Risk and Returns to Education[1]

By

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Abstract: We analyze the returns to education in a life-cycle framework that incorporates risk preferences, earnings volatility (including unemployment), and a progressive income tax and social insurance system. We show that such a framework significantly reduces the measured gains from education relative to simple present-value calculations, although the gains remain significant. For example, for a range of preference parameters, we find that individuals should be willing to pay 300 to 500 (200 to 250) thousand dollars to obtain a college (high school) degree in order to benefit from the 32 to 42 percent (20 to 38 percent) increase in annual certainty-equivalent consumption. Combining these with measured costs of education, both direct and indirect (foregone wages), we obtain net gains (returns) from college enrollment varying between 78 to 365 thousand dollars (35% to 255%). This large dispersion in values highlights how the gains from education depend significantly on individual preferences, once we account for risk. We also explore how the measured value of education varies by gender and across time. In contrast to findings in the education wage-premia literature, which focuses on present values and which we replicate in our data, our model indicates that the risk-adjusted gains from college education were flat in the 1980s and actually decreased significantly in 1991-2007 period. On the other hand, the gains to a high school education have increased quite dramatically over time. We also show that both high school and college education help to decrease the gender gap in life-time earnings, contrary again to the conclusion from wage premia calculations.

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1. INTRODUCTION

Trade-offs between risk and return play a central role in standard financial and economic models of investment in physical capital. In contrast, a very large literature on investment in human capital, i.e., the returns to education, has largely focused on average returns without giving full consideration to risk. Rather, the standard approach in the returns to education literature, which traces to Mincer's (1974) seminal paper, is to regress wages (or other dollar-denominated outcomes) against the level of education, controlling for demographic and job characteristics. Such an approach does not capture variation in the value of education that arises from other life-cycle factors, including the concavity of utility over consumption, differences in unemployment risk or earnings volatility by education, or the progressive tax and social insurance system that may dampen the returns to education.

In this paper, we examine the returns to education in a utility-based model that accounts for several important life-cycle factors. Valuing human capital is equivalent to computing the price of a non-tradeable risky asset: we need an estimate of the expected dividends and an appropriately risk-adjusted discount rate. We estimate the expected dividends from micro-data and we compute the discount rate from a structural lifecycle model of consumption and saving decisions (see, for example, Gourinchas and Parker (2002), Carroll (1997) or Hubbard, Skinner and Zeldes (1995)).[2] Because it is well known that education reduces the probability of unemployment and is also associated with changes in earnings volatility (see Moffitt and Gottschalk (2011) for a recent review), we incorporate these factors into our analysis. Specifically, we model the income process by following the approach of MaCurdy (1982) and Abowd and Card (1989), combining a deterministic component (capturing the hump shape of life cycle earnings and retirement income) and two random components that capture both transitory and permanent (e.g., career) uncertainty. We estimate the earnings process – differentiated by education level – using the 1968-2007 waves of the Panel Study of Income Dynamics (PSID). For each education group, our model accounts for this stochastic labor income process, the

[2] Huggett and Kalpan (2012) use a similar approach to compute "the value of a man". Here we focus on the differential values by education and the risk-return trade-off for human capital. Padula and Pistaferri (2005) use a utility function to compute the expected discount value of alternative income streams based on different education levels, effectively under the assumption that agents consume their current income every period.

probability of unemployment, the receipt of unemployment insurance income, a progressive income tax system, and a progressive Social Security system for providing benefits in retirement.

We find that the typical high school graduate will enjoy a 24% higher level of annual consumption than those who did not attend high school at all. When expressed in terms of life-time certainty equivalent (i.e., risk-adjusted) wealth, this corresponds to an increase of $220k (after-tax) dollars. In other words, an individual with our baseline preference specifications (relative risk aversion of 2, and discount factor of 0.99) should be willing to pay as much as $220k to attend and complete high school. The gains from obtaining a college education are even larger: the (risk-adjusted) present-value of human capital of the average college graduate is over $432k (after-tax) dollars higher than the human capital of an otherwise identical high school graduate. This corresponds to a 38% increase in annual certainty-equivalent consumption, and it is substantially more than the typical cost of a college education. While substantial, these gains are significantly lower than many estimates of the returns to education that are based on average returns (and which are frequently cited in the popular press).

Our approach allows us to decompose the sources of the gains. First, accounting for a progressive income tax system and Social Security taxes and benefits generally reduces the gains from education, due to the redistributive nature of these programs, and this is particularly the case for college degrees. Second, unemployment risk and earnings volatility are important considerations, although the effects are more complex than simple intuition suggests. In a lifecycle model that ignores income shocks and considers only the average life-time income processes, the returns to education are lower than a simple present value calculation would suggest. This is because, *ceteris paribus*, agents prefer less steep income profiles so that they can avoid liquidity constraints and increase consumption early in life. Holding average income constant, steeper income profiles are less valuable because in the presence of borrowing constraints, individuals are unable to optimally smooth consumption. When we incorporate uncertainty (including transitory shocks, permanent shocks and unemployment) into this utility-based model, we find that the gains from high school increase. This is because, consistent with our estimation results, high school graduates have lower volatility of income shocks and a very similar probability of unemployment relative to agents without high school education. Therefore, a high school degree both provides an increase in average life-time income and a decrease in the volatility of potential outcomes.

In contrast, the gains from college are slightly smaller when one accounts for earnings uncertainty. College graduates do have a much lower probability of unemployment than do high school graduates, which would serve to increase the value of education. However, college graduates also face a much more skewed distribution of life-time earnings (i.e., they experience very high career earnings heterogeneity), so assigning them the average income over-estimates the value of college education for a risk-averse agent.

The importance of the utility-based calculations becomes even clearer when we compare the certainty equivalent gains for different values of the preference parameters. As previously discussed, high school graduates benefit both from a higher average income, and from a reduction in earnings risk. Naturally, the value of the second component will depend on the agent's risk preferences. Therefore, we should expect that the gains from education will vary across the population. In fact we find that, for reasonable preference parameters, the welfare gains from high school can vary from about $201k (risk aversion of 1 and discount factor of 0.99) to nearly $253k (risk aversion of 4 and discount factor of 0.99). The reverse pattern is visible for college graduates: the more risk-averse agents will assign a lower value to college education, since it implies a much higher dispersion of outcomes than a high school degree.

We also compare our measured gains with estimated costs of education. Here we include both direct costs (tuition plus room and board) and indirect cost (foregone wages). For our lower (upper) bound estimate on the costs the net gains from college enrollment vary between $157K ($78K) and $365K ($285K), which translate into returns of 110% (35%) to 255% (128%). Once again we conclude that there is a large dispersion in values, and therefore the gains from education depend significantly on individual preferences, once we take into account for risk.

We also examine trends over time. It is well-documented in the labor economics literature that education wage premia, especially those for college degrees, increased in substantially in the 1980s and again in the 1990s (see, for example, Autor, Katz, and Kearney (2008), Goldin and Katz (2007), Lemieux (2006), Card (1999), Katz and Autor (1999) or Katz and Murphy (1992)). In addition, it has been shown that earnings volatility increased in the 1980s (Moffitt and Gottschalk (2008), Cunha and Heckman (2007), and Gottschalk and Moffitt (1994)). Motivated by this evidence, we divide our sample in three different time periods: 1969-1980, 1981-1990, and 1991-2007 and repeat our analysis for each. Consistent with the previous literature, we find that volatilities have increased in the 1980s for all education groups. The patterns in the 1991-2007 period are more complex: we find that transitory earnings volatilities have increased over this period, but that the volatility of permanent earnings shocks (career uncertainty) increased only for college graduates. Interestingly, we observe noticeable reductions in the average life-time earnings for both high school and no-high school in the 1980s, followed by a small recovery for high school graduates in the last sub-period, and a further reduction for those without a high school degree. For college graduates, there was a modest decrease in average earnings in the 1980s followed by an increase in the 1991-2007 period.

As a result, if we compute the gains from education as the ratio of the present value of average life-time earnings for higher versus lower education groups, we conclude that the gains from college have increased steadily over time, consistent with the wage premia literature. Under the same calculations, the gains from high school have remained relatively constant in the 80s and increased afterwards. However, when we compute the risk-adjusted certainty-equivalents we observe very important differences, particularly in the later sample period. For college graduates, we find that the certainty-equivalent gain is significantly *lower* in the 1991-2007 period (by 14.98%), even though the average expected income is significantly higher (by 13.00%). The explanation for this striking difference lies in the very large increase in the dispersion of earnings for college graduates. In other words, average present-value calculations ignore the impact of the concurrent substantial increases in the volatility of college graduates earnings (namely in their career heterogeneity). Even though their average income is higher, most college graduates will earn much less than this average number and, even if they are mildly risk averse, this is enough to make the distribution of future earnings in the 1991-2007 period less valuable than the one in the 1981-1990 period. On the other hand, for high school graduates, the gains are actually much higher than the average present-value calculation would suggest (14.15% versus 4.26%). This is driven by the large increase in income risk for those with no high school education, relative to a much more modest increase for those with high school degrees.

Finally, we study gender differences in the returns to education. Across all education levels the volatility of income shocks is much higher for women than for men, while the average life-time present values are much higher for men than for women. On net, the gains from high school degree are much higher for women than for men (75.28% versus 16.75%), due both to larger increases in average life-time income and to a more significant reduction in earnings uncertainty. In other words, high school education helps to reduce the gender gap in life-time earnings. For college the gains are again higher for women, but the differences are smaller (40.65% versus 37.93%). Interestingly, if we had only considered expected earnings we would conclude that women benefit much less than men from college education, again highlighting the importance of computing risk-adjusted certainty equivalents. In a utility-based setting, college education helps to reduce the gender gap.

In contrast to the lion's share of the literature on returns to education, this paper is not focused on measuring causal effects of education on earnings. Rather, the aim of this paper is to show that, for a given set of age-earnings profiles by education level, accounting for preferences, earnings volatility, and fiscal parameters (e.g., taxes) have important implications for how we think about the returns to education. In doing so, we provide specific numerical estimates of the impact using longitudinal data from the PSID. We discuss below the ways in which our specific numerical estimates may be biased and why we believe such biases are likely to be small. This paper proceeds as follows. In section 1 we describe the life-cycle model used for the certainty equivalent calculations and the labor income process. In section 2 we describe the data used in the estimation of this income process, and in section 3 we present the estimation results. Section 4 reports the gains from education in a baseline case, while sections 5, 6 and 7 we study how these vary with preferences, by gender, and across time. Finally, in section 8 we offer concluding remarks.

2. LIFE CYCLE MODEL AND LABOR INCOME PROCESS

We begin with a standard life-cycle model of consumption and savings decisions along the lines of Gourinchas and Parker (2002), Carroll (1997) or Hubbard, Skinner and Zeldes (1995).

2.1 Preferences

Time is discrete and t denotes adult age, which, following the typical convention in this literature, corresponds to actual age minus 21. Each period corresponds to one year and agents live for a maximum of 79 (T) periods (age 100). The probability that a consumer is alive at time (t + 1) conditional on being alive at time t is denoted by p_t (p_0 equal to 1). Life-time preferences are given by a standard time-separable power utility function:

$$U = E\left[\sum_{t=1}^{T} \beta^{t-1} \prod_{s=0}^{t-1} p_s \frac{(C_t)^{1-\gamma}}{1-\gamma}\right] \tag{1}$$

where $\beta<1$ is the discount factor, C_t is the level of date-t consumption, and $\gamma > 0$ is the coefficient of relative risk aversion.

We consider the same starting age (22) for all education groups because, in a utility-based model, including a different number of years effectively changes the functional form of the utility function and invalidates comparisons across education groups. Therefore we consider income earned at earlier ages (by those with lower education levels) as an opportunity cost of education to be treated in the same manner as the direct cost of education (i.e., to be netted against the computed gains to education).

2.2 Income and Wealth Accumulation

Agents work during the first 44 (denoted K in equations (3) and (5) below) periods of their adult lives, and retire at age 66.[3] Before retirement, agents supply a fixed amount of labor each period, and earn labor income (Y_t) that will depend on their own productivity. Labor productivity is a function of both agent-specific shocks and education level, as described in detail in the next subsection.

Savings are invested in a risk-free account with constant gross return R = 2%, an approach that is standard in the consumption-savings literature. Introducing a portfolio decision, as in Cocco, Gomes and Maenhout (2005), should not affect our conclusions for two reasons. First, we can always calibrate different levels for the rate of return on the portfolio to approximate the average return on any given portfolio. Second, as shown in Cocco et al. (2005), the portfolio allocations implied by this model are very similar across education groups, and thus would not significantly alter the returns to education.[4] The agent's wealth accumulation equation is given by:

$$W_{t+1} = R(W_t - C_t) + Y_{t+1} \qquad (2)$$

where W_t denotes financial wealth at time t.

[3] For simplicity, we assume that the retirement age is exogenous and deterministic as in Gourinchas and Parker (2002), Carroll (1997) or Hubbard, Skinner and Zeldes (1995). We set the retirement age at 66 because we assume our stylized agent was born in 1945, and 66 is the age when people born in 1945 can retire and receive the full amount of social security benefit.

[4] There are differences in stock market participation rates across different education groups, but we could also capture these by considering different rates of return in our analysis, without actually having to endogeneize the participation decisions (as in Gomes and Michaelides (2005) for example).

We assume that the agents cannot borrow against their future labor income or retirement wealth, so: $W_{t+1} \geq 0 \, \forall_t$ This constraint is standard in this class of models, and can be motivated using the standard moral hazard and adverse selection arguments.[5] We solve the maximization problem numerically using standard backward induction methods.[6]

2.3 Labor Income Process

The income process follows closely the one originally proposed by MaCurdy (1982) and Abowd and Card (1989), and used in the life-cycle consumption and savings literature (e.g. Carroll and Samwick (1997), Gourinchas and Parker (2002), or Cocco, Gomes, and Maenhout (2005)). Before retirement, the logarithm of labor income is the sum of deterministic components that can be calibrated to capture the hump shape of life cycle earnings as well as two random components, one transitory and one permanent. More precisely, agent *i*'s labor income at time *t* is given by:

$$\log(Y_{i,t}) = f(t, e_i, Z_{i,t}) + v_{i,t} + \varepsilon_{i,t}\text{, for } t \leq K\text{,} \tag{3}$$

where $f(t,e_i,Z_{i,t})$ is a function of age (t), the individual's education level (e_i), and other individual characteristics ($Z_{i,t}$), $\varepsilon_{i,t}$ is an idiosyncratic temporary shock with a distribution of $N(0,\sigma_{\varepsilon}^2(e_i))$, $N(0,\sigma_{\varepsilon,i}^2)$, where $\sigma_{\varepsilon,i} = \sigma_{\varepsilon}(e_i)$ is a function of education level (e_i), and $v_{i,t}$ is defined as:

$$v_{i,t} = v_{i,t-1} + u_{i,t} \tag{4}$$

in which $u_{i,t}$ is uncorrelated with $\varepsilon_{i,t}$ and distributed as $N(0,\sigma_{u,i}^2)$, where $\sigma_{u,i} = \sigma_u(e_i)$.[7] So the volatilities of the different income shocks are also a function of the individual's education level.[8]

Each year agents have a probability of suffering an unemployed spell (π), in which case they will receive unemployment insurance for the duration of the spell. Therefore, the total "labor" income for that year will be the sum of the unemployment insurance collected and the

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[5] Cocco, Gomes and Maenhout (2005) and Davis, Kubler and Willen (2006) consider versions of this model that allow for some level of uncollateralized borrowing.

[6] We optimize using grid search, discretize the state-space for the continuous state variable (cash-on-hand), interpolate the value function using a cubic spline algorithm, and compute expectations using Gaussian quadrature. More details are available upon request.

[7] Other studies have estimated a general first-order autoregressive process for v_t and found the autocorrelation coefficient very close to, and often undistinguishable, from one (Guvenen 2009, Hubbard, Skinner and Zeldes 1995).

[8] Huggett, Ventura, and Yaron (2006) show that these volatilities are also age dependent. We abstract from this in our analysis because the estimation of such age-variation would be too noisy in most of our sub-samples.

wages earned before and after. For tractability, we model income in a year in which an unemployment spell occurs as a fixed fraction (θ) of the worker's current income. Both the probability and this fraction are allowed to vary with the level of education, but they are otherwise identical across households: $\pi_i = \pi(e_i)$ and $\theta_i = \theta(e_i)$

Finally, retirement income is modeled as a constant fraction $\lambda(e_i)$ of permanent labor income in the last working year, where $\lambda(e_i)$ is allowed to vary by the level of education. Thus:

$$\log(Y_{i,t}) == \log(\lambda(e_i)) + f(K, Z_{i,K}) + v_{i,K}\text{, for } t > K \qquad (5)$$

This specification significantly facilitates the solution of the model, since it does not require the introduction of additional state variables.

2.4 Selection and unobserved heterogeneity

Before proceeding, it is important to acknowledge the implicit simplifying assumptions in our estimation approach, both with respect to the level of average earnings, and the dispersion of earnings, by education level. With regard to the level of earnings, the standard concern with using OLS to estimate the effect of education on earnings is that it might be biased. For example, ability may be correlated with education choice, leading to an upward bias if those with higher abilities are more likely to spend more time in school and also have higher earnings. Of course, it might also be biased downward if those with higher abilities are more likely to enter the labor force early and gain additional experience. A very large literature has examined these biases, using IV estimation methods, sample selection models and natural experiments to isolate the causal effect of education on earnings. In his excellent survey of the literature, Card (1999) concludes that most IV estimates (using either interventions in the school system or family background as instruments) are slightly higher than standard OLS counterparts but that the difference is often quite small (with the noticeable exception of Staiger and Stock (1997)), suggesting that the (upward) ability bias in the OLS estimates may be offset by other factors inducing downward bias, such as the one mentioned above and measurement error in education. Because the aim of this paper is to show the effect of incorporating a given age-earnings profile by education into a life cycle framework, rather than trying to improve upon the vast literature on identification of causal effects, we simply estimate our earnings profile by regressing earnings on age dummy variables conditional on education and family structure.[9] To the extent that individual heterogeneity may bias the age-earnings profile, we include individual fixed-effect in our model as well. Our implicit assumption is that, consistent with the empirical findings of Card (1999), the net bias of OLS is small. Of course, our general methodology could be applied to any other estimates of age-earnings profiles by education.

With regard to the variance of earnings, the realized dispersion in observed earnings results both from unexpected income shocks and from unobserved heterogeneity across workers. Chen (2008), Cunha and Heckman (2007) and Cunha, Heckman and Navarro (2005) decompose this cross-sectional heterogeneity in income into these two components. In the context of models with an endogenous education decision, this distinction is important. Because the heterogeneity is known to the agent, only the income shocks represent risk. For our purposes, we would ideally capture only the risk, and not the unobserved heterogeneity component, and combining both would upward bias our measure of income risk. However, there is also an important selection issue that biases our estimate down: because unobserved heterogeneity affects the agents' education choice, the realized cross-sectional dispersion of income is effectively a truncated distribution, which means that observed wage inequality *understates* the potential wage inequality for a given level of education. In the PSID we can control for significant unobserved heterogeneity by including individual-specific fixed effects in the regressions, however this still leaves out time-varying unobserved characteristics. Chen (2008) explores these biases in a setting with an income process relatively similar to ours and finds that the two effects come very close to cancelling each other: after adjusting for both factors, the final estimate is within five percent of the unadjusted observed wage inequality. We explicitly rely on the Chen result that the overall bias is very small and use our estimated measure of labor income risk as a reasonable proxy for actual income risk. Nevertheless, later on we will also report results where we scale down the estimated variances to take into account for this potential bias.

3. DATA

3.1 Sample Construction and Exclusions

[9] This is equivalent to estimating an OLS model with the interactions between education and age on the right-hand side. Because we are interested in calculating life cycle earnings profiles and shocks across different population sub-groups and over time, the combination of IV and small samples would not allow for an efficient estimation.

We use the Panel Study of Income Dynamics (PSID), a longitudinal survey of representative U.S. individuals and their families. When it started in 1968, the PSID had two independent samples: a cross-sectional national sample and a national sample of low-income families. We use the core cross-sectional sample of 2,930 households, which was drawn by the Survey Research Center (SRC) and was an equal probability sample of U.S. families in contiguous 48 states.[10] The second sample (known as the Survey of Economic Opportunity sample), which we exclude from our analysis, was an over-sample of low-income families. Between 1968 and 1996, the PSID annually interviewed individuals from the households in the core sample. Household splits and merges were tracked; adults were observed as they aged, and children were followed as they grew into adulthood and formed their own family units. Since 1997, the PSID interviews have been bi-annual, and the most recent wave available at the time we began this analysis was conducted in 2007.

Only PSID household heads who are still in the labor force (self reported as "working now", "temporary laid off", or "unemployed and looking for job") and aged between 20 (or 22)[11]and 65 are included in the analysis of labor income process. We include both genders in our baseline estimates, and later we will separate the two samples and present results for each. We only include individuals who have an "exact" level of education: no high school, high school graduates, and college graduates. Those with some college education (but no college degree) or some post-secondary education are not used in our analysis, in order to obtain homogeneous education groups. Individuals who are younger than age 20 (22 if college graduate) are excluded. For those aged 66 to 80, we use only their Social Security income when estimating income profiles. In the final sample, we have 7,050 agents and 67,222 annual earnings records. Descriptive statistics of individual characteristics and labor income of household heads aged between 20 (22 if college graduates) and 65 are shown in table 1.

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[10] It is worth mentioning that, while the PSID started out as nationally representative, the manner in which they have followed people over time has led to a sample that is no longer fully representative (for example, it under-weights recent immigrants).

[11] We include earnings at age 20 and 21 for high school dropouts and high school graduates to maximize the efficiency of the labor income calibration, but we start at age 22 for college graduates. For all education groups, we use only earnings from 22 through 65 in our life-cycle, utility-based model of education value, as previously discussed

3.2 Definition of Education Levels

We obtain completed years of education from the PSID individual data. In the years for which this is not available or missing, we use the information from the most recent wave. We then split the sample according to the level of education into five mutually exclusive categories based on years of schooling information: high school dropouts (less than 12 years), high school graduates (12 years), some college (more than 12 but less than 16 years), college graduates (16 years), and post-secondary degrees (more than 16 years). In order to obtain homogenous education groups, only people who have "exact" states in education are included, so we exclude people who had some but did not finish college, as well as those who spent any amount of time in school beyond college graduation. This is important because drop-out rates among college graduates, in particular, are very high: according to data from the National Center for Education Statistics 36.8% (35.2%) of people enrolled in college in 89/90 (95/96) did not graduate and are no longer enrolled in the program after six years. These drop-out rates may imply non-trivial differences between the expected returns to education from enrolling in college and the expected returns to education conditional on actually obtaining a college degree (see, for example, Restuccia and Urrutia (2004), Athrey and Eberly (2011) or Ionescu (2011)). In our analysis we focus on the latter, so we use clean measures of completed education.

We estimate the earning equations separately for each of the three education groups: high school dropouts, high school graduates, and college graduates. Modeling income process with individual fixed effect is potentially problematic if education changes endogenously over the life cycle. However, since we only use individuals older than 20 (or 22 if the agent is a college graduate), there is not much variation in the level of education within each individual. In the small number of cases where an individual spent enough years in school and moved to a higher level defined-above, we consider the individual as a new entity once the level of education is changed.

3.3 Definition of Income

Three sources of income are used in our analysis: labor income, unemployment income, and Social Security benefits. We convert all income figures to 2010 U.S. Dollars using CPI-W.

Annual labor income is obtained through the household questionnaires in all years. Because the income is subject to progressive income taxation, thus lowering the net-of-tax returns to education, we perform our analysis based on post-tax labor income. For purposes of applying taxes, we effectively create a synthetic cohort from our observations. Specifically, we calculate the mean earnings at each age, regardless of the actual year of earnings. We then assume that our stylized agent turns 66 and retires on the first day of 2011, and then apply prior year income tax schedules based on age. For example, we apply the 2010 federal income tax schedule to age 65 earnings, the 2009 schedule to age 64 earnings, and so forth, back to age 20.[12] We assume our stylized agents file individual (rather than married) tax returns and do not have any additional sources of earnings other than labor income, unemployment compensation, and Social Security benefits. We hence ignore earnings made by other household members. We apply only the federal income tax schedule and do not consider state income taxes. For simplicity, only labor income is subject to taxes: unemployment and Social Security benefits are assumed to be exempt from the income tax in our model.[13] Finally, because we include Social Security benefits in our analysis, we also include in the total federal tax burden the portion of the FICA payroll tax that is dedicated to Social Security. Only the employee portion of the Social Security tax is included because the labor earnings we observe in the PSID are already net of the employer portion. We do not include the taxes or benefits associated with Medicare due to the difficulty of valuing the future benefits by income group (see, for example, Bhattacharya and Lakdawalla (2006)). Similar to the way we apply the federal income tax, we also apply the Social Security payroll tax rate based on the age when the earnings are made, assuming that they retire at age 66. In the remainder of the paper, unless otherwise specified, we use post-tax earnings unless otherwise specified, and the term "post-tax" is omitted to simplify exposition.

[12] In order to do so, we have to deflate the earnings to the nominal earnings of the year that the income tax is used. The after-tax earnings are then adjusted to 2010 dollars.

[13] Based on the current tax scheme, the first $2,400 of unemployment benefit and first $25,000 of social security benefits are exempted from the federal income tax. Only 1.5% of the observations in the PSID have unemployment income larger than $2,400, and the taxable part of unemployment benefit among these people is on average $2,000. This implies this 1.5% of the sample would see their annual after-tax earnings decrease by $200 or $300 if unemployment earnings become taxable in our framework. This is at most 1% of the consumption certainty equivalent. Also, our estimates of Social Security benefits based on the benefit calculator suggest that high school dropouts and high school graduates have average annual Social Security benefits lower than the $25,000 threshold. College graduates do have social security benefits higher than $25,000, but including tax would only decrease the replacement rate by around 0.2%. Assuming all of unemployment and Social Security benefits are not taxable would therefore have only a trivial effect on our numerical results and does not change our main arguments and findings.

Annual unemployment income is also available in 1968-1992, 2005, and 2007 waves of PSID household questionnaires.[14] For the remaining period (1993 to 2003), the PSID provides two pieces of information on unemployment insurance income: the amount and the unit of time (weekly, bi-weekly, or annually). Along with weeks of unemployment, we can calculate the amount of unemployment income that an individual received each year, assuming that unemployed workers receive unemployment compensation during the whole spell of unemployment. This probably overestimates unemployment income because benefits are typically available for only 26 weeks after the initial claim.[15] As a quick robustness check, we examined whether there is a discontinuity in the amount of unemployment benefits received around 1993, and found no evidence of a spike in the pattern of mean individual unemployment income when the measure changed.

Measuring Social Security income is more complicated. Social Security benefits at the individual level are only available in limited waves (1986-1993, 2005, 2007). Most of the time the PSID only asks for these benefits at the household level, and therefore includes spousal benefits as well as other family benefits, such as those paid to any minor children in the household. Because it is impossible to recover Social Security benefits at the individual level, we feed the pre-tax age-earnings profile into the Social Security benefit calculator provided by the Social Security Administration to calculate individual level benefits, assuming the stylized agent turns 66 on January 1st, 2011 and starts to receive benefits on that day. To calculate the average Social Security replacement rate for each education group, we take twelve times the amount of the monthly Social Security benefit (which is equal to the Social Security "Primary Insurance Amount" for those retiring at the Normal Retirement Age), and divide it by mean annual earnings. We assume the replacement rate is the same for all agents who have the same level of education. As a check on our methodology, calculating Social Security benefits in this manner gives numbers very close to those reported in the PSID if we evenly distribute the household level benefits reported in the PSID among potentially eligible household members (those who are older than 65).

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[14] Between 1968 and 1976, unemployment income is reported in brackets rather than actual numbers. In these years, the median of each bracket is used as an individual's unemployment income instead.

[15] The federal government may extend the eligibility during economic downturns. For example, during the recent recession, the federal government pays up to 73 weeks of unemployment benefits, bringing the total duration of unemployment insurance benefits up to 99 months.

3.4 Mortality Rates

The present value of the lifetime benefits of education will also depend on the distribution of possible life spans. We use cohort mortality rates from the U.S. Social Security Administration. We use the 1945 birth cohort table because we assume our stylized agents were born in 1945 and turn 66 in the beginning of 2011. We use these mortality rates to calculate the cumulative survival probabilities in equation [1] above. It is well-known that education is negatively correlated with mortality rates (i.e., more highly educated individuals live longer). We do not incorporate this into our calculations, however, because the survival probabilities enter the lifetime utility function in equation [1], and the calculation of certainty equivalents is not well-defined when the utility function itself differs across the two states being compared.

4. ESTIMATING THE INCOME PROCESS

4.1 Labor income profile and shocks

We first estimate the labor income process (equation (3)), by regressing the logarithm of income on age dummies, individual fixed effects, and a set of other control variables. In the estimation stage, we consider two alternative types of income: labor income only, and labor income plus unemployment compensation. In our main analysis we will consider the first set of estimations because, as previously discussed, we will model unemployment separately as a different state. Nevertheless, we find it useful to compare the estimation results with those obtained when combining all sources of income because this alternative specification is often used both in the life-cycle consumption and savings and literature and in the labor economics literature. For those aged 65+, only Social Security benefits are counted toward income. Consequently, we are excluding records of people who work beyond age 65 or retire before 65. This is done both for both practical and conceptual reasons: practically, it substantially simplifies the computational process; conceptually, it allows us to abstract away from individual decisions about whether to consume part of potential income in the form of earlier retirement. As is standard in the literature, for purposes of solving the numerical model, we will capture the age component of the income process as a third-order polynomial of age. Therefore, after estimating this process, we regress the age dummies coefficients from the estimated income process on a set of age polynomials. Figure 1 shows the fit of the third-order age polynomials over life cycle labor income profile.

--- Insert figure 1 about here. ---

Finally, we compute the retirement income replacement ratios as described in section 3.3. As noted above, the benefits and replacement ratios calculated based on the SSA benefit calculator are very similar to the PSID household numbers after adjusting for the number of individuals over age 65 in the household. As expected given the design of the non-linearity of the Social Security benefit formula, the average Social Security benefits increase with the education level ($1,532, $1,845 and $2,266, respectively for the different groups), while the replacement ratios of average life-time earnings decrease (64.55%, 61.05% and 47.56%, respectively for the different groups).

4.2 Variance Decomposition

After obtaining the residuals from equation (3), we now decompose the income variation into a permanent and a transitory component.[16] As previously discussed, we assume that the permanent component follows a random-walk process, and we apply the methodology proposed in Carroll and Samwick (1997) to estimate the variances of the two shocks. If we define $r_{i,d}$ as

$$r_{i,d} \equiv \log(Y^*_{i,t+d}) - \log(Y^*_{i,t}),\ d \in \{1,2,...,39\} \qquad (6)$$

where Y^*_t is given by

$$\log(Y^*_{i,t}) \equiv \log(Y_{i,t}) - \hat{f}(t, Z_{i,t}) \qquad (7)$$

it follows that

$$Var(r_{i,d}) = d * \sigma^2_u + 2 * \sigma^2_\varepsilon \qquad (8)$$

We can thus estimate σ^2_u and σ^2_ε with any two difference series of $r_{i,d}$ by running an OLS regression of $Var(r_{i,d})$ on d and a constant term (for all *d*). By doing so, we constrain the estimates of σ^2_u and σ^2_ε to be the same across all individuals. In our estimates, we include all possible series of $r_{i,d}$ to maximize efficiency. We also apply Winsorization on $r_{i,d}$ and replace extreme values (below 1st percentile or above 99th percentile) with the values of 1st percentile and

[16] In section 3.2 we discussed the potential impact of biases due to unobserved heterogeneity and sample selection, and evidence suggesting that they probably have a very small impact on our estimates.

99th percentile, respectively. Our results of variance decomposition are shown in table 2. We first use annual labor income of those who are fully employed in a given year (that is, hour of unemployment is zero) only, and then use labor plus unemployment income and also include those who have experienced unemployment.

--- Insert table 2 about here. ---

Comparing across education groups we find a decreasing pattern for transitory shocks, and a u-shape for permanent shocks. The null hypotheses that transitory shocks are the same and permanent shocks are the same across education groups are both rejected. These results suggest that less-educated workers face more year-on-year income risk, while college graduates have significantly higher career hetereogeneity. Previous studies have found mixed results on this dimension. For example, Low, Meghir, and Pistaferri (2010) used both the SIPP and PSID, and estimate higher volatility of both permanent and transitory shocks for those with higher education level. However, they only consider two different education groups ("high school or less" versus "at least some college"), which might explain the differences in the case of the permanent shocks. Hubbard, Skinner, and Zeldes (1994) used a limited time period - the 1983-1987 PSID sample - and the same definition of levels of education as in our study, and find a decreasing pattern for both types of shocks. Carroll and Samwick (1997) consider the 1981-1987 PSID sample and obtain a decreasing pattern for permanent shocks and a u-shape for transitory shocks, across five different education groups.[17,18]

The magnitudes of the volatilities for the permanent component (table 2) are slightly lower than those reported in previous studies, but the differences are attributable to our use of post-tax earnings. We have also run our analysis using pre-tax income and found results similar to the previous literature. For example, in the specification that is more directly comparable with ours, Low, Meghir, and Pistaferri (2010) obtain a standard deviation of 0.152 (pooled for all education levels) for the permanent component. Guvenen (2009) utilizes the PSID from 1968 to

[17] The five groups are: some high school, high school degrees, some college, college degrees, and post-secondary degrees.

[18] Other studies either do not provide the same decomposition of shocks or do not report comparable numbers, but overall the results are again mixed. Some found college graduates have the smallest wage variations (see, for example, Jensen and Shore (2008), Dynan et al. (2007), Heckman et al. (2003), or Cameron and Tracy (1998)), while others found higher educated group actually have larger wage variations (see, for example, Moffitt and Gottschalk (2011), or Cunha and Heckman (2007)).

1993 and estimates volatilities between 0.100 and 0.158 for the permanent component, depending on the education group and the earnings process specification. Carroll and Samwick (1997) estimated volatilities of permanent income shocks between 0.107 and 0.166 across five different education groups, and Hubbard, Skinner, and Zeldes (1994) using the 1983-1987 PSID sample and the same definition of levels of education as in our study, obtain volatilities of permanent shocks between 0.126 and 0.181.

Our estimates of transitory volatility are higher than those most commonly found in the consumption and savings literature. For example, Carroll and Samwick (1997) estimate standard deviations of transitory shocks between 0.185 and 0.257, while Hubbard, Skinner, and Zeldes (1994) estimate values between 0.118 and 0.200. Four main factors contribute to our higher estimates. First, as discussed above we consider after-tax income, and while this decreases the volatility of the permanent component of income, it increases the volatility of its transitory component because tax rate changes become an additional source of (transitory) shocks. Second, the other two studies exclude income outliers while we prefer instead to winsorize the data.[19] Third, they estimate their profiles at the household-income level, while we use individual income data because we want to measure the returns to education for a given individual. Naturally, when measured at the household level, income volatility decreases due to the smoothing across household members. Our choice of individual income data also follows standard practice in the labor economics literature (see, for example, most of the papers cited in the previous paragraph). Finally, we consider a different time period and, as we will show below (when we present Table 10), these variances have increased over time, consistent with the results in Moffitt and Gottschalk (2011), Cunha and Heckman (2007) and Gottschalk and Moffitt (1994).

Estimates of the volatility of transitory shocks can be upward biased due to measurement error, and for this reason some authors prefer to "scale down" the estimated values. Gourinchas and Parker (2002) argue for this type of adjustments to correct for measurement error and potential upward estimation bias due to mis-specification of the earnings process. Bound and Krueger (1991) study measurement error in a similar panel (the CPS), and conclude that 35% to 20% of the variance is indeed due to mis-measurement. Hubbard, Skinner and Zeldes (1995)

[19] For example, Carroll and Samwick (1997) exclude households whose income in any year is less than 20% of average over sample period, while Hubbard, Skinner, and Zeldes (1994) exclude households with annual income less than $3,000. Including these exclusion criteria would eliminate several unemployed individuals from our sample, and we want to capture this dimension of income risk as well.

assume that the transitory shocks are purely measurement error and exclude them completely from their analysis. Given the possibility that these are over-stated, we will report two alternative scenarios for the volatility parameters: one with the estimated parameters values and one where we have scaled down our estimates by 25% (i.e., multiplying them by ¾).

As previously discussed, even though we included individual fixed effects in the estimation, there is still a potential upward bias in the estimate of the volatility of permanent shocks due to time varying individual-level heterogeneity. Therefore, robustness analysis, we also scale down these estimates by the same factor (¾).

4.3 Probability of unemployment, and income in unemployment-spell year

Our estimate of the income process for the employed is based on the sample those who have positive labor income and zero hours of unemployment in that year. We then estimate separately the income of those who were unemployed for some period during the year, and the probability of such event occurring within our sample. In the U.S., an unemployed individual can receive the unemployment insurance for up to 26 weeks.[20] However, the average duration of unemployment is substantially less than this: the mean unemployment spell in the U.S. is 9 weeks (McCall 1996, Meyer 1990). The mean replacement rate of weekly unemployment benefits is around 45% of pre-displacement weekly earnings (McCall 1996). Hence, it is not plausible to assume an agent is either fully-employed or fully-unemployed in an entire year when we attempt to account unemployment risk in our model. To address this, we define "unemployment rate" in a year as the proportion of individuals who ever experience unemployment in that given year, regardless of the length of unemployment spell. The "unemployment earnings" of these individuals are then defined as their unemployment benefits when they are not working plus the labor earnings when they are working. In other words, the "unemployment earnings" in our framework is the expected annual income from unemployment benefits and labor earnings among those who experience any unemployment spells in a year. Similarly, the replacement rate of unemployment earnings is calculated as the ratio of annual income, including labor earnings and unemployment benefits if applicable, between those who experience unemployment and those who do not experience unemployment in a given year.

[20] This is sometimes extended by Congress during macroeconomic downturns.

Table 3 tabulates the probability of experiencing an unemployment spell within a year in our sample, across the different education groups ($\pi(e_i)$). Similarly, for the different education groups, we also report the average yearly income for the two separate samples (those with and without an unemployment spell) which we then use to compute the replacement rate of income during an unemployment state within our model ($\theta(e_i)$). The averages are computed using the PSID sample weights.

--- Insert table 3 about here. ---

As expected, the probability of unemployment decreases significantly with education, as did the volatilities of transitory income shocks above. This confirms that short-term income risk is more severe for workers with less education. In particular, college graduates have a much lower probability of being unemployed than the other two groups (7.15% versus 14.7% for high school graduates, and 20.05% for those with no high school). Of course, higher income individuals lose a higher fraction of their income when unemployed (with a replacement rate of 52.87% versus 73.89% for high school graduates and 78.17% for those with no high school), owing in large part to the fact that unemployment benefits are capped.

5. BASELINE RESULTS

By solving the model for a given income process (and hence a given level of education), we can compute the life-time expected utility of the agent conditional on education. Following the convention in the literature, we express life-time utility as a certainty equivalent level of consumption. In addition, we convert these certainty equivalents into wealth levels, since those provide risk-adjusted present-values of human capital, and can thus be compared with direct measures of the costs of education.

5.1 Gains from education: expected life-time earnings

In this section, we start by calculating the gains from education by comparing average outcomes conditional on education, without incorporating of the utility consequences of unemployment and income risk. These results will allow us to disentangle the different components of the returns to education

Relative to the bulk of the existing literature on the returns to education, even our baseline case has several important differences. First, we are computing lifetime present values as opposed to wage differentials conditional on age. Second, we incorporate income and payroll taxes, mortality rates and Social Security benefits. To understand the impact of these different elements, we start with pre-tax earnings in the first two panels of table 4. Those are the only two cases in paper in which the gains from education are expressed in pre-tax terms.

--- Insert table 4 about here. ---

In the first panel of table 4, we show the gains from education simply as the undiscounted summation of mean pre-tax inflation-adjusted labor earnings between 22 and 65 multiplied by the conditional survival probabilities for each age, by different education groups. In the second panel we repeat this calculation using a 1% real annual discount rate. We set the discount rate for this calculation to 1% because our baseline discount factor in the utility-based model is 0.99, thus allowing for an easier comparison of results between the two approaches. The percentage gains are almost identical in the two cases, so we can focus on panel B. The net-present value of a high school degree is $1,549,627, corresponding to a gain of $349,413 (29.1%) relative to the no-high-school scenario, while the net-present value of a college degree is $2,543,858, corresponding to a gain of $994,231 (64.16%) relative to a high school degree. These simple present-value calculations are very much in-line with estimates of the value of a college degree reported in the popular press.[21]

In Panel C we repeat the calculations from Panel B, but using after-tax income. Naturally, all present-values decrease and, due to the progressive nature of income taxation, it decreases more for those with higher education. Workers with a high school degree have average *after-tax* discounted lifetime earnings $257,858 higher than those without high school diploma (a 26.6% increase), while individuals with college degrees have *after-tax* lifetime earnings which are $667,072 higher than those of high school graduates (a 54.4% increase).

In the panel D we show how the gains from education change after we add unemployed agents to the sample. The gains from education here are calculated as the expected value of

[21] For example, http://usgovinfo.about.com/od/moneymatters/a/edandearnings.htm reports the results of Census Bureau estimates that a college degree is worth about $1 million more over ages 25 to 65 than a high school degree.

earnings, which are equal to the likelihood of employment times expected labor earnings plus the likelihood of unemployment multiplied by the level of unemployment benefits (discounted and adjusted for mortality as in the previous panels). The comparison between panels C and D confirms that considering the likelihood of unemployment will increase the value of education due to the higher probability of unemployment for less educated people. The gains from high school education increase to 27.3% and the gains from college increase to 55.16%.[22] The effect here is not very large because, as shown in table 3, the reduction in income during unemployment is more severe for those with higher education. However, it is important to recall that this calculation ignores risk preferences (we are only computing expected values) and, as shown later on, the impact of income risk is much larger when we take into account for individuals' risk aversion.

In the final panel (E) we include Social Security income, i.e., income received during the retirement period. Naturally all present-values increase and, as a result, the dollar gains are also higher. The percentage gains, however, are lower, reflecting the non-linear Social Security benefit structure that provides higher replacement rates for individuals with lower lifetime earnings. This is particularly noticeable for college graduates, for whom the percentage gain decreases from 55.2% to 50.5%.

Overall, these numbers are lower than those mentioned in conventional estimates of the value of college education, especially those reported in the popular press, which often range from \$800,000 and \$1,000,000.[23] This is due to the inclusion of taxes, Social Security benefits, unemployment probabilities, mortality adjustments and time-discounting. The results in Panel B, which only adjust for discounting and mortality risk, are actually very similar to conventional estimates, suggesting the importance of the other factors. By comparing the results in the different panels, we can see that the largest difference in levels and percentage gains comes from the inclusion of income taxes. Next, we turn to a discussion of how these results change when one takes into account risk preferences in a utility-based model.

5.2 Gains from education: a baseline case

[22] The dollar gains are slightly smaller since the net-present values are naturally lower for all.

[23] As another example, see a Wall Street Journal article on February 2, 2010 by Mary Pilon (http://online.wsj.com/article/SB10001424052748703822404575019082819966538.html?mod=WSJ_hps_sections_personalfinance).

We now compute the returns to education from our utility-based calculations. In our baseline case, we assume that all agents have a relative risk aversion coefficient (γ) of 2 and a discount factor (β) of 0.99. We report both the certainty-equivalent consumption levels (standard calculation within a utility-based model) and the corresponding certainty equivalent initial wealth levels, the latter of which are more directly comparable to the results in Table 4. These measures can be compared to the cost of education and with the typical estimates in the returns to education literature. The results are shown in Table 5.

--- Insert table 5 about here. ---

In Panel A we first report the results without unemployment risk and without income shocks, to facilitate the transition from Table 4. In other words, these calculations assume that all agents within a given education group will receive the average income within that group, just like the ones in the previous table. Comparing the results we find much lower certainty equivalent gains for both levels of education. For high school (college) the improvement in the present value of after-tax life-time average earnings is now $219k ($545k) versus $287k ($696k) in Panel E of Table 4, corresponding to percentage gains of 19.33% (40.30%) versus 26.25% (50.49%) in the previous calculations. Since risk-preferences are still irrelevant in this calculation, the differences in the results are coming exclusively from life-cycle aspects. In particular, with upward sloping age-income profiles, agents are liquidity constrained early in life, and therefore the marginal utility of current consumption is high. As one approaches retirement, we observe the opposite. As a result, conditional on the *level* of average lifetime income, steeper income profiles, such as the one for college graduates, are not as highly valued in utility terms as they are in a simple present-value calculation.

In Panel B we report results from the lifecycle model that include all sources of income shocks. We find that the typical high school graduate will enjoy a 24% higher level of consumption, per year, than those who did not attend high school at all. When expressed in terms of life-time certainty equivalent (i.e. risk-adjusted) wealth, this corresponds to an increase of $220k. The risk-adjusted present-discounted value of the human capital of an agent without any high school education is $903k, while for a high school graduate that number rises to almost $1.1

million. In other words, an individual with relative risk aversion of 2, and discount factor of 0.99 should be willing to pay as much as $220k to attend and complete high school.

The net gains from college education are again larger. The (risk-adjusted) present-value of human capital of the average college graduate is more than 1.5 million dollars, and $432k higher than the human capital of an otherwise identical high school graduate. This corresponds to a 38.5% increase in annual certainty-equivalent consumption. The net benefit is far lower than the "million dollar" figures often cited in the popular press.

By comparing the results in Panels A and B, we see that while the gains from high school increase when we take into account earnings heterogeneity and risk preferences (from 19.33% to 24.36%), the gains from college actually decrease slightly (from 40.30% to 38.47%).[24] These results can be understood from the estimations results reported in tables 2 and 3. Relative to workers without high school education, high school graduates have much lower income volatilities (for both permanent and transitory shocks) and a much lower probability of suffering an unemployment spell (with a very similar replacement ratio), Therefore, a high school degree also decreases life-time earnings variability thus increasing its value even further once we take into account for risk aversion. On the other hand, relative to high school graduates, college graduates face a much more skewed earnings distribution with much higher career heterogeneity (higher volatility of permanent earnings shocks). This is partially attenuated by the fact that they are less subject to temporary shocks (lower volatility of transitory earnings shocks and a much lower probability of unemployment), but the overall earnings distribution is more uncertain, and, therefore, the corresponding percentage certainty equivalent gain is slightly lower when we account for risk aversion.

Finally, as previously discussed, the estimates of the volatility of earnings shocks are potentially subject to measurement error and/or inflated due to unobserved individual-level heterogeneity. To take this into account, in Panel C we repeat our calculations under alternative volatility measures (we decrease our estimated numbers by multiplying by a factor of ¾). The results are very similar and therefore we conclude that these potential concerns do not seem to

[24] If we compare dollar gains, the certainty equivalent wealth increase for high school graduates is almost unchanged (from $219,234 to $220,004). But certainty equivalents are naturally much smaller once we account for uncertainty. Therefore a given percentage gain would now correspond to a lower dollar value benefit. For the same reason, the small reduction in the percentage wealth certainty equivalent gain from college actually corresponds to a very large decrease in the dollar gain (from $545,477 to $432,053).

have a significant impact on our calculations. Consequently, for the remainder of the paper, we only report results for the first case.

5.3 Net gains and returns to education

In this section we compare the present-value of education with the cost to obtain a measure of the return to the investment in education. This calculation is subject to some important caveats, discussed below, which is why in the paper we focus mostly on the present-value calculations only. Nevertheless we feel that these are also useful numbers to report.

There are two sources of costs to education: the direct costs and the opportunity cost in terms of foregone wages. In the academic year of 2008-2009, average tuition and fees for a four-year public (private) college is $6,585 ($25,243) and the cost for room and board is $7,707 ($8,996) per year, for a four-year (non-discounted) total of $57,168 ($136,956).[25] Naturally the expected payoff in terms of the present-value of earnings is also likely to be much higher for those graduating from private colleges, than from those graduating from public ones. Unfortunately we cannot distinguish these in our data, so we will instead treat the private college and public college costs numbers as giving us a lower and an upper bound on the return, respectively.

We compute the opportunity cost by measuring the average expected after-tax income of high school graduates households in our sample, during the ages of 18, 19, 20 and 21, which corresponds to $85,496. This represents an upper bound on the opportunity cost for two reasons. First we are considering the expected value wages without adjustment for risk. Second we exclude those households that are currently college, even though some of them might be working part-time and thus already earning an income.

We can now combining these calculations with the previous gains since those are already discount present-values. We find that the measured net benefit from college ranges from $209,601 and $289,389, with a corresponding rate of return between 94% and 202%. Therefore, even taking into account the direct costs and the forgone earnings from age 18-22, college education is a significant positive net present value investment.

6. GAINS FROM EDUCATION: THE ROLE OF PREFERENCE HETEROGENEITY

[25] http://militaryfinance.umuc.edu/education/edu_college.html

The previous results apply to an agent with a risk aversion coefficient of 2, and a discount factor of 0.99. In this section we now consider different alternative values for the preferences parameters, and explore how the gains from education might vary across different groups of the population, and in particular they might be affected by the agents' risk preferences.

In Panel A of table 6 we report the gains from high school education measured in (risk-adjusted) present-value of life-time human capital, both in dollar terms and in percentages.

--- Insert table 6 about here. ---

The gains from high school education increase as risk aversion increases. For example, moving from 2 to 4 increases the certainty equivalent gain by \$20-22k. As previously shown (Tables 2 and 3), high school graduates have much lower income volatilities (for both permanent and transitory shocks) and much lower unemployment risk than those without high school education. Therefore, in addition to providing higher average income, a high school degree also decreases life-time earnings variability which is particularly valuable for the more risk-averse agents. Overall we find that, for reasonable preference parameters, the welfare gains can vary from just over \$201k (risk aversion of 1 and discount factor of 0.99) to nearly \$253k (risk aversion of 4 and discount factor of 0.99). These numbers highlight the role of preference heterogeneity, and in particular risk preferences, when computing the certainty equivalents from education.

In panel B of Table 6 we report the returns to college education for different values of the preference parameters. These gains are also sensitive to risk preferences, but they decrease with risk aversion. For individuals with risk aversion of 1 the gains are close to \$500k, while for those with risk aversion of 4 they are approximately \$300k. Part of this difference is simply due to the fact that the dollar value of certainty equivalents naturally decreases with risk aversion, hence even for the same percentage gain, the dollar value improvement would be lower. However, we can see that, even in percentage terms, the gains are lower for the more risk-averse agents: close to 30% versus approximately 40% for the less risk-averse agents.

To understand these results we again need to consider the empirical estimates in tables 2 and 3. Relative to high school graduates, college graduates are less subject to temporary shocks (lower volatility of transitory earnings shocks and a much lower probability of unemployment), but they have more career heterogeneity (higher volatility of permanent earnings shocks). In other words, although the average life-time earnings are much higher than for high school graduates, the distribution is much more skewed. Therefore, the more risk-averse agents will place a lower value on this this distribution of potential income realizations than would agents with lower risk aversion coefficients. The significant heterogeneity in certainty equivalent gains highlights again the importance of taking into account for heterogeneity in risk preferences when computing the gains from education. Moreover, if we compare these numbers with the ones reported in calculations in Table 4, we find that the gain for an agent with risk aversion of 4 is actually less than half of the one computed by the simple baseline which implicitly assumes risk neutrality (300 thousand dollars versus 696 thousand dollars).

If we now repeat the calculations in section 5.3, we find that the net gains from college investment, assuming the upper bound on the estimate of the cost, can vary from as low as \$78,001 (for the more risk-averse agents) to as high as \$284,490 (for the less risk-averse agents). In terms of returns, this corresponds to a range between 35% and 110%. The wide dispersion in these numbers reflects once again the importance of considering preference heterogeneity and risk-adjustments when measuring the benefits of education. If we instead consider the lower bound estimate of the cost we reach similar conclusions, as the net gains will vary from \$157,789 to \$364,278, and the returns from 110% to 255%.

7. GAINS FROM EDUCATION: GENDER DIFFERENCES

In this section we study how the returns to education vary across genders. We start by estimating the after-tax income process from the PSID for the male and female sub-samples separately. In Table 7 we report the standard deviations of the different income components (transitory and permanent) for men and women separately.

--- Insert table 7 about here. ---

Without exception, all 6 standard deviations are higher for women than for men, both for transitory (8.2%, 4.5% and 4.2%) and for permanent shocks (5.1%, 4.2% and 1.8%). These differences are statistically significant and economically very large.

In Table 8 we compute the average present-discounted value of life-time earnings, i.e. the valuations under risk-neutrality, for both men and women separately. To account for the gender difference in longevity, we compute the results in this section based on the mortality rates from male and female cohort tables of 1945, respectively.

--- Insert table 8 about here. ---

There are three main results. First the average present-values are much smaller for women than for men, for all education categories. The average discounted after-tax life-time earnings of a woman with a high school degree are \$968k versus \$1,429k for a man with the same level of education. Equally large differences apply for those without high school education (\$633k for women versus \$1,162k for men) and for those with a college degree (\$1,341k for women versus \$2,144k for men).

Second, the improvement in average discounted after-tax life-time earnings for high school graduates is much higher for women than for men, \$334k versus \$266k, which, given the much lower base earnings for women (discussed above), maps into a percentage gain of 52.72% versus 22.92%, respectively. Third, this result is reversed for college graduates. While women with a college degree enjoy an increase in discounted after-tax life-time earnings of \$373k, the equivalent number for men is \$716k. In percentage terms the difference is "smaller" due again to the lower base for women, but the result remains: 38.53% versus 50.10% respectively.

In Table 9 we now report the gains from education for the men and women sub-samples separately, under the utility-based calculations.

--- Insert table 9 about here. ---

The certainty equivalents for each level of education are much lower for women than for men. This comes naturally from the results in both table 8, where we found the same pattern for the average present-discounted values, and table 7, which showed that the earnings distribution for women exhibits much higher volatility than the male counterpart. The results in table 7 also suggested that the gains from education should increase much more for women than for men in the utility-based calculations, because they benefit from much more significant reductions in earnings volatility. Indeed this is what we find. The percentage certainty equivalent gain from high school is dramatically higher for women than for men (75.28% versus 16.75% respectively). A similar effect is present in the welfare gains from college degree where we now observe a higher percentage gain for women than for men (40.65% versus 37.93%, respectively) even though table 8 documented lower average life-time earnings increases for women (38.53% versus 50.10%, respectively). These results once again re-enforce the importance of the utility-based calculations.

8. GAINS FROM EDUCATION OVER TIME

It is well-documented in labor economics literature that the education wage premia have increased over time (for example, Autor, Katz, and Kearney (2008), Goldin and Katz (2007), Lemieux (2006), Card (1999), Katz and Autor (1999) or Katz and Murphy (1992)), particularly in the 1980s.[26] In addition, it has also been shown that earnings volatility has increased since 1980s (Moffitt and Gottschalk (2008), Cunha and Heckman (2007), and Gottschalk and Moffitt (1994)).

These findings have several possible implications for our study. Naturally, increases in baseline returns to college education will increase the certainty equivalents. However, *if* the simultaneous increase earnings variation is concentrated among the more educated workers, this may decrease the gains from education for risk-averse agents. We address these issues in this section.

8.1 Volatility Estimates for different time periods

In the following analysis, we repeat our calculations for three separate sample periods: 1969-1980, 1981-1990, and 1991-2007. Even though these three periods have different length (both in terms of time and waves of data), we consider these splits based on the (previously-discussed) evidence that returns to education, especially to college degrees, have increased over time, particularly during the 1980s. Our results also reflect the changes in the tax system: we

[26] Different explanations have been proposed and discussed, namely an increased demand for college graduates (Katz and Murphy (1992)). Related to this, some authors argue in favor of a skill-biased technological change (Krueger (1993) and Autor, Katz, and Krueger (1998)), which asserts that the technology development in 1980s and early 1990s was biased toward higher-educated people. Although this theory has been challenged by some recent studies (for example, Card and DiNardo (2002) or Lemieux (2006)), it also provides an explanation for the increase of wage inequality in the U.S. since 1980s (Autor, Katz, and Kearney 2008).

assume stylized agents retire in the end of 1980, 1990, and 2010, respectively, for the three subsamples. And hence, in the 1969-1980 subsample, we apply 1980 payroll and federal income tax schedules to earnings at age 65, the 1979 tax schedule to earnings at age 64, and so forth. Similarly, the 1990 tax schedule is applied to age 65 earnings in the 1981-1990 subsample, the 1989 tax schedule is applied to age 64 earnings, etc. We use the same tax scheme as what we used in previous two sections for the 1991-2007 subsample. Because the payroll tax was not levied until 1937, earnings in 1935 and 1936 (i.e., age 20 and 21 earnings for the cohort retiring in the end of 1980) are not subject to the payroll tax. The U.S. income tax has, in general, become less progressive over time. In Table 10 we report the standard deviations of the different income components (transitory and permanent) for the three education groups in each sub-sample.

--- Insert table 10 about here. ---

Consistent with the above-mentioned previous findings in the literature, 5 out of the 6 standard deviations are higher in the 1980s than in the first part of the sample (with the 6th difference being statistically insignificant). The estimates for transitory volatility are significantly higher for both college graduates (+4.4%) and high school graduates (+5.2%). For permanent shocks, there are very large increases for college graduates (+3.6%) and for those with no high school (+3.2%).

In the later part of the sample we observe even larger increases in the point estimate of transitory volatility for all groups: +11.8% for college graduates, 7.8% for high school graduates, and +19.3% for those without high school. With regards to the permanent shocks, we now find decreases for the two lowest education groups and a further increase for college graduates.

Overall, college graduates have experienced significant increases in both sources of earnings dispersion over time, i.e., both career heterogeneity and transitory earnings volatility are much higher in the later sample. High school graduates have large experienced consistent increases in transitory volatility, but the impact of permanent shocks has remained relatively constant. Finally, those with no high school registered a very large increase in career uncertainty in the 1980s, followed by a decrease in the later part of the sample when transitory volatility almost doubled.

8.2 Certainty equivalent gains for different time periods

As before, we start by reporting the simple average present-discounted value of life-time earnings. This is shown in Table 11 for the three different sub-periods. To reflect the change in longevity over time, we use the cohort mortality tables in 1915, 1925, 1945 for the 1969-1980 (age 66 in 1981), 1981-1990 (age 66 in 1991), and 1991-2007 (age 66 in 2011) subsamples, respectively. We also account for the changes in Social Security benefits schedule by feeding the age-earnings profile into the benefit calculator provided by the Social Security Administration assuming stylized agents retire in the end of 1980, 1990, and 2010. Interestingly, we observe noticeable reductions in the certainty equivalents from both high school and no-high school in the 1980s (from \$1,464k to \$1,284k, and from \$1,128k to \$991k, respectively), followed by a small recovery for the former in the third part of the sample (to \$1,301k) and a further marginal reduction for the latter (to \$973k). For college, there was also a decreased in the certainty equivalent in the 80s but a modest one (from \$1,963k to \$1,904k) followed an increased in the 90s and beyond (to \$2,099k).

--- Insert table 11 about here. ---

As a result, the gains from college education have increased consistently over time, both in percentage terms (from 34.06% to 48.31% and then 61.31%) and in dollar value (from \$499k to \$620k and then \$798k). In percentage terms, the gains from high school remained constant in the 1980s (29.47% versus 29.74%) and increased afterwards (to 33.73%). Due to the lower certainty equivalent values in the 1980s, this corresponds to a decrease in the dollar gain measure for that period (\$292k versus \$336k).

In Table 12 we now report the gains from education for the three sub-samples, under the utility-based calculations.

--- Insert table 12 about here. ---

For high school education, we again observe a slightly decrease in the percentage gain in the 1980s, but a much larger gain in the final part of the sample. As shown in table 10, in the

1980s, the volatility of earnings increased both for high school graduates and for those without high school (particularly for transitory shocks for the former, and for permanent shocks for the latter). As a result the change in gains from education is mostly driven by the change in the average expected value therefore this result is very similar to the one in Table 11. In the 1991-2007 period, while both groups experienced reductions in career uncertainty and increases in the volatility of transitory shocks, these increases were much more pronounced for the lower education group. As a result the gains under the utility-based evaluation increase much more than under the simple present-value comparison: 14.15% (from 33.65% to 47.80%) versus 4.26% (from 29.47% to 33.73%).

The results for college graduates exhibit even more significant differences. While in the 1980s we again observe similar changes in the certainty equivalent gains in Tables 11 and 12 (+14.25% and +17.95%, respectively), in the 1991-2007 period we actual find the opposite result: the 13% increase in Table 11 is now a 14.98% decrease in Table 12. So, although the average present-value of labor income for a college graduate has increased over this period, the dispersion of outcomes is now significantly larger, particularly when compared with the one for high school graduates (as previously shown in Table 10): in the 1980-1990 period both groups had almost the same exact volatility of permanent shocks (9.4% and 9.6%) while in the 1991-2007 period this volatility has decreased for high school graduates (to 8.5%) and increased for college graduates (to 11%).

Interestingly, under the utility-based calculations, the certainty equivalent gains from college in the final part of the sample are significantly lower than the certainty equivalent gains from high school, (34.06% versus 47.80%, respectively), and as a result even the dollar value gains are very similar, ($391k versus $371k, respectively). Finally, it is interesting to compare the magnitudes of gains from college in Tables 11 and 12. The simple average present-value calculation (Table 11) suggests that the average agent should have been willing to pay (in tuition and foregone earnings while in school) $620k to attend college in the 1980-1990 period, and $798k in the 1991-2007 period, which dramatically over-estimate the actual certainty equivalents (Table 12): $499k and $391k, respectively.

9. CONCLUSION

The main theme of this paper is to show that life cycle factors, preference parameters, earnings volatility, and fiscal parameters have important implications for how we think about the returns to education. Using a utility-based model that is standard in the life-cycle consumption and saving decisions analysis, we show that accounting for earnings risks and individual risk preference significantly changes the relative values of three different education levels—no high school, high school degree, and college degree. A high school degree confers not only higher expected lifetime earnings, but also reduced earnings volatility and lower risk of unemployment. College graduates on average have much higher expected lifetime earnings compared to high school graduates, but because they also face higher earnings volatility our results suggest the value of college degree declines with risk aversion. Accounting for progressive income taxation, unemployment insurance, and Social Security taxes and benefits further reduce the value of education. Overall, we conclude that the value of a college (high school) degree to be \$300k to \$500k (\$200k to \$250k), depending on the parametric assumption of risk aversion. While the returns to a college education remain high relative to the cost of a college education (both in terms of direct costs as well as foregone earnings while in school), the net gains are substantially below those commonly reported in the popular press.

We also find that while the value of education is larger for men in dollar terms, it is larger for women in percentage terms. Similar to the other studies in returns to education, we also find the value of education changed significantly over the past 40 years. Overall, these results show the importance of accounting for risk, preferences, and the tax-and-transfer environment when calculating the value of education. Finally it is important to mention that our analysis ignores non-monetary payoffs from education, such as happiness, longevity, improved democratic processes, lowered crime rates, or better connections, as studied by McMahon (2009), Orepoulos and Salvanes (2009) or Cohen, Frazzini and Malloy (2010).

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Figure 1: Labor Income Profile over Age

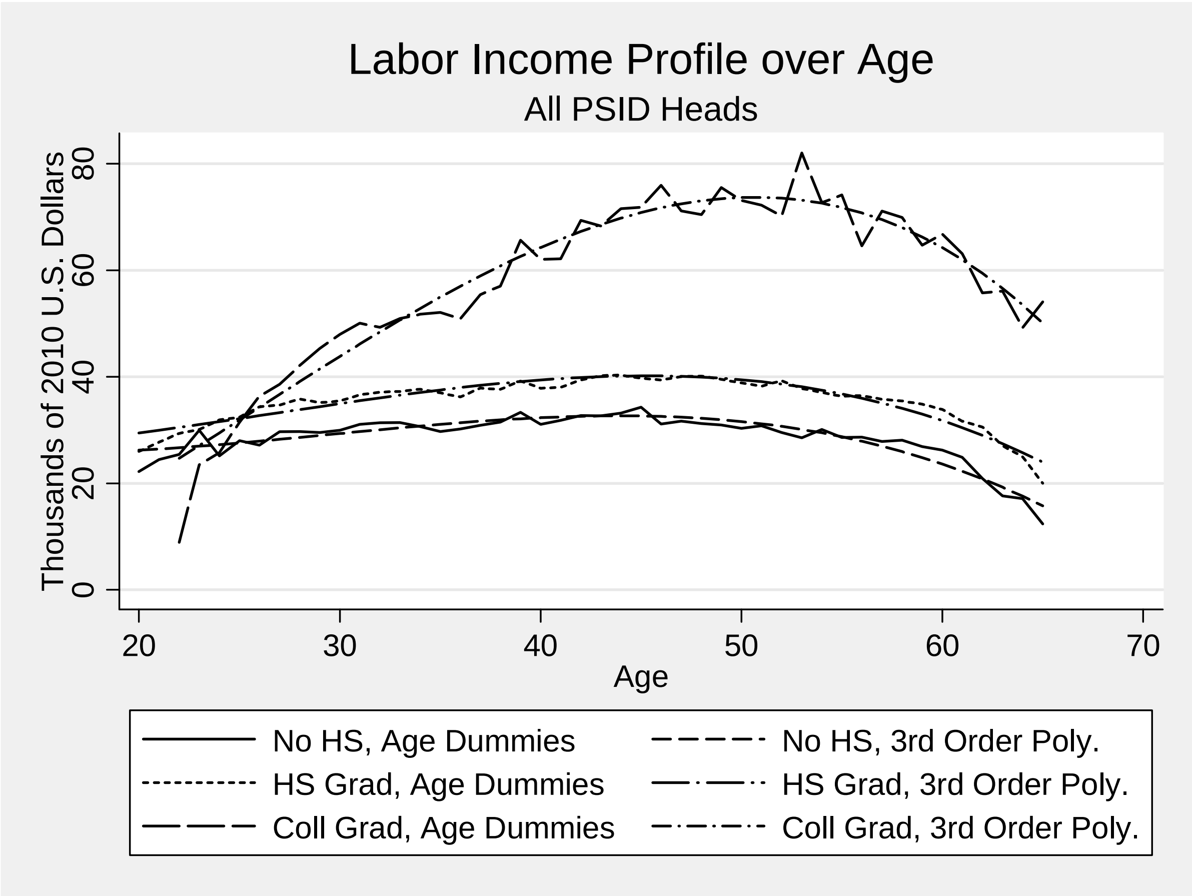

Table 1: Descriptive Statistics, PSID Household Head Aged 20-65

Panel A			
	No High School	High School Graduates	College Graduates
Number of Agents	1,785	3,706	1,389
Average Number of Records Each Agent	8.3	9.4	11.0

Panel B					
Year	Proportion of Male	Age	Years of Education	Labor Income in 2010 USD	Number of Agents
1970	85.98%	42.59	11.02	$50,240	1,397
1980	81.07%	39.34	12.18	$50,222	1,860
1990	77.88%	39.50	12.73	$49,430	1,907
2001	77.87%	41.13	12.98	$55,957	2,314

Table 2: Variance Decomposition

Panel A: Labor Income Only			
	No High School	High School Graduates	College Graduates
σ_ε (Transitory)	0.473 (0.018)	0.329 (0.008)	0.326 (0.009)
σ_u (Permanent)	0.112 (0.003)	0.097 (0.001)	0.100 (0.002)
Panel B: Labor Income Plus Unemployment Income			
	No High School	High School Graduates	College Graduates
σ_ε (Transitory)	0.541 (0.018)	0.397 (0.009)	0.375 (0.009)
σ_u (Permanent)	0.119 (0.003)	0.097 (0.002)	0.101 (0.001)

Note: Numbers are standard deviations of the variance components with clustered standard errors in parentheses.

Table 3: Expected Income, Unemployment Rate, Unemployment Income and Replacement Rate of Average Employed Worker's Income, by Levels of Education

	No High School	High School Graduates	College Graduates
Expected Annual Labor Income without Unemployment Spells in a Year	$28,481.93	$36,266.45	$57,117.56
Likelihood of Experiencing Unemployment in a Year	20.05%	14.79%	7.15%
Expected Annual Labor plus Unemployment Income with Unemployment	$22,264.32	$26,797.27	$30,198.05
Replacement Rate of Income, with versus without Unemployment	78.17%	73.89%	52.87%
Expected Annual Social Security Earnings upon Retirement	$18,384.00	$22,140.00	$27,192.00
Replacement Rate of Retirement Earnings	64.55%	61.05%	47.56%

Table 4: Gains from Education: Expected Life-Time Earnings

Panel A: Pre-Tax Lifetime Labor Earnings between Age 22 and 65, without Adjustment for Likelihood of Unemployment, No Discount			
Education Level	Lifetime Earnings	Earnings Gain	Percentage Gain
No High School	$1,469,279	--	--
High School	$1,905,949	$436,670	29.72%
College	$3,179,050	$1,273,101	66.80%
Panel B: Discounted Pre-Tax Lifetime Labor Earnings between Age 22 and 65, without Adjustment for Likelihood of Unemployment (Discount Rate = 1%)			
Education Level	Lifetime Earnings	Earnings Gain	Percentage Gain
No High School	$1,200,215	--	--
High School	$1,549,627	$349,413	29.11%
College	$2,543,859	$994,231	64.16%
Panel C: Discounted Post-Tax Lifetime Labor Earnings between Age 22 and 65, without Adjustment for Likelihood of Unemployment (Discount Rate = 1%)			
Education Level	Lifetime Earnings	Earnings Gain	Percentage Gain
No High School	$969,071	--	--
High School	$1,226,929	$257,858	26.61%
College	$1,894,001	$667,072	54.37%
Panel D: Discounted Post-Tax Lifetime Labor Earnings between Age 22 and 65, with Adjustment for Likelihood of Unemployment (Discount Rate = 1%)			
Education Level	Lifetime Earnings	Earnings Gain	Percentage Gain
No High School	$926,652	--	--
High School	$1,179,551	$252,898	27.29%
College	$1,830,184	$650,633	55.16%
Panel E: Discounted Post-Tax Lifetime Labor Earnings between Age 22 and 65 plus Social Security Earnings between Age 66 and 100, with Adjustment for Likelihood of Unemployment between Age 22 and 65 (Discount Rate = 1%)			
Education Level	Lifetime Earnings	Earnings Gain	Percentage Gain
No High School	$1,091,859	--	--
High School	$1,378,510	$286,651	26.25%
College	$2,074,542	$696,032	50.49%

Note: All numbers in panels A through E are adjusted for likelihood of survival based on the Social Security 1945 cohort mortality table.

Table 5: Gains from Education in the Baseline Case (Risk Aversion Equal to 2 and Discount Rate Equal to 0.99).

Panel A: Without unemployment risk or income risk				
Education Level	Consumption CE	Percentage Gain	Total Wealth CE	Total Wealth CE Increase
No High School	\$26,518	--	\$1,134,150	--
High School	\$31,644	19.33%	\$1,353,384	\$219,234
College	\$44,398	40.30%	\$1,898,861	\$545,477
Panel B: Baseline				
Education Level	Consumption CE	Percentage Gain	Total Wealth CE	Total Wealth CE Increase
No High School	\$21,116	--	\$903,111	--
High School	\$26,260	24.36%	\$1,123,116	\$220,004
College	\$36,362	38.47%	\$1,555,169	\$432,053
Panel C: With adjusted volatilities				
Education Level	Consumption CE	Percentage Gain	Total Wealth CE	Total Wealth CE Increase
No High School	\$21,611	--	\$924,282	--
High School	\$26,824	24.12%	\$1,147,237	\$222,955
College	\$37,344	39.22%	\$1,597,168	\$449,931

Note: In Panel C we report results for the case in which the estimated volatilities were scaled down by ¾ to take into account for potential measurement error.

Table 6: Gains from Education for Different Values of the Preference Parameters, with Unemployment and Income Risks

Panel A: High School Education				
Education Level	γ	β	Total Wealth CE Gain	Wealth Percentage Gain
High School	1	0.97	\$215,086	20.94%
High School	1	0.99	\$201,357	19.95%
High School	2	0.97	\$222,912	24.34%
High School	2	0.99	\$220,004	24.36%
High School	4	0.97	\$242,757	34.38%
High School	4	0.99	\$252,936	38.49%
Panel B: College Education				
Education Level	γ	β	Total Wealth CE Gain	Wealth Percentage Gain
College	1	0.97	\$486,797	39.19%
College	1	0.99	\$506,942	41.87%
College	2	0.97	\$406,178	35.67%
College	2	0.99	\$432,053	38.47%
College	4	0.97	\$300,453	31.66%
College	4	0.99	\$301,009	33.07%

Table 7: Variance Decomposition by Gender Subsamples

Panel A: Men			
	No High School	High School Graduates	College Graduates
σ_ε (Transitory)	0.454 (0.018)	0.324 (0.007)	0.325 (0.008)
σ_u (Permanent)	0.105 (0.003)	0.093 (0.001)	0.098 (0.001)
Panel B: Women			
	No High School	High School Graduates	College Graduates
σ_ε (Transitory)	0.536 (0.033)	0.369 (0.007)	0.367 (0.017)
σ_u (Permanent)	0.156 (0.005)	0.135 (0.001)	0.116 (0.003)

Note: Numbers are standard deviations of the variance components with clustered standard errors in parenthesis. Calculated with labor earnings only using agent-year records with no unemployment spells in a given year.

Table 8: Gains from Education: Expected Lifetime Earnings by Gender

Panel A: Males			
Education Level	Lifetime Earnings	Earnings Gain	Percentage Gain
No High School	$1,162,280	--	--
High School	$1,428,640	$266,359	22.92%
College	$2,144,436	$715,796	50.10%
Panel B: Females			
Education Level	Lifetime Earnings	Earnings Gain	Percentage Gain
No High School	$633,847	--	--
High School	$967,997	$334,150	52.72%
College	$1,341,005	$373,008	38.53%

Note: The Table reports discounted Post-Tax Lifetime Labor Earnings between Age 22 and 65 plus Social Security Earnings between Age 66 and 100, with Adjustment for Likelihood of Unemployment between Age 22 and 65 (Discount Rate = 1%), and adjustment for likelihood of survival based on the Social Security 1945 cohort mortality table.

Table 9: Gains from Education in the Baseline Case (Risk Aversion Equal to 2 and Discount Rate Equal to 0.99), by Gender

Education Level	Men		Women	
	Total Wealth CE	Percentage Gain	Total Wealth CE	Percentage Gain
No High School	$999,261	--	$438,464	--
High School	$1,166,678	16.75%	$768,517	75.28%
College	$1,609,229	37.93%	$1,080,953	40.65%

Table 10: Variance Decomposition by Different Sub-periods

Panel A: 1968-1980			
	No High School	High School Graduates	College Graduates
σ_{ε} (Transitory)	0.433 (0.011)	0.270 (0.006)	0.239 (0.008)
σ_u (Permanent)	0.101 (0.002)	0.090 (0.001)	0.060 (0.001)
Panel B: 1980-1990			
	No High School	High School Graduates	College Graduates
σ_{ε} (Transitory)	0.419 (0.030)	0.322 (0.010)	0.283 (0.007)
σ_u (Permanent)	0.133 (0.005)	0.094 (0.002)	0.096 (0.001)
Panel C: 1991-2007			
	No High School	High School Graduates	College Graduates
σ_{ε} (Transitory)	0.612 (0.055)	0.400 (0.010)	0.411 (0.014)
σ_u (Permanent)	0.115 (0.009)	0.085 (0.002)	0.110 (0.002)

Note: Numbers are standard deviations of the variance components with clustered standard errors in parenthesis. Calculated with labor earnings only using agent-year records with no unemployment spells in a given year.

Table 11: Gains from Education: Expected Lifetime Earnings by Different Sub-periods

Panel A: 1968-1980			
Education Level	Lifetime Earnings	Earnings Gain	Percentage Gain
No High School	$1,128,494	--	--
High School	$1,464,063	$335,569	29.74%
College	$1,962,671	$498,608	34.06%
Panel B: 1980-1990			
Education Level	Lifetime Earnings	Earnings Gain	Percentage Gain
No High School	$991,335	--	--
High School	$1,283,529	$292,194	29.47%
College	$1,903,626	$620,096	48.31%
Panel C: 1991-2007			
Education Level	Lifetime Earnings	Earnings Gain	Percentage Gain
No High School	$972,850		
High School	$1,300,993	$328,142	33.73%
College	$2,098,588	$797,595	61.31%

Note: The Table reports discounted Post-Tax Lifetime Labor Earnings between Age 22 and 65 plus Social Security Earnings between Age 66 and 100, with Adjustment for Likelihood of Unemployment between Age 22 and 65 (Discount Rate = 1%), and adjustment for likelihood of survival based on the Social Security 1945 cohort mortality table.

Table 12: Gains from Education in the Baseline Case (Risk Aversion Equal to 2 and Discount Rate Equal to 0.99), by Different Sub-Periods

Education Level	Panel A: 1968-1980		
	Total Wealth CE	Total Wealth CE Increase	Percentage Gain
No High School	$936,476	--	--
High School	$1,264,795	$328,319	35.06%
College	$1,658,062	$393,267	31.09%
Education Level	Panel B: 1981-1990		
	Total Wealth CE	Total Wealth CE Increase	Percentage Gain
No High School	$761,847	--	--
High School	$1,018,213	$256,366	33.65%
College	$1,517,548	$499,335	49.04%
Education Level	Panel C: 1991-2007		
	Total Wealth CE	Total Wealth CE Increase	Percentage Gain
No High School	$776,173	--	--
High School	$1,147,194	$371,021	47.80%
College	$1,537,933	$390,739	34.06%