and method (fixed component, overtime, bonuses); and labor market conditions including compensating differentials, supply and demand, and the business cycle. Since these and other factors can influence the variation of wages, it is not surprising that some variables such as education and age have a complex relationship with variation. Therefore, and unlike the results from human capital's contribution to average earnings, an analysis of human capital's relationship on the variance of earnings may not produce one-directional results.

This paper makes several contributions to the literature. First, this work provides a partial explanation of the observed heterogeneity within the variance of annual earnings by regressing the standard deviation of the natural log of annual earnings on demographic factors. Second, this work uses portfolio theory to explain for the bi-directional nature of education's contribution to wage variation (whereas education decreases wage variation for workers educated to the college level, but then education increases wage variation for those who obtain schooling beyond the undergraduate level. Finally, it proposes an alternative to Mincer's

explanation of the u-shape age-variance (or experience-variance) profiles that considers age, education, and the characteristics of the data to all be important contributors to the profile's shape.

This paper proceeds as follows. A brief literature review is followed by a section that details the data set. Section III presents an empirical model and results that detail the complex nature of the relationship between education and annual wage variation. The fourth section provides an economic intuition based on portfolio theory that supports the multi-faceted impact of education affect on wage variation. While it is more typical for the theory section to precede the empirics, this alternative order was selected since the results at least partially contradict the widely accepted theory that human capital accumulation increases the variance of wages, and these results allow an alternative theory to be presented. The last section summarizes this paper and indicates possible directions for additional research.

## ***II. Literature Review***

At this time, I am not aware of any paper that directly examines the impact of human capital on the variation of annual earnings and provides a theory or explanation on the multi-faceted role education has in predicting wage variation throughout the work life. However, several classic works have noted the importance of income variation, including Roy (1951), Mincer (1974), and Becker (1993). Roy's ideas, including the interpretation by Willis (1986), indicate that an individual is concerned with both the expected earnings of his/her occupation and the distribution of those earnings. In other words, both mean and variation of earnings are considered in the occupational decision-making process (which includes the human capital

investment decision). Several chapters of Jacob Mincer's *Schooling, Experience, and Earnings* (1974) provide a more formal introduction to this topic, including an early analysis of wage variance for the individual based on level of education and years of work experience using data from the 1960 Census. Mincer's general observations on the u-shaped age-variance profile are still frequently cited today, but his statements were largely based on an unobservable variable, post-schooling human capital investment, which Mincer believed was correlated with the school level.<sup>3</sup> In *Human Capital* (e.g. Table 9 of Chapter 5), Becker discusses observations on annual wage variation using data from the 1940 and 1950 Census. Becker acknowledges that education is a cumulative process that can impact the variance of wages. In his chapter on the variation in rates of return, he comments that, "A college graduate is, however, usually also a high-school and elementary-school graduate ... a person deciding whether to go to college wants to know how much *additional* variation is caused by going ..." (p. 198, emphasis in the original). This indicates that Becker was aware of a relationship between education and wage variation, but it also implies that the relationship between education and wage variation is positive.<sup>4</sup>

Heckman, Lochner, and Todd (2006) revisit the Mincer model and consider both the returns to schooling and the variation of those returns. Their work finds a positive return to schooling (when measured by internal rate of return in a calculation that considers opportunity cost, tuition, and income taxes), and they examine the heterogeneity and uncertainty in those returns. These authors also consider the implications if education is modeled as a real option,

Other works that empirically examine the variation of wages using cross-sectional data include Lemieux (2006) and Dooley and Gottschalk (1984). Lemieux presents an extensive

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<sup>3</sup> Specifically, see Mincer (1974) section 6.1.3. In general, this discussion refers to the work in Mincer's Chapter 6 that relates to the variation of the natural log of earnings. Perhaps Mincer's reliance on an unobservable is the reason why there has been little intervening empirical work in this area.

<sup>4</sup> This observation is partially contradicted by the results below that indicate education reduces annual wage variation.

analysis of hourly wage variation for males and females (separately) using Current Population Survey (“CPS”) data from the early 1970’s and the early 2000’s. His focus is on the hourly rate, and his data set excludes any influence from overtime, seasonal factors, unemployment, or other factors that might have a greater impact on annual wages than on hourly wages. Lemieux finds that for male workers, within-group variation increases monotonically as education increases (see Table 1A, p. 470). However, because of the restrictions on his data set, his results do not necessarily generalize to explain annual wage variation. Dooley and Gottschalk (1984) repeat several analyses from Mincer (1974), including calculations of wage variation conditional on educational level and experience. Using CPS data from survey years 1968 through 1979 for white males 16 to 62 strongly attached to the workforce and two education categories (high school graduates and those with at least 16 years of education), these authors test and find support for some of Mincer’s observations, but their primary focus is on wage variation and labor force growth.

Chen (2008) decomposes wages into permanent and transitory components using longitudinal data to examine the potential level of variation of earnings based on the hypothesis that observed data understates the potential variation because of selection bias issues. Chen uses the National Longitudinal Survey of Youth and focuses on a random sample of males from age 25 to 42 from survey years 1991 to 2000 and four education categories. In addition to her primary findings and complex econometric model, Chen reports that the observed variance of natural log wages is highest for those with a college degree (or more) education and for those below (without) a high diploma; the variance of wages is slightly lower for those with some

college and lowest for those with a high school diploma. These results are largely consistent with the findings below.<sup>5</sup>

There have been several articles in labor economics that connect human capital investment to portfolio theory and wage variation. This research relates to the broader area of human capital research since portfolio-based models assume that human capital assets may be correlated with other assets held by the same individual, and later in this paper, portfolio theory will be used to provide the economic intuition for these empirical results. Palacios-Huerta (2003) uses CPS data from survey years 1964 to 1996 divided into 2,880 cells based on race, gender, years of schooling, and years of potential work experience to test if returns to human capital exhibit behavior that is similar to the behavior of financial assets. His primary findings were largely consistent with the bulk of human capital research, including the result that more education produces favorable outcomes when compared to those who are less educated. Christiansen, Joensen, and Nielsen (2007) uses Danish data from 1987 through 2000 for birth cohorts of 1947 through 1957 that included actual educational attainment (e.g. PhD in engineering, MS in economics) to analyze the residual variance from sub-groups of the data. Their results imply that human capital choices are not always consistent with the objective as financial assets investment, but these results may partially be driven by the specific assumptions and data conditions.<sup>6</sup> Other work that is consistent with using portfolio models includes the work of Shaw (1996) and Ehrlich, Hamlen, and Yin (2008) who have considered possible interactions between human capital and financial market assets.

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<sup>5</sup> For a broader review of the decomposition of wage variation into observed and unobserved components (based on cross-sectional data) or permanent and transitory components (based on longitudinal data) see Katz and Autor (1999).

<sup>6</sup> These authors dismissed the possibility of diversification gains through education (p. 974), and they use data that is based on conditions unique to Denmark (including no-cost educational policies). The authors also drop periods of unemployment from the data set. These assumptions and conditions restrict these results from being generalized.

While not directly related to this paper, it should be noted that a large body of research on wage variation focuses on wage inequality (the dispersion of average wages across populations or sub-populations). Noted recent works in this area include Autor, Katz, and Kearney (2008) and Goldin and Katz (2007). My research complements the work on income inequality, but any direct contribution to those areas will be addressed in future work.

I am not aware of any work that explains why education reduces overall annual wage variation. While Mincer and others have observed and commented on the increase in annual wage variation in the later part of the work life for higher educated workers, I am not aware of the use of portfolio theory to explain this complex relationship between education and wage variation. I believe the work below contributes to this research.

### ***III. Data Details***

Data from the 1960 and 2000 U.S. Census (1% sample) were obtained from IPUMS at the Minnesota Population Center for white male workers between the ages 18 and 66. Individuals who did not report any salary and wage income as well as those who were in the armed services, students, or those not in the labor force were dropped from the sample. Additionally, individuals who reported farm income or self-employed/business income were dropped from the sample since these amounts may represent a return to capital (in addition to market wages), and those earnings may also indicate that a worker has divided his interest between his own capital and the work he does for an employer. Based on these activity and employment restrictions, approximately 65% in 1960 and 63% in 2000 of the white male adults from the U.S. population remain in the sample.

Observations that had imputed values for wage and salary income were also dropped. This restriction eliminated approximately 2.4% in of the remaining sample 1960 and 24.5% of the remaining sample in 2000. Top-coded values remained as provided by the IPUMS and the U.S. Census, and there were 0.4% top-coded observations in 1960 and 2.0% in 2000. Dollar values from the 1960 Census were converted to 1999 dollars based on the U.S. Consumer Price Index.<sup>7</sup>

In both the 1960 and 2000 data sets, education obtainment was recoded to five categories: less than high school, high school (graduate or equivalent, assumed), some college, college (four-year degree, assumed), and beyond college. These categories are also referred to as educational group 10, 12, 14, 16, and 18, respectively. I acknowledge that educational content and value may have changed over time and make no representations or assertions that these categories are equivalent or accurately measured by the Census.<sup>8</sup> However, I believe these categories retain their relative ordinal relationship throughout and that this is an appropriate transformation of the data. Finally, all observations with less than one year of potential experience (i.e. age *minus* educational group *minus* 7) or a Census-provided person weight less than 0.1 were dropped from the data set. After these adjustments, the “All Workers” data set has 274,616 observation from the 1960 Census and 311,806 observations from the 2000 Census.

A second data set for full-time full-year (“FTFY”) workers is also used. In the FTFY data, workers who reported working less than 35 hour per week or less than 40 weeks per year were dropped.<sup>9</sup> The “FTFY” data set has 221,487 observation from the 1960 Census and 274,466 observations from the 2000 Census. No adjustment was made for the extreme values

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<sup>7</sup> See <http://usa.ipums.org/usa-action/variableDescription.do?mnemonic=INCTOT>

<sup>8</sup> Additionally, the Census does not provide consistent information on degree or diploma completions.

<sup>9</sup> For the hours worked restriction, the variable “usual hours worked” was selected in 2000 and “hours worked last week” was used in 1960.

(i.e. a calculated hourly wage less than the prevailing minimum wage) in the above data sets, but additional regressions were run when these extreme values were dropped and those results are discussed below.<sup>10</sup> Summary statistics and educational attainment are shown in Tables 1 and 2, respectively.

The primary variables used throughout this analysis include age, potential experience, the natural log of earnings and educational group (i.e. educational attainment). From Table 1 it should be noted that the means of age and experience have remained constant over time, but the average earnings have increased. Concurrent with this rise of income, the distribution of educational attainment has significantly changed between the two Censuses (Table 2).

#### ***IV. Empirical Model and Results***

An underlying assumption of this work is that residual variation of annual wages can be explained. The standard earnings equation is often used to analyze the variation of wages, and for this work, these equations will serve as the theory supporting the empirical model:

$$Y_i = X_i B + \varepsilon_i \quad (\text{Eq. 1})$$

$$\text{var}(Y_i) = \text{var}(X_i B) + \text{var}(\varepsilon_i). \quad (\text{Eq. 2})$$

In these equations,  $\varepsilon_i$  represents the omitted variables and/or measurement error. In the empirical work that follows, Equation 2 will be slightly altered so that the standard deviation of annual wage variation, or the absolute value of the residual of Equation 1, will be the dependent variable in a second-stage regression. These methods are detailed below.

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<sup>10</sup> It is not clear if these low hourly earnings were the result of unpaid work (which includes many full-time religious workers in the U.S.) or mis-reporting. Extreme values were any calculated hourly earnings (i.e. (annual wage and salary income) / (average hours per week \* weeks worked)) that were below the contemporaneous minimum wage. In 1960, the U.S. minimum wage was \$1.00, and in 2000, it was \$5.15. ([http://www.dof.ca.gov/HTML/FS\\_DATA/STAT-ABS/documents/D23.pdf](http://www.dof.ca.gov/HTML/FS_DATA/STAT-ABS/documents/D23.pdf))

Using a basic statistical approach, the mean is required in order to estimate the variance. Two methods frequently used to calculate a standard deviation of wages in the labor economics literature are the cell-based and the regression-based methods. In the cell-based method, observations with similar characteristics (similarity as defined by the econometrician) are collected into a single “cell” and the mean and standard deviation are calculated based on that sub-sample; this process is then repeated for every combination of age and education.<sup>11</sup> In the regression-based method, the dependent variable is the variable whose mean and standard deviation are of interest, and independent variables enter the regression as a series of control variations (i.e., dummy and interacted dummy variables) in an ordinary least square (“OLS”) regression.<sup>12</sup> Using the regression-method, the variation measure that is estimated is the residual for the individual observation (which is converted to the absolute value of the residual). Both methods will produce the same variance measure for a specific group (e.g. white males who are 25 years old with a college degree), but the cell-based method greatly reduces the number of observations that can be used in subsequent analysis. In either case, the variation estimate of the natural log of annual wages calculated in the “first stage” is used as the dependent variable in an OLS regression in the “second stage” where independent variables are used to explain the variation of annual wages. In this analysis, both the cell-based and regression-based methods are used, and all regressions use person weights as provided by the Census.

For the cell-based method, cells are defined by gender, race, age, and educational attainment. This produces 225 observations and the personal weights are carried forward to the

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<sup>11</sup> In other words, all of the annual wage observations for 25-year-old white males with 12 years of schooling are in one cell and the mean and standard deviation is calculated for that cell. The process is then repeated for the 26-year olds, etc.

<sup>12</sup> For other examples of this method, see Lemieux (2006) and Palacios-Huerta (2003),

second-stage regression.<sup>13</sup> In the second stage, the variation of annual wages is estimated by two models:

$$\begin{aligned} \text{standard deviation } (\ln(\text{wage}))_c &= B_0 + B_1 \text{age}_c + B_2 \text{age-squared}_c & (\text{Eq.3}) \\ &+ B_3 \text{education group}_c \\ &+ B_4 \text{age*educational group}_c + e_c, \end{aligned}$$

and

$$\begin{aligned} \text{standard deviation } (\ln(\text{wage}))_c &= B_0 + B_1 \text{age}_c + B_2 \text{age-squared}_c & (\text{Eq.4}) \\ &+ B_3 \text{education group}(d)_c \\ &+ B_4 \text{age*educational group}(d)_c + e_c. \end{aligned}$$

Where the subscript “c” denotes values from the cells, “(d)” denotes a series of dummy variables, and  $B_3$  and  $B_4$  are vectors. The two specifications of this model differ in that, in the first, education and the age-education interaction terms each have one variable (whereas education takes the values of 10, 12, 14, 16, and 18); and in the second, education and the age-education interaction terms are a series of dummy variables (for a total of 8 education variables with education group 10 as the omitted category). While education does not have a simple linear relationship with wage variation, both sets of results are provided.<sup>14</sup> The regression results from Equation 4 for All Workers data are presented in column 1 and the results from the FTFY data are in column 2 in Table 3 (1960 Census) and Table 4 (2000 Census). (Note: the dependent variable has been multiplied by 100 in order to improve the readability of the coefficients. This transformation has no impact on the relationship between the dependent and independent variables.) In these regressions, the coefficients increase or decrease the standard deviation of the natural log of wages in absolute terms, and the dependent variable is a relative measure of wage

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<sup>13</sup> Because the data set is restricted to those who have at least one year of potential experience, there are 49 observations for those with less than high school education (inclusive from age 18 to 66); 47 observations for those with a high school education (inclusive from age 20 to 66); etc.

<sup>14</sup> Results for when the educational groups enters the regression as a single variable (Equations 3 and 7) are presented in the Appendix, Table A-1, for both 1960 and 2000.

variation. In other words, based on column 1 in Table 3, an additional year of age would decrease the standard deviation by 3.9 percentage points (e.g. from 70.0% to 66.1%) if all other variables are held constant.

As an alternative approach, the regression-based method was applied. In the first stage, “ $i$ ” refers to the individual observations from the Census data and “ $e_{1i}$ ” are the residuals from the first stage, which are then used as the dependent variable in the second stage:

$$e_i = Y_i - X_i \hat{B} \quad (\text{Eq. 5})$$

Where  $e_i$  is from the regression<sup>15</sup>:

$$\ln(\text{wage})_i = B_0 + B_1 \text{age}(d)_i + B_2 \text{educational group}(d)_i + B_3 \text{age}(d)*\text{educational group}(d)_i + e_{1i} . \quad (\text{Eq. 6})$$

The second stage is either Equation 7 or 8:

$$|e_i| = B_0 + B_1 \text{age}_i + B_2 \text{age-squared}_i + B_3 \text{education group}_i + B_4 \text{age}*\text{educational group}_i + e_{2i} \quad (\text{Eq. 7})$$

$$|e_i| = B_0 + B_1 \text{age}_i + B_2 \text{age-squared}_i + B_3 \text{education group}(d)_i + B_4 \text{age}*\text{educational group}(d)_i + e_{2i} \quad (\text{Eq. 8})$$

The results of the second stage regressions are presented in column 3 for the All Workers data set and in column 4 for the FTFY data of Tables 3 and 4. Alternative results from the regression-based model when the low hourly wage observations are dropped are presented in columns 5 and 6 for the same respective data sets.<sup>16</sup> (Note: as above, the dependent variable has been multiplied by 100 in order to improve the readability of the coefficients.)

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<sup>15</sup> Equation 6 includes fully interacted dummy variables and has 225 independent variables.

<sup>16</sup> One difference between the two methods that should be noted is that the r-squared is much lower when the regression-based first stage is used, but this result is not uncommon when using large data sets. This issue could be examined by another econometric method, but I have no reason to believe a different method would produce alternative results.

The most interesting result from the 1960 data (Table 3) is that all coefficients on education (in isolation) are negative, and that these coefficients decrease monotonically through 16 years of education. This indicates that education reduces annual wage variation through college, but additional education beyond the undergraduate level increases variation. Meanwhile, the coefficients on the age-education interaction terms are all positive, but these coefficients display a pattern opposite to education-only terms and increase monotonically through 16 years of education. The interaction term, which predicts increasing wage variation as the worker ages conditioned on having obtained a certain level of education, is consistent with Mincer's observation that variance increases later in life for those with more education.<sup>17</sup> However using cross-sectional data (and the same data set Mincer used), one cannot determine if this is caused by the worker's increased age or by an increase in human capital (as suggested by Mincer).

In all estimations from the 1960 data, the coefficients on age are negative while the coefficients on age squared are positive. This indicates that age (isolated from education) contributes to the u-shaped experience-variance profiles. An economic explanation for this relationship may be the weaker attachment to the labor market by younger and older workers, and it may also indicate that a u-shape profile is not directly caused by education as opined by Mincer. Based on my analysis, age contributes to the downward (left) side of the "u" while a combination of age and education causes the rise (right side). However, it appears that any u-shape is really driven by the diversity of the level of labor force participation within the sample. Support for this alternative explanation of the profile shape is found in the results from the FTFY data in Table 3. By comparing the All Workers results to the FTFY results (i.e. columns 1 to 2, 3 to 4, and 5 to 6), it is easy to see that the coefficients on age and age-squared terms (and most of

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<sup>17</sup> Mincer (1974) did not consider educational attainment above 16 years.

the education-based terms) decrease when the more restrictive data set is used. The FTFY experience-variance profiles are flatter, and this transformation from a curve to a straight line appears to have strengthened over time (discussed below and detailed in Table 4). However, for the 1960 Census, all variables from the All Workers and FTFY data are consistent in that the sign and magnitude of the coefficients are the same for each variable across all models.

The results from the 2000 data are consistent with the 1960 results in that education continues to reduce the annual wage variation though college (and then variation increases), and the pattern of the age-education interaction terms remains the same. However, for the coefficients estimated on the educational variables in the 2000 FTFY data set, two changes are apparent in Table 4. First, education beyond college now has a positive coefficient. While this result is only significant in model 6 of FTFY workers when the low hourly wage has been dropped, it implies that workers with graduate education in 2000 have more wage variation than the omitted category of less than high school. In all other data sets and models, the beyond college education category coefficients implied higher variance than college but lower variation than the omitted category. A second change in the 2000 FTFY (and the cell-based All Workers) results is that the education-age interaction term at 12 years is no longer significant. This indicates that earning a high school diploma does not necessarily increase income variation in later life over those in the omitted category.

Another contrast in the 2000 FTFY results is that the signs on the age variables are reversed from the estimates from the 1960 data or from the 2000 All Workers data (Table 4, columns 2, 4, and 6). Age now has positive and significant coefficients and the age-squared coefficients are negative (and significant in most models). Given the size of these coefficients and the range of ages to which they are applied, these results indicate that age alone would

produce a straighter line in the age-variance profile (when compared to the results from the 1960 data). As shown in Figure 1, which presents the experience-variance profiles from the high school educational attainment group from both periods, the flattening of the experience-variance profiles are evident, and the profile is now much closer to a straight line (with a slight rise as the workers age). A similar change is observed the experience-variance profiles from the college educational attainment group for FTFY workers between 1960 and 2000.

Several results are presented graphically in Figures 2 through 5.<sup>18</sup> For reference, the traditional experience-earnings profiles for the All Workers data for are shown in Figure 2 (1960) and Figure 3 (2000), and the profiles for the FTFY data are presented in Figure 4 (1960) and Figure 5 (2000). The experience-variance profiles from the same data sets for three educational groups (less than high school, high school, and college) are shown in Figures 6 through 9, respectively. By comparing Figures 6 to 7 and Figures 8 to 9, it should be noted that over time, experience-variance profiles have straightened, and white males in 2000 have higher overall variation than their respective counterparts from 1960. Figures 6 through 9 also highlight that experience-variance profiles, unlike experience-earnings profiles, are very sensitive to data set restrictions and conditions. For example, in the 2000 All Workers data (Figure 7), workers with less than a high school education spend most of their work life with greater wage variation than those workers with a college education; for the 2000 FTFY workers (Figure 9) this relative ranking is reversed. This sensitive is shown by the changing shape of the profiles (and the changing relative order) as the All Workers data is reduced to the FTFY data.<sup>19</sup>

In the Appendix, Tables A-2 and A-3 present the results from the All Workers and the FTFY data (columns 3 and 4, respectively) from the 1970, 1980, and 1990 Censuses. In Table

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<sup>18</sup> These graphs are derived from the results of the first stage from the cell-based model.

<sup>19</sup> For a graphical representation of a data set more encompassing than the All Workers data (and a more robust u-shape profile), see Heckman, Lochner, and Todd (2006).

A-2, education is entered as a single variable (as in Table A-1), and in Table A-3 education is entered as a series of dummy variables (as in Tables 3 and 4). These results are consistent with the previously reported results from 1960 and 2000.

Summarizing these empirical results, I have found that for all data sets and all models, education investment through college lowers annual wage variation, but graduate education increases variation. Age-education interaction terms increase annual wage variation as potential experience increases, and this factor is stronger for those with more education. From the All Workers data, age, age-squared, and age interacted with education contribute to a u-shaped experience-variance profile, but the impact of the age only variables have weakened over time. In almost all cases, the results from the FTFY data set are similar but smaller than the results from the All Workers data. Combined, these results indicate that through the first 16 years, education has a diversification effect whereas the human capital investment allows a worker to obtain higher mean earnings while lowering the overall variance of those earnings. I have also found that graduate education increases both wage and variance (when compared to those with only a college education). This result implies that human capital investment beyond college does not improve diversification, and it appears that graduate education is concentrating the human capital portfolio on certain assets. These ideas are expanded in the next section.

## ***V. Economic Intuition from Portfolio Theory***

The above empirical section indicates that the worker's age (or potential experience), educational attainment, and the specific nature of the data set used will produce (or flatten) the typical u-shaped experience-variance profile. I also found a positive coefficient on the age-

education interaction term, which indicates that annual wage variation continues to increase over the work life, and that this increase is greater for those with more education. While those results support and extend Mincer's work, this section will focus on and offer economic intuition for why the coefficient on education, when separated from age, is consistently negative up through the investment in a college education for all periods and all models. To the best of my knowledge, this relationship between education and wage variance has not been well explored, nor has it been connected to portfolio theory. Such a connection could contribute to the research on human capital investment by providing an explanation for the changing nature of the coefficients on education in variance regressions.

It has often been stated that investment in human capital is risky. This is economically logical since education requires a real investment (opportunity costs, tuition, etc.) and the benefits or results are uncertain in both the short and long run. In the labor economics literature, human capital investment is often compared to the investment in other capital assets (for examples, see Becker (1993) and Heckman, Lochner, and Todd (2006)). Portfolio theory provides an explanation on how the addition of a risky asset (education) to a portfolio (assets owned before the addition) can lower the overall variation of the new portfolio. As will be detailed below, within a portfolio framework, additional assets alter the variance of the existing portfolio based on the weighted proportion of the assets and the correlation between the assets. In addition to the use of portfolio theory, the following also assumes that education is a real option that increases opportunities and that the educational process is primarily cumulative. In other words, it is assumed that new skills are in addition to, and not a replacement for, pre-existing skills.

While some aspects of human capital and financial asset portfolios differ, it is reasonable to assume that the mathematics for these two types of portfolios are similar. A financial portfolio's mean and variance are based on the combination of the means and variances of the underlying assets, where the proportion of the assets within the portfolio and the covariance between the assets determine the portfolio's characteristics (mean and variance). The equations for a two-asset portfolio's mean and variance are:

$$\mu_p = w_a \mu_a + w_b \mu_b \quad (\text{Eq. 9})$$

$$\sigma_p^2 = w_a^2 \sigma_a^2 + w_b^2 \sigma_b^2 + 2w_a w_b \sigma_a \sigma_b \rho_{ab}. \quad (\text{Eq. 10})$$

Where  $\mu_i$  is the mean;  $w_i$  is the proportional weight of each asset;  $\sigma_i$  and  $\sigma_i^2$  are the standard deviation and variance, respectively;  $\rho$  is the correlation coefficient (whereas  $\sigma_{ab} = \sigma_a \sigma_b \rho_{ab}$  and  $-1 \leq \rho \leq 1$ ); subscript  $p$  denotes characteristics of the portfolio, and subscripts  $a$  and  $b$  denote characteristics of the underlying assets. It should be noted that the equations above for mean and variance of a portfolios are the same as the equations for the combination of two normal distributions with the condition that the sum of all of the assets' weights ( $w_i$ ) must equal one. Furthermore, in the case of a human capital portfolio, there is no leveraging or hedging; therefore, not only must the sum of the weights of the human capital assets equal one, each weight remain between zero and one (i.e.  $0 \leq w_i \leq 1$ ).<sup>20</sup> This is not an unusual constraint, for when a worker gets more education (e.g. completes a college degree) he is still one worker. Human capital portfolios also differ from financial portfolios in that there is no trading, no divestiture, and no risk-free asset. This implies that an individual can only hold one portfolio at any one time (e.g. someone cannot be a 45-year old white male and be a 35-year old white male

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<sup>20</sup> There is no leveraging in human capital portfolios because one cannot use some assets as collateral for the instant use of another asset. For instance, one cannot take 10 years of experience and use them to immediately gain the benefits of an advance degree.

at the same time). Similarly, an individual cannot take two masters degrees and trade them for a doctorate, nor can he lend or borrow time. Due to these restrictions, the application of financial portfolio theory to human capital portfolios is more of an analogy-based analysis (as opposed to an empirical-based analysis) at this time.

There are two more important differences between human capital and financial portfolios. The first is that it takes significant time to acquire human capital assets. The minimum investment analyzed above was one year (for potential experience) and approximately two years (for the difference between educational groups), while changes within a financial portfolio can happen almost instantly. The second difference is that while it is possible to observe an individual stock's (or bond's) variance outside of a financial portfolio, observing the variance from an isolated unit of human capital (outside of a portfolio) is more difficult. For instance, someone can own (and the econometrician can observe) the stock of Exxon-Mobile without owning a share of Microsoft, but no one can have a 14<sup>th</sup> year of schooling without having the 13<sup>th</sup> year. For this reason, the following is based on observations of the human capital portfolios without any observations of the underlying human capital assets.

Returning to the general financial portfolio, Figures 10 and 11 display how the frontier (the line of possible portfolio combinations between A and B) responds to various correlation coefficients and weight-combinations of the two assets. These graphs are in mean-variance space. In Figure 10, point A is the lower variance, lower mean asset and point B is the higher mean, higher variance asset. Any two non-identical assets would have this relative relationship based on the assumption that higher returns require greater risk. Points C1 and C2 are the two portfolios that are formed from the same weight combination of assets A and B, but each curve (moving right to left) show the impact of decreasing the correlation coefficient ( $\rho$  in the Equation

10). Figure 11 shows similar interactions, but in this graph, point B2 represents an asset with a higher mean and greater variance than B1 since it is to the northeast of asset B1. In this case, the owner of combination of A and B2 may have an portfolio with *higher* mean and *lower* variance (point C2) then someone who own a combination of A and B1 (point C1). This is a result of the correlation between assets A and B2 and the weight combination of the two assets. That C2 is to the northwest of C1 provides significant support of the greater diversification between A and B2 as compared to A and B1. Thus, although education is considered a risky asset, investment in educational assets can lower the overall variance of an individual's portfolio while concurrently increasing the mean earnings (or returns). Due to the mathematics of a portfolio, the lower the  $\rho$ , the greater the diversification between the two terminal assets (A and B1 or A and B2). This correlation will result in a higher expected mean and a lower expected variation of portfolio C2 when compared to C1.<sup>21</sup>

One final intuition that will be transferred from financial to human capital portfolios is that the correlation coefficient is a function of the underlying assets. In other words, the underlying assets predict the performance of the portfolio, and those same assets predict the correlation between all assets (or the correlation between the new asset and the existing portfolio). Therefore it is rational to assume that when a worker decides to obtain a new educational asset, this decision is based on the (all in expectation) costs, returns (or means), variance of the returns (or means) of the new portfolio, and that this decision includes consideration of the correlation of the new asset with his pre-existing human capital portfolio. In many cases, it is rational for the worker to assume the addition of a risky asset will decrease his

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<sup>21</sup> The terms "portfolio" and "asset" are occasionally used as synonyms since once formed, a portfolio takes on the characteristics of an assets with a single mean and variance. The ability to interchange the concepts of assets and portfolios also explains how the multi-asset financial portfolio model can be generalized to the two-asset financial portfolio model.

overall earnings variance, and this is why, even through the returns to education may be risky (and have an increasing variance), certain educational investments produces a lower annual wage variation. The empirical analysis in the previous section provides support for this intuition by showing that adding education to a worker's portfolio decreases the overall variance of the worker's earnings from his human capital portfolio.

The generalization of Figure 11 to human capital portfolios is based on the assumption some combinations of two assets (A and B1 or A and B2) are held by the same worker over his lifetime. The first asset/portfolio (point A) is "owned" when the worker is young and this portfolio contains completed schooling, little experience, and lots of potential. The second portfolio (asset B1 or B2) is at the end of his work life and contains the same (or more) schooling, lots of experience, and little potential. As the worker ages, the portfolio evolves from the "young portfolio" to the "old portfolio," and the weights within the portfolio shift as potential is replaced by experience. Based on the assumption that education influences the variation of earnings through the correlation coefficient, as long as the  $\rho$  is less than one, the variance of the portfolio at any given time will be less than the weighted average of the variance of the two terminal portfolios. This same analogy holds for all workers (and their respective portfolios) when examining the impact of education in the aggregate labor market.

When incorporating the empirical results into human capital portfolios, it appears that education materially changes the portfolios held by workers. This is shown graphically when the five educational groups from the 2000 All Workers data set are plotted in mean-variance space in Figure 12. These curves are based on the combination of the estimated means (Figure 3) and estimated standard deviation (Figure 7, but for all educational groups). The importance of the relationship between education and annual wage variation for the aggregate labor market

becomes apparent in Figure 12 and when the individual educational groups are compared to each other as presented in Figures 13 through 16.<sup>22</sup>

Figure 13 shows the work-life frontier for white males with a high school degree and those with education less than high school. The frontier starts at the lower right (point 1(A) for the less than high school educated), and moves counter-clockwise as the worker ages (point 49 (B)). It is significant that the work-life frontier of the high school educated worker is to the northwest of the frontier of the less educated worker. This shift is a graphic presentation of the diversification effect of education. From Table 4, column 1, it was estimated that adding the high school completion “asset” to the less than high school portfolio should decrease the annual wage variation by about 13.5 percentage points, and this result is clear in Figure 13. The increase of the average earnings is also noticeable in this figure. By adding a high school education, the mean earnings increases and the variance of annual wages decreases, which is an expected outcome based on portfolio theory. (This result is analogous to moving from portfolio C1 to C2 in Figure 11.)

Figures 14, 15, and 16 compare the remaining educational groups, one-to-one, in increasing increments. In Figure 14, men who have obtained high school education are compared to those with some college. Most of the work life of the worker with some college education has a higher mean and lower (or similar) variance than those with only a high school education.<sup>23</sup> A similar pattern is found in Figure 15. When the college-educated workers are compared to those with only some college, the variances remain the same or is lower for much of the work life (the diversification effect) while mean earnings increase. By completing the

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<sup>22</sup> The results and relationships from the 1960 data are similar.

<sup>23</sup> The higher variance near the end of the work life was also estimated in the regression results by the positive coefficients on the age-squared and age-education interaction terms (Table 4, column 1).

standard college degree, it appears that an individual increases their return without any increase in volatility for most of their work life.

However, this beneficial relationship between education and annual wage variation does not continue indefinitely. Based on Figure 16 (and the regression results), it appears that education beyond an undergraduate degree adds little diversification to the pre-existing portfolio. As shown in Figure 16, individuals whose education is above the bachelor's degree level generally have greater average earnings and greater earnings variance when compared to those who hold only a four-year degree. This movement to the northeast implies that the portfolio is becoming more concentrated in a higher-variance, higher-mean asset. Referring back to the theoretical portfolio frontier, the individual who obtains an advanced degree appears to be moving along the upper portion of the frontier (Figure 11, moving from asset C2 to asset B2). The decision to obtain more education may still be perfectly rational, but this educational asset (graduate school) has a more substantial risk return trade-off, and this type of investment decision may require significant analysis to determine if the return is worth the risk. As shown in Table 4, column 1, the expected variance increases by 18 percentage points as a worker increases their educational holdings (assets) beyond 16 years of schooling.

While human capital portfolio theory has been here presented without rigorous mathematics or formal modeling, the empirical results and graphical analysis are consistent with the predictions from this theory. While still a new concept, the application of portfolio theory to human capital investment appears to be a research area with many opportunities, as it can explain both the increasing and decreasing variation of wages that is observed over the work life. Portfolio theory predicts the variations of wages could respond to an increase of human capital assets by first lowering and then increasing the variation. Human capital portfolio theory

provides a model that better accommodates the complex relationship between human and the labor market.

## ***VI. Summary, Conclusions, and Future Work***

This research found several striking results that contribute to the explanation of the heterogeneity observed in annual earnings. The first of these results was that, in regressions designed to explain annual wage variation, education obtainment (in isolation and up to 16 years of schooling) lowers the variation of annual wages, and when this result is placed in a portfolio framework, this indicates that education has a diversification effect. Another finding was that when age is interacted with education obtainment, the coefficient is always positive, and variation increases over the work life based on the level of schooling. Combined, these results may also imply that labor markets respond differently to education and to the interaction of age and education. This research also found that the u-shape often used to describe age-variance (or experience-variance) profiles appears to be the result of wide (or unconditioned) data sets, the extreme values within those data sets, and a multi-faceted interaction between age and education. If one examines full-time full-year workers, the age-variance profiles flatten. Based on this analysis, it does not appear that education is the sole contributor to the profile shape. Instead, this analysis indicates that the profile is based on a combination of age and education, and its shape is a direct result of the type of workers being observed.

This work also introduced human capital portfolio theory as the intuition behind the complex interaction of education on annual wage variation. The empirical results provide strong support for the use of portfolio theory in the analysis of human capital investment as this theory

provides a better explanation, the impact of diversification, which predicts the variation of wages throughout the work life and the labor market. These results indicate (based on the assumption that education gives a worker more options and more diversification), that the more educated workers are using this option to first secure steady employment, and then, once a full-time position is obtained, workers use their education to expand their opportunities.

Another important result of this research indicates that analysis of annual wage variation is very sensitive to the conditions within the data. While this issue has been noted by other researchers, this work highlights that human capital investment affects the variance of earnings differently based on the type of worker being analyzed. This result stands in strong contrast to the established relationship between human capital and average earnings (where increases in human capital usually predicts greater earnings), which is consistent in most data sets. This also indicates that for labor markets with more regulation and restriction than the U.S., similar analytical methods may produce different results. For instance, if regulatory constraints restrict worker participation and/or the range of compensation, and wage variation may be limited, and the impact of the regulation may overwhelm the influence from human capital on wage variation.

There are several directions for additional work in this area. An analysis of the variation in annual wages for women is an obvious next step, and that work may produce very different results than those capture above since female participation in the labor force has changed greatly during this forty-year period. Other data sources, including large longitudinal data sets, could be analyzed, and other econometric methods could be applied. I believe there are many extensions to modeling human capital accumulation within a portfolio theory framework, and this additional research could yield interesting new insights into human capital investment decisions.

## *References*

- Autor, David H., Lawrence F. Katz and Melissa Schettini Kearney. 2008. Trends in U.S. Wage Inequality: Revising the Revisionists. *Review of Economics and Statistics* 90, 2 p. 300 – 323.
- Becker, Gary S. 1993. *Human Capital* 3rd Ed. University of Chicago Press.
- Chen, Stacey H. 2008. Estimating the Variance of Wages in the Presence of Selection and Unobserved Heterogeneity. *Review of Economics and Statistics* 90, 2 p. 275-289.
- Christiansen, Charlotte, Juanna D. Joensen, and Helena S. Nielsen. 2007. The Risk-Return Trade-Off in Human Capital Investment. *Labour Economics* 14, p. 971 - 986.
- Dooley, Martin D. and Peter Gottschalk. 1984. Earnings Inequality among Males in the United States: Trends and the Effect of Labor Market Growth. *The Journal of Political Economy* February p. 59-89.
- Ehrlich, Isaac, William A. Hamlen Jr., and Yong Yin. 2008. Asset Management, Human Capital, and the Market for Risky Assets. *Journal of Human Capital* 2, no. 3: p. 217-261.
- Goldin, Claudia and Lawrence F. Katz. 2007. Long-Run Changes in the Wage Structure: Narrowing, Widening, Polarizing. *Brookings Papers on Economic Activity* 2, p. 135-165.
- Heckman, James J., Lance J. Lochner, Petra E. Todd. 2006. Earnings Functions, Rates of Return, and Treatment Effects: The Mincer Equation and Beyond. *Handbook of the Economics of Education* Vol 1 ed. Eric A. Hanushek and Finis Welch. Elsevier BV.
- Katz, Lawrence F. and David H. Autor. 1999. Changes in the Wage Structure and Earnings Inequality. *Handbook of Labor Economics* Vol 3 ed. Orley Ashenfelter and David Card. Amsterdam: North Holland.
- Lemieux, Thomas. 2006b. Increased Residual Wage Inequality: Composition Effects, Noisy Data, or Rising Demand for Skill. *American Economic Review* 96, p. 461 - 498.
- Mincer, Jacob. 1974. *Schooling, Experience, and Earnings*. New York: National Bureau of Economic Research.
- Palacios-Huerta, Ignacio. 2003. An Empirical Analysis of the Risk Properties of Human Capital Returns. *The American Economic Review* 93, No. 3, p. 948-964.
- Roy, A.D. 1951. Some Thoughts on the Distribution of Earnings. *Oxford Economic Papers* 3 No. 2, p. 135 - 146.

Ruggles, Steven, J. Trent Alexander, Katie Genadek, Ronald Goeken, Matthew B. Schroeder, and Matthew Sobek. 2010. *Integrated Public Use Microdata Series: Version 5.0* [Machine-readable database]. Minneapolis: University of Minnesota. (Source of Census Data.)

Shaw, Kathryn L. 1996. An Empirical Analysis of Risk Aversion and Income Growth. *Journal of Labor Economics* 14, no. 4: p. 626-653.

Willis, Robert. 1986. Wage Determinants: A Survey and Reinterpretation of Human Capital Earnings Functions. *Handbook of Labor Economics* Vol 1 ed. Orley Ashenfelter and Richard Layard. Amsterdam: North Holland.

**Table 1**  
**Summary Statistics, White Male Workers**  
*(weighted values; observations with zero weight dropped)*

<i>All Workers in the Labor Force</i>			<i>Full-time, Full-year Workers "FTFY"</i>		
	<b>Census 1960</b>			<b>Census 1960</b>	
	<i>Observations = 274,616</i>			<i>Observations = 221,487</i>	
	<b>Mean</b>	<b>Standard Deviation</b>		<b>Mean</b>	<b>Standard Deviation</b>
Age (years)	40.55	12.04	Age (years)	40.71	11.63
Potential Experience (years)	21.95	12.51	Potential Experience (years)	21.97	12.14
Wage and Salary Income (1999 dollars)	\$ 30,653	\$ 17,774	Wage and Salary Income (1999 dollars)	\$ 33,474	\$ 17,284
ln ( Wage and Salary Income (1999))	10.145	0.707	ln ( Wage and Salary Income (1999))	10.302	0.508
Educational Group	11.61	2.18	Educational Group	11.74	2.23
	<b>Census 2000</b>			<b>Census 2000</b>	
	<i>Observations = 311,806</i>			<i>Observations = 274,466</i>	
	<b>Mean</b>	<b>Standard Deviation</b>		<b>Mean</b>	<b>Standard Deviation</b>
Age (years)	40.95	11.09	Age (years)	41.05	10.70
Potential Experience (years)	20.08	11.02	Potential Experience (years)	20.11	10.67
Wage and Salary Income (1999 dollars)	\$ 48,637	\$ 49,287	Wage and Salary Income (1999 dollars)	\$ 52,014	\$ 49,863
ln ( Wage and Salary Income)	10.470	0.835	ln ( Wage and Salary Income)	10.607	0.670
Educational Group	13.86	2.33	Educational Group	13.95	2.30

**Table 2**  
**Educational Summary Statistics, White Male Workers**  
*(weighted values; observations with zero weight dropped)*

<b>1960 Educational Attainment</b>	<b>All Workers</b>	<b>FTFY Workers</b>	<b>All Workers</b>	<b>FTFY Workers</b>	<b>2000 Educational Attainment</b>
No schooling completed	0.7%	0.5%	0.3%	0.3%	No schooling completed
Kindergarten	0.1%	0.1%			
Grade 1	0.3%	0.2%			
Grade 2	0.6%	0.4%	0.2%	0.2%	Nursery school to grade 4
Grade 3	1.1%	0.9%			
Grade 4	1.6%	1.3%			
Grade 5	2.0%	1.7%	0.6%	0.7%	Grade 5 or 6
Grade 6	3.4%	3.0%			
Grade 7	6.0%	5.4%	0.9%	1.0%	Grade 7 or 8
Grade 8	15.9%	15.0%	1.2%	1.3%	Grade 9
Grade 9	7.4%	7.1%	1.8%	1.9%	Grade 10
Grade 10	8.7%	8.5%	1.8%	1.9%	Grade 11
Grade 11	6.1%	6.2%	2.2%	2.4%	12th grade, no diploma
Grade 12	26.0%	27.7%	28.0%	27.6%	High school graduate or GED
Some college, but less than 1 year	1.3%	1.4%	8.3%	7.7%	Some college, but less than 1 year
1 year of college	3.5%	3.8%	15.1%	15.4%	College credit ≥ 1 year, no degree
2 years of college	4.0%	4.3%	8.2%	7.4%	Associate's degree
3 years of college	1.6%	1.7%			
4 years of college	6.0%	6.7%	20.3%	21.0%	Bachelor's degree
5+ years of college	1.6%	1.7%	7.8%	7.4%	Master's degree
6+ years of college	2.4%	2.6%	2.1%	2.5%	Professional degree beyond bachelor's
			1.1%	1.5%	Doctoral degree
<b>Educational Groups</b>	<b>1960</b>	<b>1960</b>	<b>2000</b>	<b>2000</b>	<b>Educational Groups</b>
10	53.8%	50.2%	9.0%	9.5%	10
12	26.0%	27.7%	28.0%	27.6%	12
14	10.4%	11.3%	31.7%	30.4%	14
16	6.0%	6.7%	20.3%	21.0%	16
18	3.9%	4.3%	11.1%	11.5%	18
<i>Observations</i>	<i>274,616</i>	<i>221,487</i>	<i>311,806</i>	<i>274,466</i>	

**Table 3**  
**1960 Census Data**  
(Omitted Category: Less than High School)

<i>Dependent Variable:</i>	<i>Cell-based standard deviation</i>				<i>Absolute value of individual residual</i>				<i>Absolute value of individual residual</i>			
	All Workers		FTFY		All Workers		FTFY		All Workers		FTFY	
	(I)	(II)	(III)	(IV)	(V)	(VI)	(V)	(VI)	(V)	(VI)		
<i>age</i>	-3.940 *** (0.181)	-1.857 *** (0.132)	-3.496 *** (0.053)	-1.418 *** (0.044)	-2.572 *** (0.048)	-0.219 *** (0.033)						
<i>age squared</i>	0.046 *** (0.002)	0.022 *** (0.002)	0.040 *** (0.001)	0.016 *** (0.001)	0.030 *** (0.001)	0.004 *** (0.000)						
<i>educ 12 (d)</i>	-31.736 *** (2.609)	-20.816 *** (1.841)	-25.869 *** (0.762)	-14.436 *** (0.611)	-20.821 *** (0.676)	-7.543 *** (0.449)						
<i>educ 14 (d)</i>	-34.647 *** (3.767)	-25.340 *** (2.568)	-28.287 *** (1.100)	-19.669 *** (0.852)	-22.507 *** (0.957)	-11.281 *** (0.613)						
<i>educ 16 (d)</i>	-37.423 *** (5.069)	-35.194 *** (3.389)	-32.757 *** (1.480)	-27.567 *** (1.124)	-24.373 *** (1.274)	-16.115 *** (0.802)						
<i>educ 18 (d)</i>	-16.579 ** (6.620)	-8.938 ** (4.417)	-14.569 *** (1.932)	-9.819 *** (1.465)	-13.450 *** (1.678)	-6.217 *** (1.055)						
<i>age * educ 12 (d)</i>	0.408 *** (0.065)	0.382 *** (0.045)	0.353 *** (0.019)	0.264 *** (0.015)	0.327 *** (0.017)	0.182 *** (0.011)						
<i>age * educ 14 (d)</i>	0.578 *** (0.091)	0.584 *** (0.062)	0.491 *** (0.027)	0.466 *** (0.021)	0.451 *** (0.023)	0.354 *** (0.015)						
<i>age * educ 16 (d)</i>	0.683 *** (0.126)	0.912 *** (0.084)	0.670 *** (0.037)	0.753 *** (0.028)	0.574 *** (0.032)	0.563 *** (0.020)						
<i>age * educ 18 (d)</i>	0.229 (0.159)	0.382 *** (0.106)	0.266 *** (0.046)	0.377 *** (0.035)	0.287 *** (0.040)	0.313 *** (0.025)						
<i>constant</i>	147.170 *** (3.734)	83.937 *** (2.788)	117.624 *** (1.090)	61.059 *** (0.925)	90.013 *** (0.992)	28.236 *** (0.695)						
<i>r-square</i>	0.841	0.762	0.031	0.017	0.023	0.026						
<i>F-Statistic</i>	113	68	867	372	599	563						
<i>observations</i>	225	225	274,616	221,487	259,177	210,579						

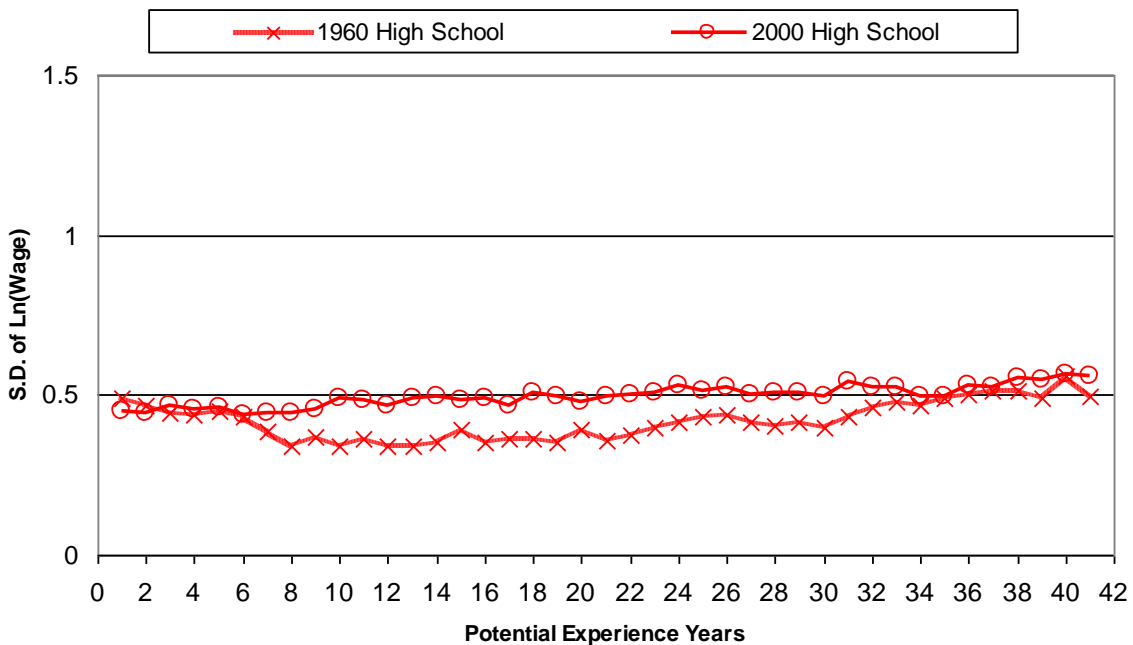
Standard errors in parenthesis; Statistical significance noted by \*\*\* (1%), \*\* (5%), and \* (10%)

**Table 4**  
**2000 Census Data**  
(Omitted Category: Less than High School)

<i>Dependent Variable:</i>	<i>Cell-based standard deviation</i>				<i>Absolute value of individual residual</i>				<i>Absolute value of individual residual</i>			
	All Workers		FTFY		All Workers		FTFY		All Workers		FTFY	
	(I)	(II)	(III)	(IV)	(V)	(VI)	Drop Low	Drop Low	Drop Low	Drop Low		
<i>age</i>	-2.720 (0.216)	***	0.470 (0.128)	***	-2.409 (0.061)	***	0.257 (0.052)	***	-1.774 (0.056)	***	0.608 (0.049)	***
<i>age squared</i>	0.033 (0.003)	***	-0.003 (0.001)	**	0.029 (0.001)	***	-0.001 (0.001)		0.023 (0.001)	***	-0.005 (0.001)	***
<i>educ 12 (d)</i>	-13.577 (3.817)	***	-6.553 (2.299)	***	-13.006 (1.083)	***	-3.934 (0.940)	***	-10.497 (1.015)	***	-1.433 (0.894)	
<i>educ 14 (d)</i>	-36.213 (3.934)	***	-12.646 (2.335)	***	-27.182 (1.116)	***	-8.633 (0.955)	***	-18.029 (1.036)	***	-3.815 (0.904)	***
<i>educ 16 (d)</i>	-39.300 (4.326)	***	-12.069 (2.531)	***	-28.612 (1.228)	***	-9.025 (1.035)	***	-16.617 (1.128)	***	-2.760 (0.973)	***
<i>educ 18 (d)</i>	-21.260 (5.692)	***	0.844 (3.255)		-13.952 (1.615)	***	1.126 (1.332)		-4.135 (1.460)	***	5.769 (1.236)	***
<i>age * educ 12 (d)</i>	0.048 (0.093)		0.055 (0.056)		0.100 (0.026)	***	0.004 (0.023)		0.135 (0.025)	***	-0.017 (0.021)	
<i>age * educ 14 (d)</i>	0.564 (0.095)	***	0.266 (0.056)	***	0.429 (0.027)	***	0.156 (0.023)	***	0.344 (0.025)	***	0.092 (0.022)	***
<i>age * educ 16 (d)</i>	0.793 (0.104)	***	0.474 (0.061)	***	0.589 (0.030)	***	0.321 (0.025)	***	0.448 (0.027)	***	0.224 (0.023)	***
<i>age * educ 18 (d)</i>	0.511 (0.128)	***	0.327 (0.073)	***	0.369 (0.036)	***	0.218 (0.030)	***	0.279 (0.033)	***	0.156 (0.028)	***
<i>constant</i>	131.009 (4.806)	***	40.832 (2.925)	***	102.352 (1.364)	***	32.733 (1.197)	***	79.174 (1.280)	***	20.599 (1.138)	***
<i>r-square</i>	0.797		0.913		0.021		0.025		0.023		0.032	
<i>F-Statistic</i>	84		224		661		707		709		883	
<i>observations</i>	225		225		311,806		274,466		300,394		267,121	

Standard errors in parenthesis; Statistical significance noted by \*\*\* (1%), \*\* (5%), and \* (10%)

**Figure 1: 1960 & 2000, White Males, Standard Deviations  
FTFY, 12 Years of Education**



**Figure 2: Mean Earnings, White Male, 1960, All Workers**

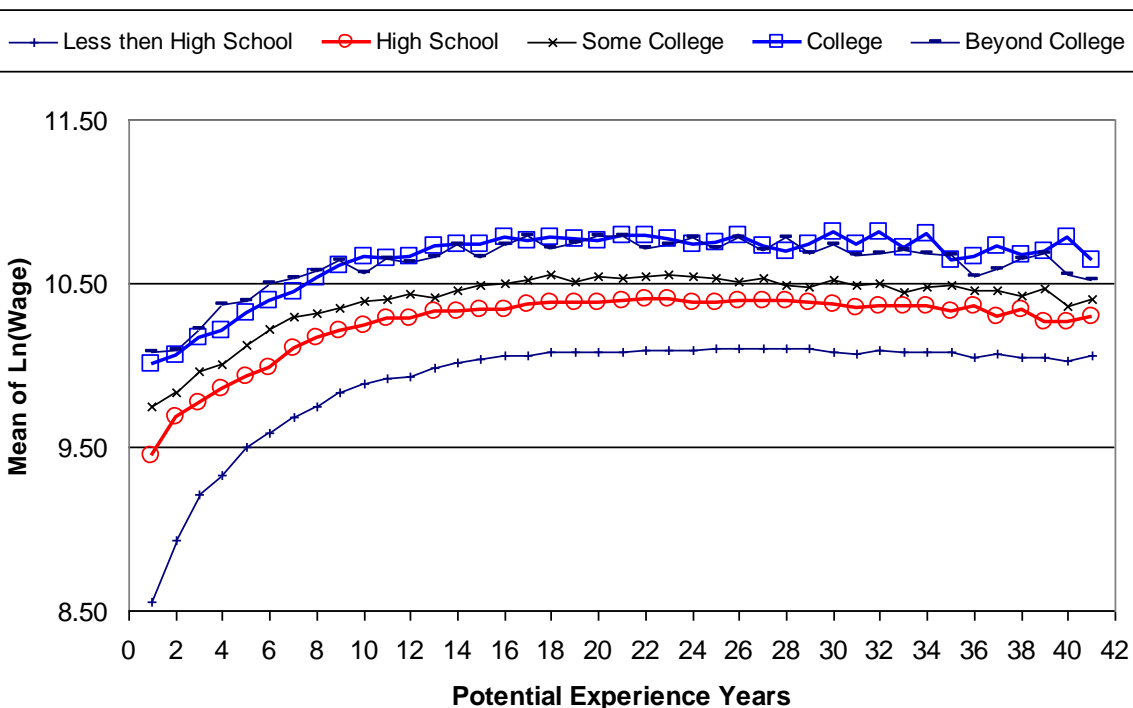


Figure 3: Mean Earnings, White Male, 2000, All Workers

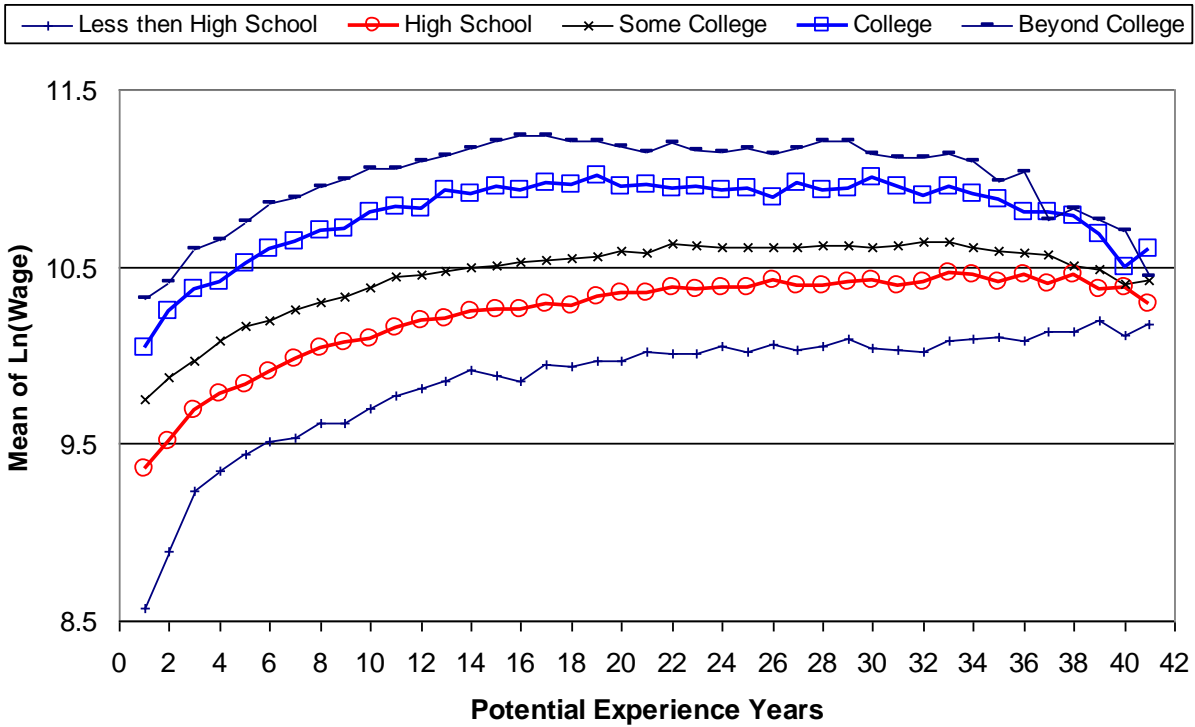
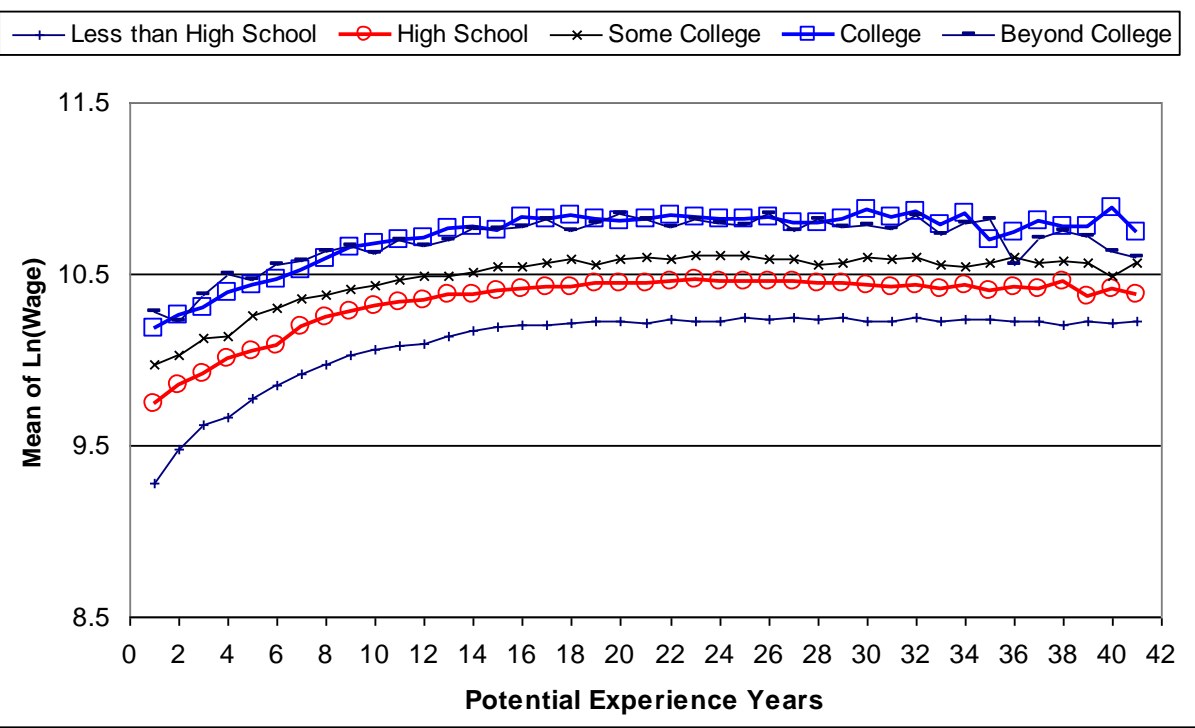
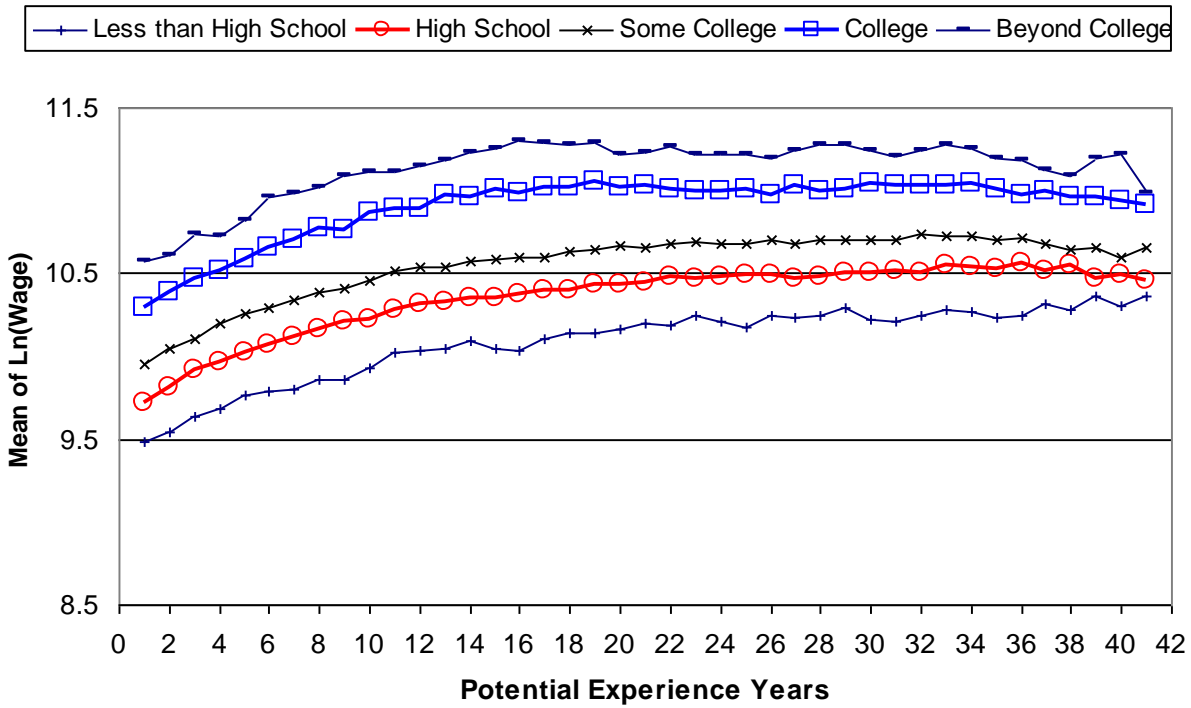


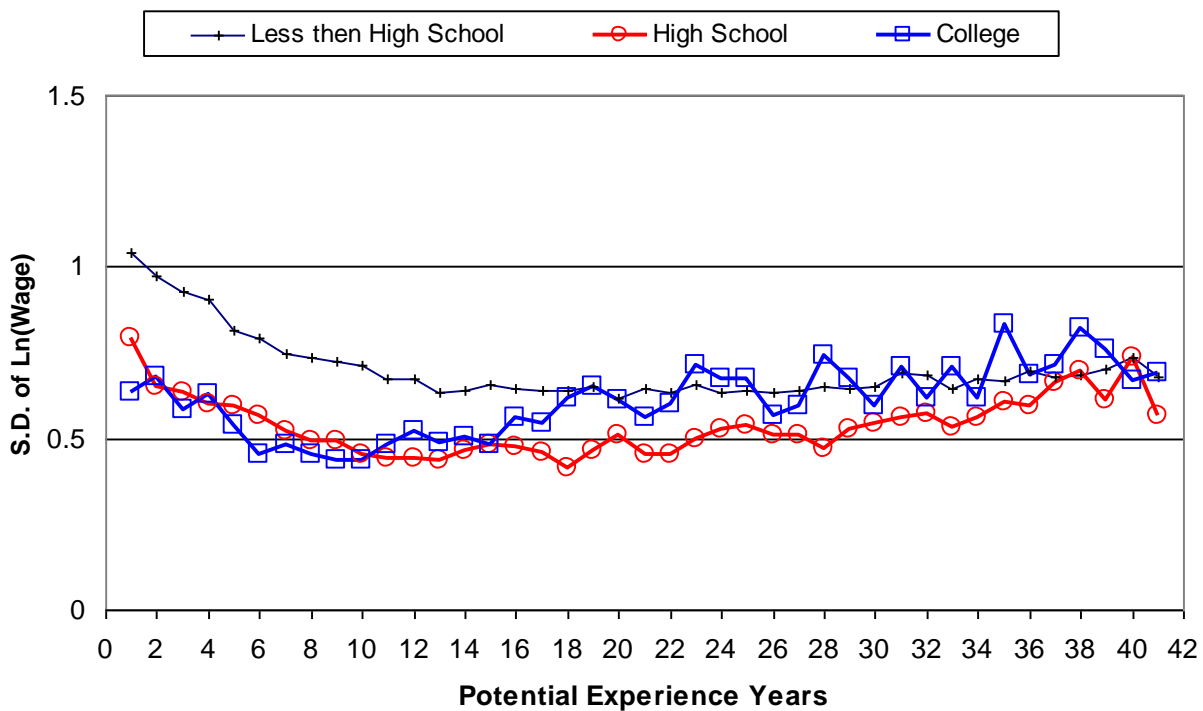
Figure 4: Mean Earnings, White Male, 1960, FTFY Workers



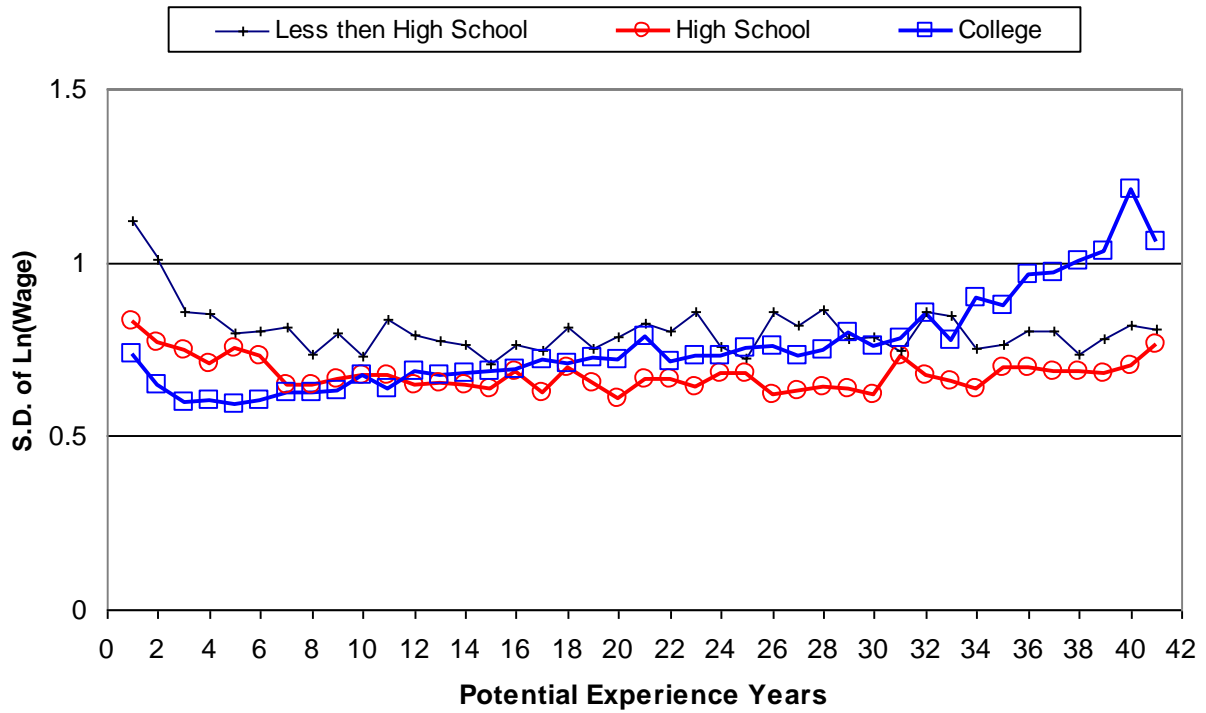
**Figure 5: Mean Earnings, White Male, 2000, FTFY Workers**



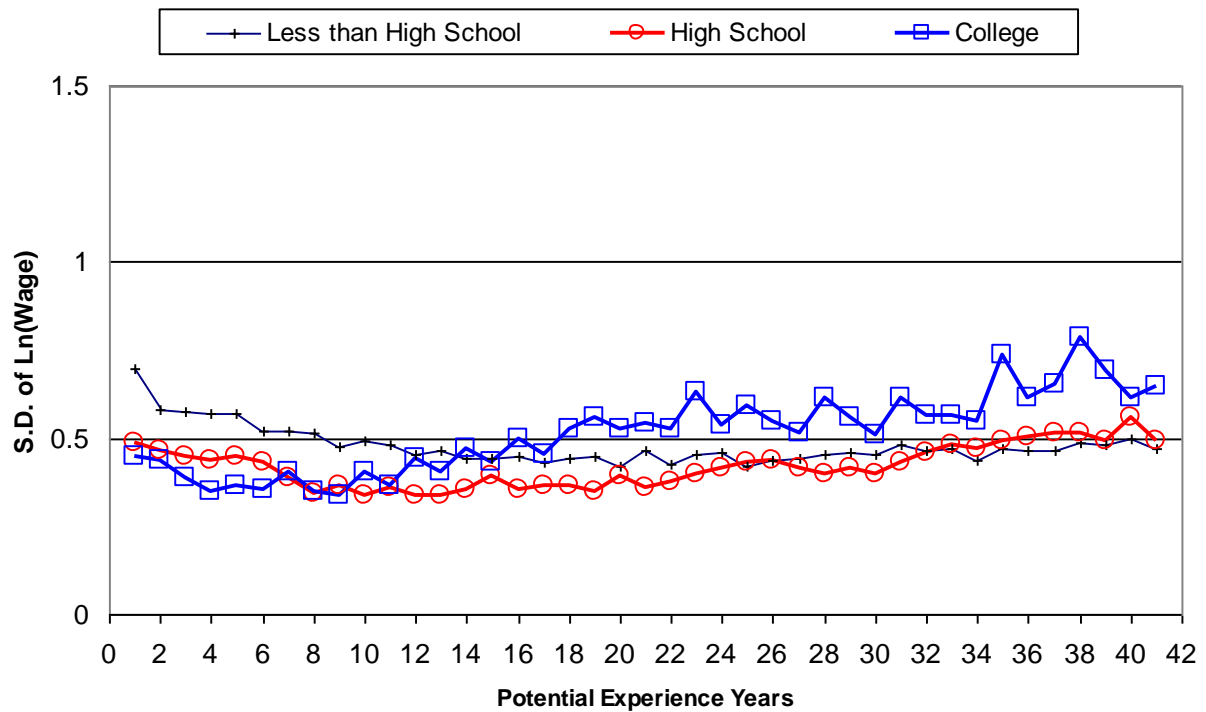
**Figure 6: White Male, 1960, All Workers, Standard Deviations**



**Figure 7: White Male, 2000, All Workers, Standard Deviations**



**Figure 8: White Male, 1960, FTFY Workers, Standard Deviations**



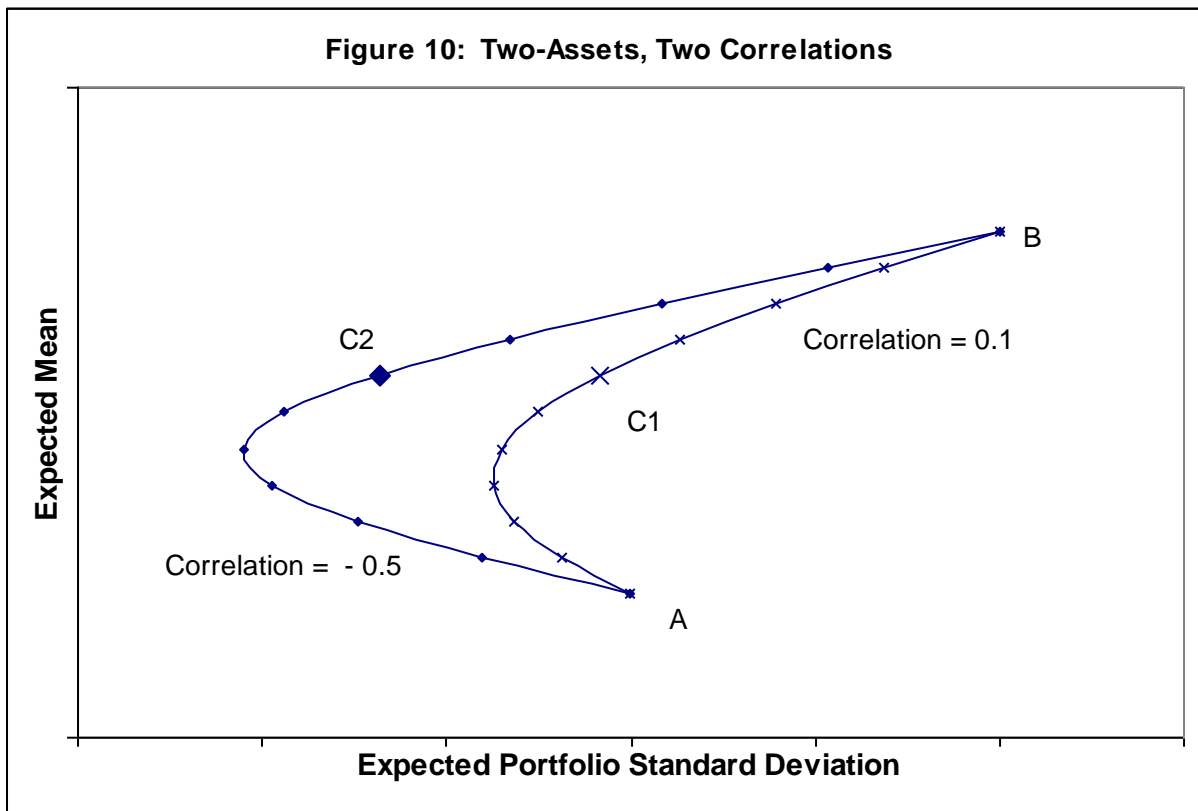
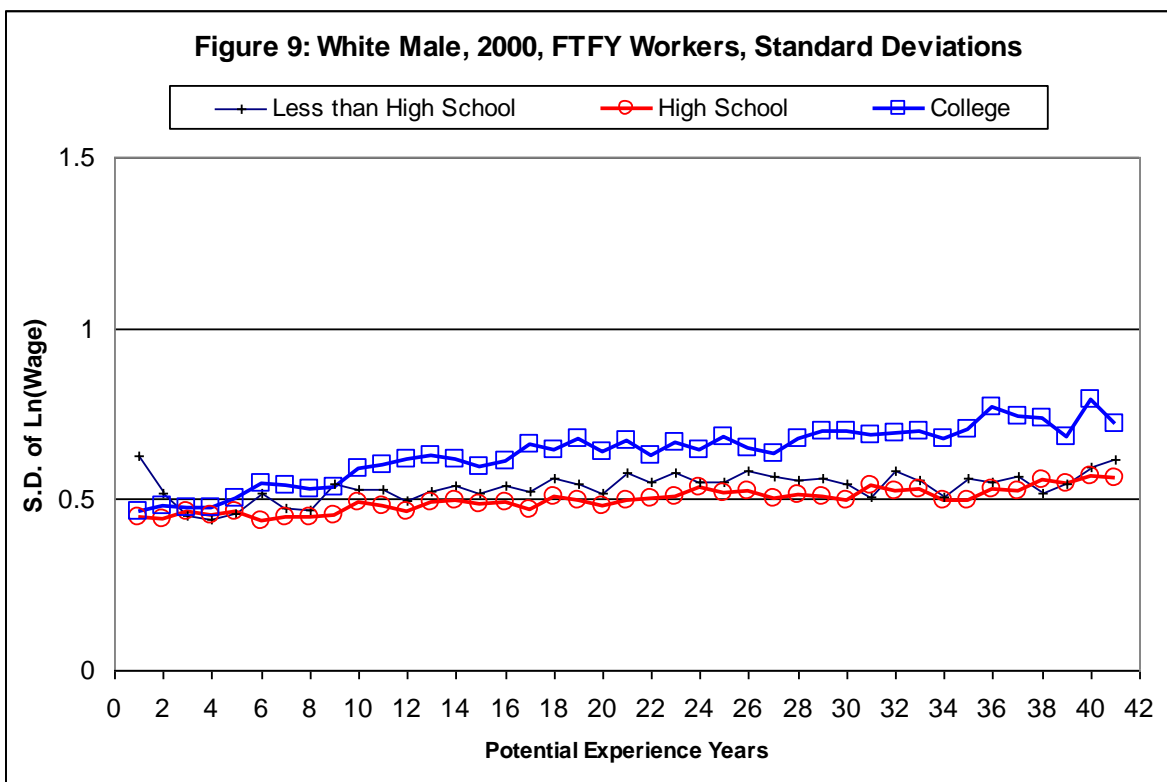


Figure 11: Three-Assets, Two Correlations

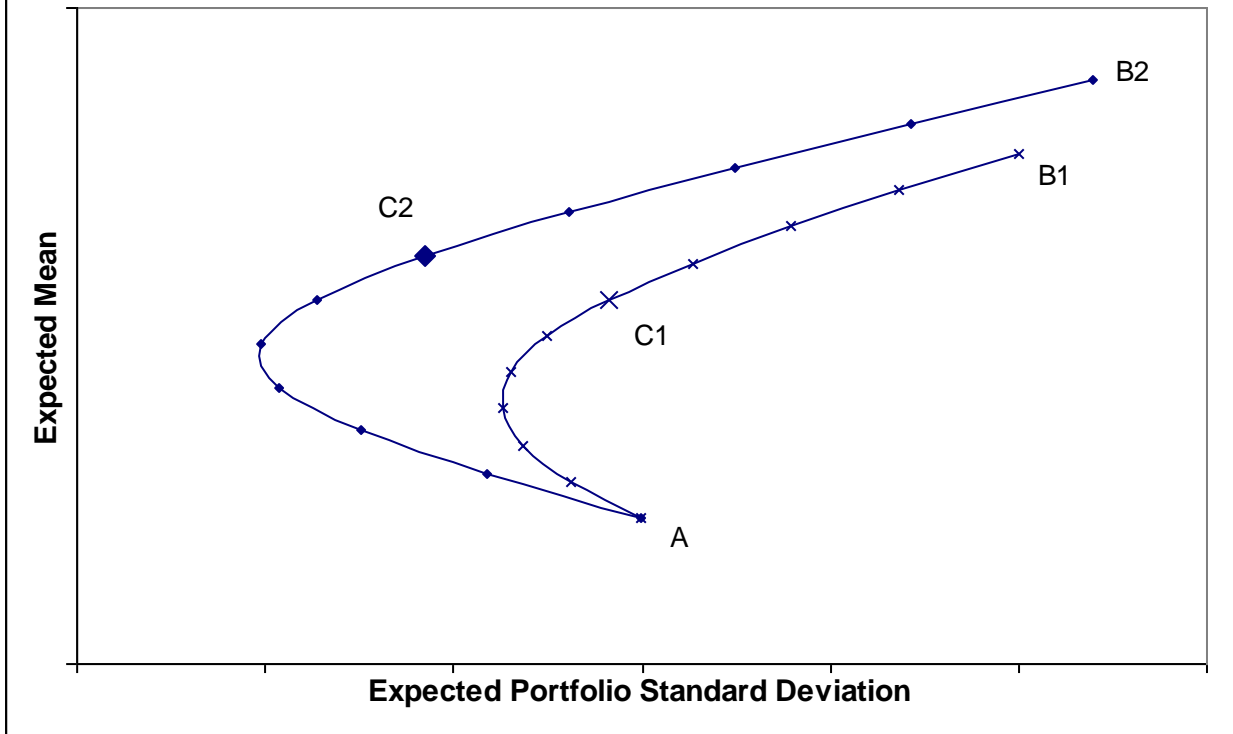
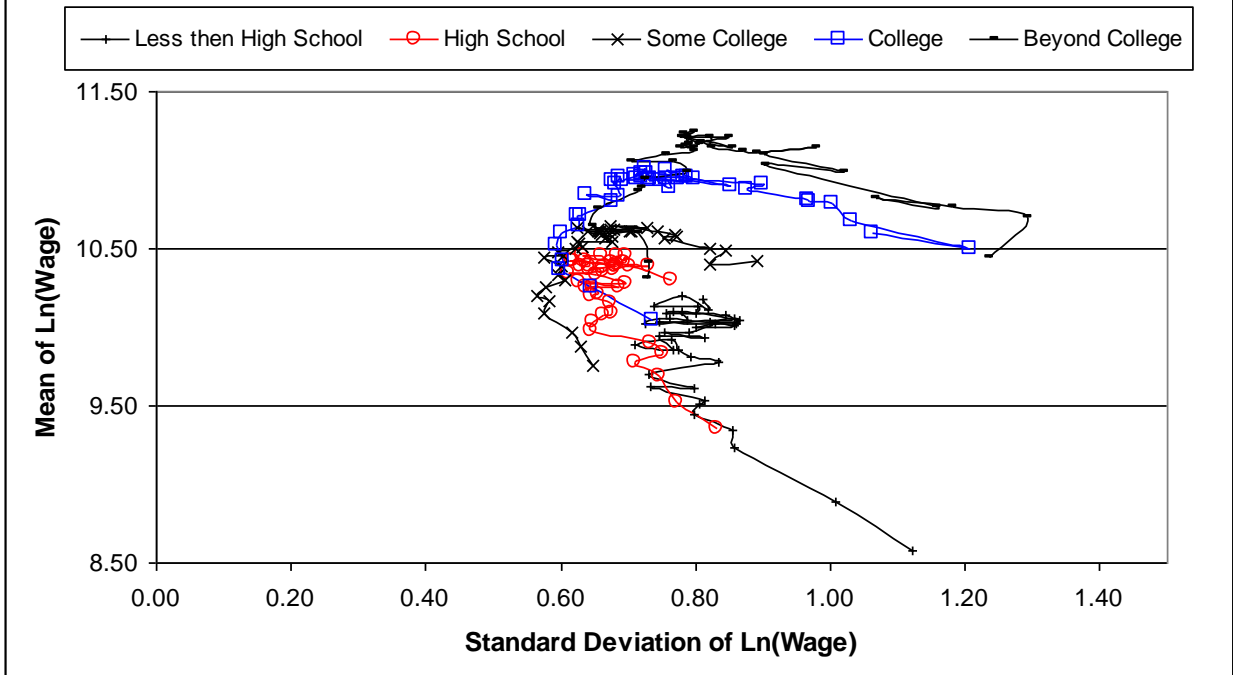
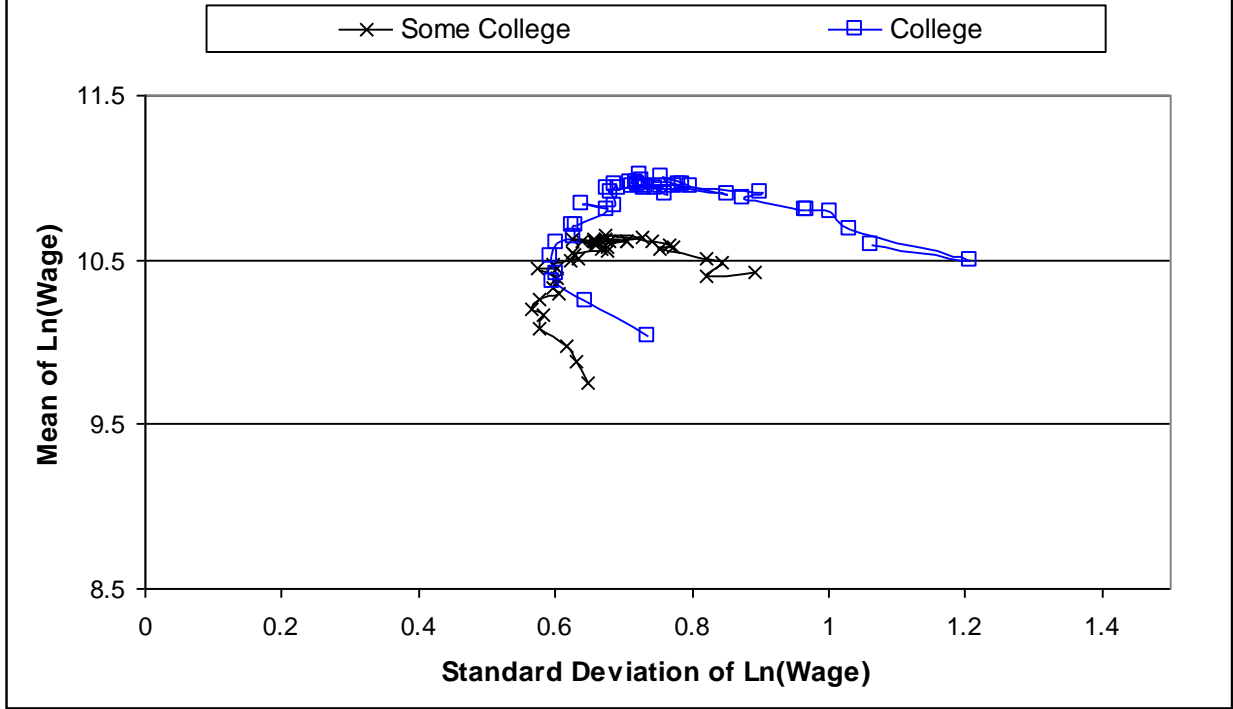


Figure 12: White Male, 2000, All Workers, Mean-Standard Deviation Plots

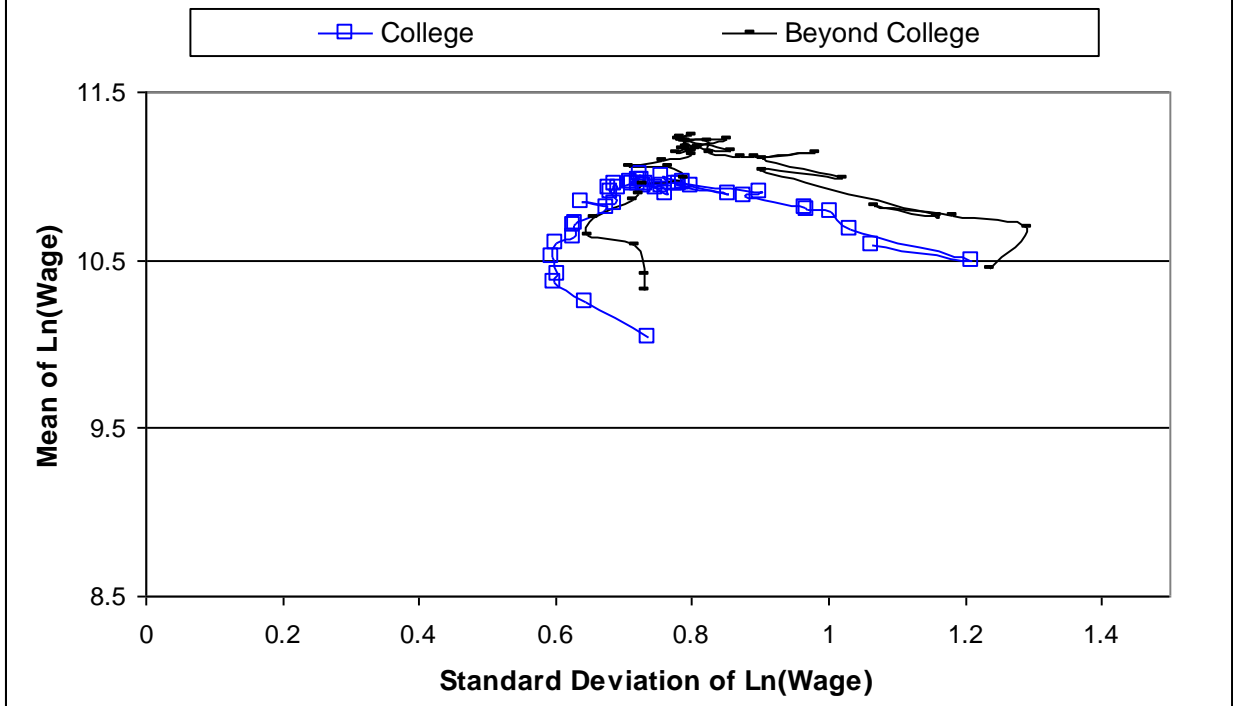




**Figure 15: White Male, 2000, All Workers,  
Mean-Standard Deviation Plots**



**Figure 16: White Male, 2000, All Workers,  
Mean-Standard Deviation Plots**



## Appendix Tables

**Table A-1**

**1960 Census Data**

<i>Dependent Variable:</i>	<i>Cell-based standard deviation</i>		<i>Absolute value of individual residual</i>				<i>Absolute value of individual residual</i>					
	All Workers		FTFY		All Workers		FTFY		All Workers		FTFY	
									Drop Low		Drop Low	
	(I)		(II)		(III)		(IV)		(V)		(VI)	
<i>age</i>	-4.607	***	-2.700	***	-4.156	***	-2.173	***	-3.129	***	-0.818	***
	(0.371)		(0.240)		(0.068)		(0.055)		(0.060)		(0.041)	
<i>age squared</i>	0.044	***	0.020	***	0.039	***	0.016	***	0.029	***	0.003	***
	(0.003)		(0.002)		(0.001)		(0.000)		(0.001)		(0.000)	
<i>educ group</i>	-5.547	***	-4.079	***	-4.685	***	-3.263	***	-3.605	***	-1.881	***
	(0.861)		(0.531)		(0.157)		(0.122)		(0.137)		(0.088)	
<i>age * educ group</i>	0.093	***	0.108	***	0.087	***	0.090	***	0.077	***	0.068	***
	(0.021)		(0.013)		(0.004)		(0.003)		(0.003)		(0.002)	
<i>constant</i>	191.177	***	115.861	***	155.303	***	87.999	***	117.900	***	44.065	***
	(11.362)		(7.264)		(2.068)		(1.669)		(1.841)		(1.229)	
<i>r-square</i>	0.575		0.487		0.021		0.011		0.016		0.024	
<i>F-Statistic</i>	74		52		1480		630		1025		1266	
<i>observations</i>	225		225		274,616		221,487		259,177		210,579	

**Table A-1 (Continued)**

**2000 Census Data**

<i>Dependent Variable:</i>	<i>Cell-based standard deviation</i>		<i>Absolute value of individual residual</i>				<i>Absolute value of individual residual</i>	
	All Workers		FTFY		All Workers		FTFY	
	(I)	(II)	(III)	(IV)	Drop Low (V)	Drop Low (VI)		
<i>age</i>	-4.293 *** (0.345)	-0.433 * (0.228)	-3.500 *** (0.069)	-0.458 *** (0.058)	-2.461 *** (0.063)	0.053 (0.055)		
<i>age squared</i>	0.034 *** (0.004)	-0.003 (0.002)	0.030 *** (0.001)	-0.001 (0.001)	0.023 *** (0.001)	-0.004 *** (0.001)		
<i>educ group</i>	-5.459 *** (0.780)	-1.089 ** (0.502)	-3.696 *** (0.156)	-0.932 *** (0.128)	-1.652 *** (0.141)	-0.052 (0.119)		
<i>age * educ group</i>	0.140 *** (0.018)	0.080 *** (0.012)	0.100 *** (0.004)	0.060 *** (0.003)	0.068 *** (0.003)	0.045 *** (0.003)		
<i>constant</i>	181.790 *** (10.831)	47.914 *** (7.155)	134.495 *** (2.161)	40.244 *** (1.831)	89.667 *** (1.994)	19.922 *** (1.719)		
<i>r-square</i>	0.576	0.770	0.015	0.020	0.019	0.028		
<i>F-Statistic</i>	75	184	1203	1429	1463	1925		
<i>observations</i>	225	225	311,806	274,466	300,394	267,121		

Standard errors in parenthesis; Statistical significance noted by \*\*\* (1%), \*\* (5%), and \* (10%)



