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DISCUSSION PAPER SERIES

IZA DP No. 16936

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ABSTRACT

Demography, Human Capital Investment, and Lifetime Earnings for Women and Men

Can the demographic trends of increased life expectancy and decreasing birth rates, along with the labor market patterns of returns to human capital investment and changes in real hourly earnings, account for changes in women's and men's lifetime earnings? Using a Vector Error Correction Model to analyze annual US CPS data from 1964 to 2019, we find patterns linking these factors and demonstrating that they have significant roles to women's lifetime earnings but not to men's. These findings are consistent with the convergence of gender earning gap has occurred mainly due to women's responses to changing demographic and socioeconomic factors.

JEL Classification: J3, J16, J24

Keywords: life expectancy, lifetime earnings, human capital investment, VECM

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INTRODUCTION

One of the most notable trends of the last half-century has been women's increased labor force attachment, measured both by increased labor force participation and increased earnings [Goldin 2014; Fernández 2013]. While these trends have certainly been duly noted, measured, and analyzed, most recent papers have not taken a longer time span approach to this topic and also have not focused on the full impact of demography and human capital investments on lifetime earnings.[1] Meanwhile, many earlier researchers who attempted to tackle the more macro view of the labor market and who were interested in demographic effects on macro variables like women's earnings,[2] did not have the data available to analyze these dimensions over a sufficiently long time horizon to allow for formal testing.[3] The longer time span that we use in this paper, covering over a half century, allows us to test whether changing returns to human capital investment and changing demography, in particular increasing lifespans and decreasing birth rates, can explain much of these trends both through encouraging greater investments in human capital, and through direct effects on labor force attachment.

In this paper, we use fifty-six years of US Census Annual Demographic Files, from 1964 to 2019, to track the changes in US women's and men's lifetime real earnings. We calculate returns to education and potential experience from these data, and also construct a measure of lifetime real earnings to consider what the lifetime payoff is for labor market participation. We then consider what forces could have affected lifetime earnings measures. For women, lifetime earnings have risen steadily, both because of rising hourly earnings rates and because of higher lifetime hours worked, where lifetime hours worked has increased both because of extended years of labor force participation and because of more hours worked per year of participation. For men, lifetime earnings have moved upwards over time, but over a less steady path, and appear to be driven more by changes in hourly real earnings rates than by either increased participation or increased hours worked.

We analyze the relationships that may have driven the increased amounts of lifetime work and earnings for women, both absolutely and relative to men. Figure 1 gives a schematic diagram of our hypothesized relationships, which provide the justification for our variable selection and econometric tests of the long-run relationships. Changes in technology (i.e., external shocks to the demographic-economic system) can affect outcomes through two main pathways: 1) effects on demographics (e.g., changes in medical technology that increase life expectancy and/or make family planning easier), where we differentiate between effects on life expectancy and effects on family structure; 2) effects on household productivity, where while it is also of course quite likely that nonmarket productivity has increased, effects on market productivity (e.g., changes in work techniques such as labor-saving devices) have both increased market labor productivity, particularly for skilled labor, and possibly shifted the relative productivity of women's to men's market labor.[4] We argue that as technology has increased productivity, this will have increased the returns to investments in human capital in the forms of both education and work experience, thus raising earnings and thus—assuming income effects do not outweigh substitution effects—increasing hours of lifetime work. In addition, through the demographic pathway, the lowered birth rate would be expected to have a similar effect of raising payoffs for women as they can now spend more time in the market, but would be expected to have less effect on men (or have the effect of reducing their labor through the income effect in households of women's higher earnings). Regarding increased life expectancy, both genders would have higher potential payoffs to investment in human capital through having more years in which to utilize it, and also then may increase their hours of lifetime work (in part due to the need to accumulate more deferred earnings for retirement).

We contribute new insights on several dimensions to the literature on gender differences in work. First, because we employ individual-level data over a long timespan of fifty-six years, we are able to calculate annual returns to both education and experience from this dataset. We run regressions separately for each tranche of annual data (and separately by gender within year) and use the coefficients from these regressions as our returns measures. Other papers employing a time-series approach to studying gender differences in work patterns have only used aggregated annual data series, which has made it impossible for them to calculate the marginal returns to human capital investment [McNown and Rajbhandary 2003]. Thus, in addition to tracking the effects of real earnings, or the price of women's and men's labor—on lifetime earnings, we can also track the effects of changing returns to human capital—measured in terms of the returns to college education and to an additional midcareer year of work experience, where these marginal returns are calculated through estimation of comparable hourly earnings equations at each point in time.

Second, we utilize an aggregated measure of earnings to capture the changes over time in the amount that women and men can expect to earn during their prime earning years (25 to 65). This measure abstracts from year-to-year changes in earnings by instead showing longer evolution of earnings as each cohort experiences gradually different demographic and labor market patterns.

In addition, we consider how demographic factors, in particular both lengthening lives and declining births, have impacted these aggregate earnings amounts over this time span.[5] Other studies have neglected inclusion of information on life expectancy, favoring instead a narrower focus on fertility trends, thus missing one of the other most important trends over the past century or more in human demography [Salamaliki et al. 2013; McNown and Rajbhandary 2003; Hondroyiannis and Papapetrou 2002].

While this paper addresses themes of long-held interest in the area of the economics of gender, its focus on lifetime work patterns differentiates it from other contributions in this area. This paper builds on our earlier work [Jacobsen, Khamis, and Yuksel 2015], which documents the changes over the first fifty years of this time frame in the returns to human capital and also how selection effects are critical to the analysis, both in terms of correctly measuring the returns to human capital and in the large switch over this time period between women negatively selecting into the labor market and in later decades positively selecting into the labor market. The most comparable recent project to ours is Mulligan and Rubenstein [2008], which focuses on increased within-gender inequality as the main driver of overall increases in women's work.[6] In contrast to Mulligan and Rubenstein's paper and other recent papers [e.g., Autor et al. 2008] that focus on the importance of differential returns to skill, we emphasize factors that have increased work for all women, including rising wages for women, decreasing birth rates, and higher returns to education, and argue for their primacy in explaining the overall pattern of increased gender convergence over this period in lifetime earnings of women and men (albeit not full convergence by any means). We also consider that longer life expectancies may have led to fundamental changes in how both women and men approach paid work.

DATA AND EMPIRICAL METHODOLOGY

For this paper we employ data from the U.S. Census Annual Demographic Files (March Current Population Survey) for the 56-year period, 1964 to 2019.[7] Our variables for returns to experience and education (the human capital investments), real hourly earnings, and expected primetime earnings are calculated from the CPS data as described below.

Our annual demographic data on life expectancy at birth for women and men separately and the overall birth rate (number of births per thousand people in the population) were obtained respectively from the World Bank World Development Indicator Database and the US National Vital Statistics Reports.

From the CPS data, returns to 15 years of experience and returns to college graduation were calculated based on a Mincerian regression framework run separately by gender that is consistent in variable definition over the entire sample period.[8] We restrict our sample to individuals ages 25 to 65 and use the variables of race (grouping for whites, blacks, and other races which also includes Hispanic origin), urban setting, Census region dummies, educational attainment (less than high school, high school diploma, bachelor degree and above), and potential experience (years of education—coded from 0 to 22, plus 6, subtracted from age) entered as a quadratic function, with the log of hourly earnings as the dependent variable.

Our analysis is based on the Heckman selection corrected estimates of returns to experience and college. While such a correction for selection into the labor force is not always done in other papers, Blau et al. [2021] also emphasize the importance of controlling for selection in order to get an accurate appraisal of true differences in earnings by gender, and we document in our earlier paper [Jacobsen et al. 2015] that the OLS and Heckman results tell very different stories, as the Heckman results document the plausible pattern that selection has shifted over this half-century period from negative (women working who have less desirable unobserved labor force characteristics) to positive selection (women working who have more desirable unobserved labor force characteristics). Following on both Mulligan and Rubenstein [2008] and Jacobsen et al. [2015], we use marital status (spouse present vs. all other categories) as the exclusion restriction for selection into labor force participation for both men and women. While Mulligan and Rubenstein also use children as a selection control variable (and do not use marital status for men), we do not have this variable available for the full sample period. However, in comparing our results for the period where it is available and we can estimate it both ways, they do not differ significantly from the results using marital status alone.

We have selected 15 years of experience and college graduation as the most significant changes over time and by gender have occurred at these two points in terms of human capital returns, which we documented in Jacobsen at al. [2015]. As returns to potential experience are calculated based on a quadratic specification, they are evaluated at the specific point of fifteen years; returns to having a bachelor's degree or greater is the regression coefficient for this educational outcome (in a dummy variable specification, measured relative to the base of less than high school attendance). The coefficient on 15 years of experience, while measured with some error related to their regression origins, has much less variance than returns at earlier ages (5 and 10 years specifically) and similar low variance to returns at higher levels of experience (20 years specifically); additionally, the variance from year varies little. The coefficient for education has higher variance than the coefficient for experience but again varies little in variance over time. Thus, we do not think that our time series results are heavily influenced by the error in measurement of these returns.

Real hourly earnings for men and women are calculated from the CPS setting 2019 as the base year and using standard corrections for reasonableness (rounding up or down on numbers that are very given the available information on annual earnings, usual hours worked per week (or, in the earlier samples, hours worked in the preceding week), and number of weeks worked per year. Their function in the analysis is to serve as the base earnings rate for male and female labor over time; given that they are averages over the whole population, their function is to serve as the base earnings rate for male and female labor in each year over time and to capture that effect separately from changes in the marginal returns to human capital over time.

At each point in time, we calculate expected values for lifetime earnings for a woman or man of age 25 in the given year, considering both the probability of survival to each age and the probability of working at each age conditional on survival, and multiplying those by the actual average annual earnings experienced by each gender-age cohort in the given year. So the expected lifetime earnings = $E(LTE)_{jt} = \sum_{i=25}^{65} p_{ijt} \ \bar{e}_{ijt}$, where $E(LTE)_{jt}$ is the expected lifetime earnings for a person aged 25 of gender j in year t, and $\bar{e}_{ijt}$ the annual earnings for employed individuals in age group i of gender j in year t. This concept of expected lifetime earnings should be thought of as the mean value in a steady state where the current experience of each cohort is mirrored by all cohorts after it. Of course, the evolving pattern in this variable makes clear that the states are not steady but rather changing from year to year, where we are trying to predict part of the evolution by using the other variables in our set of annual time-series data.

In viewing the data over time for our key variables of interest: life expectancy; birth rate; return to fifteen years of experience, return to college graduation; hourly earnings; and expected lifetime earnings for both men and women; several distinct patterns for the actual demographic data, the estimated data, and the expectational calculations emerge, which we discuss in the following paragraphs in more detail and display in the accompanying Figure 2 (for women) and Figure 3 (for men).

The first panel in Figure 2 shows that actual life expectancy for women has increased over time from the mid-1960s to 2019, albeit with some flattening at the end of the time period. During the same period, the birth rate has declined, as shown in the second panel over, albeit with some fluctuation related to earlier boom and bust periods (in particular, the echo effect from the post-war baby boom). This is consistent with decreasing but fluctuating fertility rates over the period, so birth rate and fertility rate data are essentially measuring the same trend and are highly correlated (0.94 from 1960 through 2022); we use the birthrate series in this paper, as it refers in the base to both women and men.

The third panel in Figure 2 shows that the estimated marginal returns to fifteen years of experience for women over this 50-year period has increased. There are also increasing returns to college completion for women from the mid 1980s onwards, as shown in the fourth panel in Figure 2 (first panel in the second row). While returns to college increase for women, the fifth panel in Figure 2 also depicts an increase in real hourly earnings for women starting in the early 1980s up until the early 2000s followed by a more recent rise. Over the entire 50-year period under consideration, the calculated expected lifetime earnings increase steadily over time for women, as shown in the final panel in Figure 2.

For women, the steady increase in life expectancy and decrease in birth rates or fertility are clear demographic trends. The returns to human capital are also increasing over time, as well as real hourly earnings and expected lifetime earnings.

Some of these trends can also be observed for men. The first panel in Figure 3 demonstrates that men have also experienced steady increases in life expectancy at birth over this time span, with the same leveling off at the end of the time series. This general demographic trend in increases in life expectancy at birth can probably be largely attributed to a range of medical advances and improvements in socioeconomic well-being (made possible in large part by higher incomes) that have affected both men and women, while the birth rate decline (reiterated in the second panel of Figure 3) echoes the fertility transitions that most developed countries experienced over this time range [Guinnane 2011].

However, as shown in the third panel of Figure 3, the marginal returns to 15 years of experience for men are not as clearly increasing over time as for women, with a very different pattern of greater fluctuation and flattening than that experienced by women. In terms of returns to college education, as shown in the fourth panel of Figure 3, men also experienced increases from the mid-1980s onwards, so this is more similar to the women's pattern of returns to college, albeit with an earlier plateauing in returns circa 2000, while women's returns continue to rise. At the same time, men's real hourly earnings (the fifth panel) and expected lifetime earnings (the final panel) do not exhibit a clear increasing trend throughout the fifty-six years, with hourly earnings back to where they are in the early 1970s, while lifetime earnings have increased over the full time series.

So, while the variables of interest exhibit clear trends for women over the time period, this is not the case for all of the men's variables. The men's variables for returns to experience, hourly earnings, and expected lifetime earnings show much greater disruption in the labor market for men than in the labor market for women, including a steep decline in real earnings from 1974 to 1994 (roughly mirroring the period of significant drops in manufacturing employment and private sector unionization in the US), followed by a period of flat earnings in the first part of the twenty-first century. The fluctuations in real hourly earnings for men are reflected in the fluctuations in their expected lifetime earnings, indicating that lifetime earnings for men are not influenced heavily by changes in participation or hours worked, but rather by earnings per hour.

Looking at the summary statistics, as shown in Table 1, from the beginning of the period, 1964, to the end, 2019, large increases in life expectancy and a large decrease in the birth rate occur over this time frame. Women's life expectancy increases by 7.7 years, from 73.7 to 81.4 years, and men's increases by 9.5 years, from 66.8 to 76.3 years, narrowing the female-male gender life expectancy gap from 6.9 years to 5.1 years. Returns to experience and returns to college for both genders show large increases over this time, with returns to fifteen years of experience rising from -9 percent up to 45 percent relative to base earnings for women by the end of the period, and rising from 14 percent to 45 percent for men; meanwhile returns to college (or higher) completion rose from 59 to 137 percent of base earnings for women and from 26 to 77 percent of base earnings for men. Note these numbers also reflect that college completion allows one to achieve additional postgraduate education and increase educational returns further, as well as that the gap in earnings between those with a college degree and those without a high school degree has widened substantially over this timespan. Real hourly earnings increases occur, with women's earnings rising by 59 percent and men's by 30 percent over this period, increasing the unadjusted women-to-men's earnings ratio from 65 to 79 percent. Expected real lifetime earnings increases also occur, with women's lifetime earnings rising by 133 percent and men's by 45 percent over this time period, increasing the women-to-men's lifetime earnings ratio from 43 to 69 percent.

Variables have different standard deviations as well as means by gender: Women have more variable returns to experience and education and more variation in real hourly earnings and expected lifetime earnings over this time period, while men have more variability in life expectancy.

Given these differences in the trends over time and summary statistics by gender, it is clear that we need to apply time-series analyses to our data separately by gender. The challenge at this stage of the analysis is to determine whether there is evidence of causal interrelationships in the data, as opposed to spurious correlation. For each gender, the questions are whether the series appear to be causally interrelated, and whether a shock to one series causes either temporary or permanent changes in another. This would indicate that possible external shocks, such as technological innovations, could cause changes in one series that then may be reflected as well in another series in the interrelated set, particularly in the outcome measure of lifetime earnings.

As a first step in this process, we test each of our data series as to whether they are stationary or non-stationary, a pre-condition for testing for cointegration [Johansen 1988; 1991; 1995]. In general, models that contain a large number of series are unlikely to be able to be estimated (indeed, we are unable to estimate a valid model containing all six series for either gender), so we look for the simplest models possible that still capture the essence of the possible interrelationships. Thus, for each gender separately, four models, each containing four series, are tested for cointegration. This allows us to model sets of interrelated series to see how much the "outcome" variable of expected lifetime earnings is affected by the alternative pathways of a demographic variable, a human capital variable, and the hourly earnings variable (which can reflect not only human capital levels in the economy, but also relative demand for and supply of labor by gender, and possibly changing levels of gender discrimination):

- Model 1 contains life expectancy at birth, returns to fifteen years of experience, real hourly earnings and expected lifetime earnings.
- Model 2 contains the birth rate, returns to fifteen years of experience, real hourly earnings and expected lifetime earnings.
- Model 3 contains life expectancy at birth, returns to college, real hourly earnings and expected lifetime earnings.
- Model 4 contains the birth rate, returns to college, real hourly earnings and expected lifetime earnings.

If the tests for cointegration hold, then we can estimate vector error correction models in order to simulate the long-run relationship and also the adjustment process [Johansen 1988; 1991; 1995]. Thereafter, we simulate innovation shocks to our demographic and economic variables to see their effect on expected lifetime earnings using impulse response functions.

RESULTS

From visual inspection of the data in Figures 2 and 3, clear increases over time in life expectancy and clear decreases in the birth rate are visible. In addition, in terms of estimated returns to human capital, real labor market earnings, and expected lifetime earnings, the increasing trends for women appear larger than for men. Our analysis below considers whether the observed patterns are consistent with an analysis that attempts to factor out general trends in order to look for correlation between shocks to a linked set of variables.

This first requires a test for stationarity and adjustment of the series to factor out any common trend.

To test whether the time series are stationary or non-stationary, Table 2 shows the results for women from the Augmented Dickey-Fuller tests, the Phillips-Peron tests, and the Dickey-Fuller test for a unit root in which the series has been transformed by a generalized least-squares regression (DF-GLS).[9] The data series are tested in levels and in first-differences, with and without trend. For the six variables of interest (life expectancy at birth, birth rate, returns to 15 years of experience, returns to college, real hourly earnings and expected lifetime earnings), these three tests indicate across the board that we cannot reject the null hypothesis of non-stationarity for the data in levels. However, once first-differences are applied to these series, we can reject non-stationarity (i.e., the test statistics are sufficiently negative, falling below the cutoff value for 1 percent in most cases). This indicates that our data series for women all appear to be I(1) processes and confirms the visual inspection results of the data in the previous section.

Table 3 shows the results from the same three tests for levels and first-differences of the data series for men, skipping the shared variable of birth rate that was already tested in Table 2. Again, the results for levels indicate that we cannot reject the null hypothesis of nonstationarity, but testing these data in first differences indicates that for men as well as for women, we can reject nonstationarity, and thus the processes underlying the series appear to be I(1) processes. From the initial data inspection this was not as obvious as for the women's data series.

Having now shown that all of our variables for women and men are integrated of the same order, we can now proceed to investigate the cointegration relationship between these variables (for women and men separately). If one were to run a regression with these variables, a concern would be that the relationship found is a spurious one. For this reason, we must first consider whether cointegration exists for these sets of variables.

In order to estimate a vector error correction model (VECM), we first perform cointegration analyses, for women and men separately. We investigate several models for women and men separately, which correspond to the models described in the previous section regarding variable choice.

Table 4 provides lag-order selection statistics for the VECM with the Akaike Information Criterion (AIC) for the separate models, where the last column in Table 4 reports the lag-order that the AIC indicates for the particular model. In Table 5 the statistics for the Johansen test for cointegration indicate the number of cointegrating equations in a VECM for the four different proposed models for women and men. Models include a linear trend in the cointegrating equations and a quadratic trend in the undifferenced data.

These results indicate that for all the models for women a cointegrating relationship exists, supporting the notion of a long-run relationship between these different variables for women. The rank order is one for Models 3 and 4 for the women, indicating a single cointegrating equation. So, for women we find support for a cointegrating relationship between returns to college, real hourly earnings, expected lifetime earnings, and either demographic variable of life expectancy or the birth rate.

In contrast to the strong cointegration relationships in the women's time series analyses for these two models, for the models for men, no cointegration relationship exists, as the Johansen test indicates a rank of 0 to be significant. Hence, there is no support for a long-run relationship between the variables for the men, while there is for the women.

We next consider the parameters of interest from these vector estimations, namely the "long-run" parameters of the cointegrating equations (β), and the short-run, or adjustment coefficients (α). Table 6 presents the results of VECMs for the two different cointegrated models for women, where the upper section shows the adjustment coefficients (the alphas), while the lower section shows the parameters of the cointegrating equations (the betas).

As shown in Table 6, the adjustment coefficients α of hourly earnings are significant in both models, and the adjustment coefficient α for the return to college is significant in Model 4. It is notable that the alphas that are most significant are the ones that one has potentially actual "choice" over and are arguably faster to adjust in the short-term, namely hourly earnings and expected earnings, while it is possible that life expectancy, the birth rate, and returns to college are not as easily adjustable in the short run, as well as potentially less under the control of an individual. Model 4 is less stable, with coefficients implying divergence rather than convergence. The β coefficients on hourly earnings and expected lifetime earnings are significant in Model 3. This suggests that actual earnings and expected earnings enter in a statistically significant way into a cointegrating vector in this Model, again implying that Model 3 is to be preferred over Model 4. Then again, divergence, including changes in the outcomes due to a shock, may be the more interesting result, as shown in Model 4. Thus we provide both models without indication that one is to be favored over the other

One way to interpret cointegration is to consider the effects of shocks to one variable on the multivariable system, particularly on the outcome variable of interest, in our case lifetime earnings. Thus, in order to model the effect of shocks on the dynamic paths of the variables in our models, we estimate impulse response functions over time following the initial shock. In particular, we are interested to see whether shocks have a transitory or permanent effect on expected labor market outcomes. In Figures 4 and 5, orthogonalized impulse response functions are depicted, using a one-standard-deviation impulse for the orthogonalized impulse response function in each case.[10] We shock each of the series in turn to see their effect on the outcome variable of expected lifetime earnings, using a one deviation positive shock for each variable except for birth rate, where we use a one deviation negative shock. In each case our prior was that such a shock would lead to either a transitory or a permanent increase in lifetime earnings, consistent with the directional patterns that we observe in the raw data.

In Figure 4, for Model 3, shocking the return to college by a one standard deviation impulse has essentially no effect on expected lifetime earnings for women, while a similar shock to life expectancy has a large permanent effect on expected lifetime earnings. A shock to hourly earnings has a large temporary effect that then dissipates over ten years. From the cointegrating equations for Model 3, it appears that a shock to life expectancy in equilibrium has a slightly lower effect than hourly earnings, and accounts for only 1 percent of expected earnings. Overall, the stability of this models implies that the responses to shocks do not tend to push women off of the long-term relationship path of these variables.

In Figure 5, the impulse response functions for Model 4 for women indicates a strong permanent effect of a negative shock to the birth rate on expected earnings, causing them to increase and stay higher over time. A standard deviation positive shock to hourly earnings has a permanent positive effect on expected earnings while a positive shock to returns to college has a permanent negative effect. The hourly earnings effect is the most notable given the significance of its alpha parameter in the VECM.

For women, a positive shock to hourly earnings leads to either unchanged (Model 3) or increased (Model 4) expected lifetime earnings, indicating that they do not offset increased earnings rates with substantial declines in participation and hours worked that would lead to an actual drop in lifetime earnings. A positive shock in the return to education leads to either unchanged (Model 3) or decreased (Model 4) lifetime earnings, implying some possible offset for women, perhaps related to marriage market effects if they marry higher-earning men and reduce their own labor market activity. The negative shock on birth rates in Model 4 has the expected positive effect on expected lifetime earnings for women.

Regarding life expectancy, the results from Model 3 imply that increased life expectancy actually reduces rather than increases expected lifetime earnings for women. This was unexpected and implies a possible shift away from a focus on earnings to a focus on enhancement of life through time spent in nonmarket activities. This could include taking more time at the beginning of adulthood to develop skills that can be used in leisure and nonmarket production as well as in market production (i.e., longer time spent in higher education without direct payback in market production) and taking more time off at the end of middle-age, so that the work time during the 25 to 64 age range is reduced on both ends, possibly with some substantial offsetting increase in work and therefore earnings after age 64. In particular, given the increased ability of women to participate in government and private savings plans over this period that could include a positive actuarial payback (i.e., social security programs), additional shocks to life expectancy need not require that persons work longer in order to provide additional income for those added years, even though in steady state this would be problematic for social savings plans. Alternatively, these shocks may require that persons actually work additionally in their late sixties and early seventies, including in response to changes in full benefit-earning age for later cohorts entering the labor market.

Our results are broadly in keeping with our underlying theoretical structure whereby technological or other shocks are transmitted through various pathways, both demographic and production-related, and thus have measurable effects on the outcome of lifetime earnings profiles for women. The contrasting lack of long-run relationships for men between these variables stands in notable contrast, implying continued less flexibility with regards to participation and hours worked on the part of men even as life expectancy increases, birth rates decrease, and returns to human capital change over time.

CONCLUSION

This paper combines economic estimates on women's and men's returns to experience, returns to college graduation, real hourly earnings, and calculations of expected lifetime earnings from the U.S. Census Annual Demographic Files over a period of fifty-six years with demographic data on life expectancy at birth and birth rates. We considered whether women and men may factor in changes in actual life expectancy and actual birth rates when making human capital investment decisions and labor force participation decisions that could then lead to changes in their lifetime earnings. We considered whether there is a long-run estimatable relationship between these various demographic and economic factors and whether it might vary for women relative to men. Furthermore, we considered in this framework how demographic shocks, possibly due to innovations in birth control and medical advances, and shocks to returns to experience and college due to technological advances in household (market and nonmarket) production and the opening up of college access to a broader population, including women, can affect lifetime labor market outcomes, in particular lifetime earnings.

Our results indicate that for women, demography—in the form of either life expectancy or birth rates, returns to education, the real wage, and lifetime earnings form a long-run relationship over this time frame. We also see women responding to shocks on the demographic variables, the real wage, and the returns to education. For men, no such long-run relationships appear to exist and the various data series are not cointegrated for men over our study period.

These results are not startling, given that women have experienced in many ways a higher degree of change relative to their baseline position as of the start of our sample period (1964). Since that time, women's educational attainment (particularly continuation to receipt of degrees beyond college) and years of work experience have increased substantially while the birth rate (and therefore also their fertility rate) has continued a long secular decline after a short spike upwards in the immediate post-World War II years (indeed, ending right around 1964). However, the effect of increased life expectancy is something that both genders have experienced relatively equally (although the increase has actually been larger over this period for men in both absolute and percentage terms), even as men continue to have shorter life expectancies than do women. It is surprising that this has had no measured effect on men's worklife patterns, but less surprising if one considers that the norm continues to be full-time work for men throughout the 25- to 64-year-old age range.

Our focus on life expectancy changes along with the other demographic and workforce changes that have occurred over this time frame is an important reminder to researchers that this change has been substantial and life altering in ways that can be measured as well. In particular, our result that shocks to life expectancy may decrease rather than increase expected lifetime earnings is an interesting reminder that persons may choose to spend their additional life years in leisure and nonmarket production rather than in market production. This is consistent with the increased number of years that persons in wealthier countries may now expect to spend in retirement as lifespans have increased. But it is a question whether such a pattern will be sustainable given the strain placed on social security systems by the aging population.

This paper is exploratory rather than a final word on these subjects, as we consider this project simply an example of how cross-sectional results can be combined with time-series modeling in order to consider longer-run trends in labor market data in conjunction with demographic data. Whether or not our results hold up to additional testing and expansion of the time frame, it is important to consider that these combined econometric techniques can be used to shed more light on fundamental questions of how women and men respond to labor market incentives and demographic change. Our results, while based on US data, can help us to consider how other countries currently undergoing demographic transition may also experience convergence in outcomes by gender. Hopefully other researchers will apply similar approaches to data from other countries in the future, as well as expanding the research on the US socio-economic system.

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NOTES

1. In the developing country context, Lleras-Muney and Jayachandran [2009] find a link between increased life expectancy and human capital investments. A decrease in maternal mortality risk over a short time period in their study was linked to a sharp increase in life expectancy in school aged girls, which in turn increased their educational attainment.

2. For example, the research project undertaken by Macunovich [1996] following on Easterlin's theory of cohort effects on economic outcomes [Easterlin 1980].

3. A different tack to this time constraint is taken by Tamborini et al. [2015], who match data from the Survey of Income and Program Participation to individuals' longitudinal tax earnings as recorded by the Social Security Administration in order to estimate the 50-year work career effects of education on earnings for men and women.

4. For literature on these various shocks see Greenwood et al. [2005], Guinnane [2011], and Jones et al. [2003].

5. We did preliminary testing on marriage and divorce rates and found less evidence of their having a clear relationship to the outcome variables in this project; hence those results are not reported herein.

6. Blundell et al. [2023] also emphasize increased within-gender wage inequality as well as focusing on differential cohort effects for women and men across recent years, but also emphasize gender wage convergence for those over 40.

7. The Census data for our project were downloaded from the Integrated Public Use Microdata Series (IPUMS) CPS webpage at the University of Minnesota (http://cps.imps.org/cps/).

8. For a more detailed discussion of variable selection and specification, see Jacobsen et al. [2015].

9. We also performed the Kwiatkowski-Phillips-Schmidt-Shin tests (KPSS) for stationarity for both women and men. The results were consistent with those presented in Table 2 and Table 3, in that we reject the null hypothesis of stationarity for the nondifferenced data and accept the null for the first-differenced data.

10. As these impulse response functions are meant to be illustrative rather than being formal tests of reactions, we forego confidence bands, following the guidance from Lütkepohl et al. [2015] that the various methods proposed to date for constructing such bands either do not achieve the stated coverage level, are too conservative, or lack a strong theoretical base in asymptotic theory.

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Figures

Figure 1: Hypothesized relationships between variables

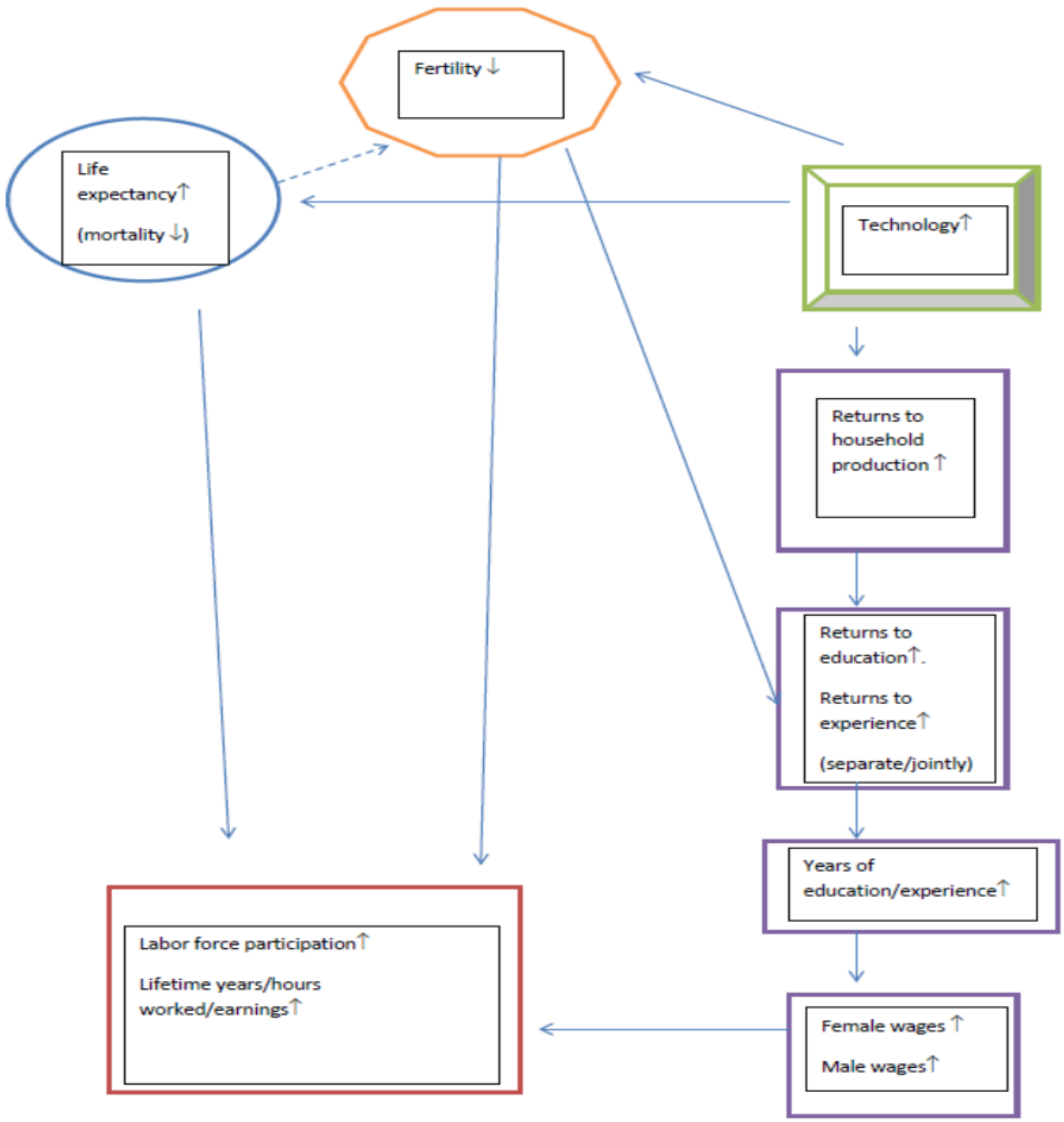

Figure 2: Descriptive Graphs, Women

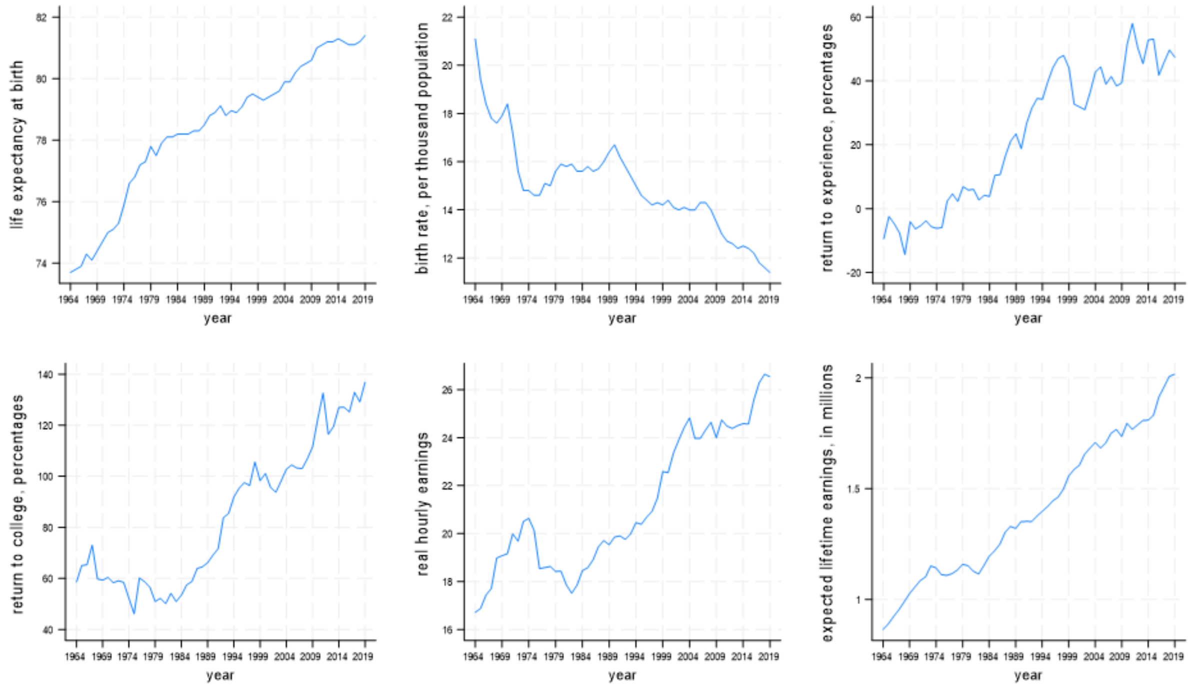

Figure 3: Descriptive Graphs, Men

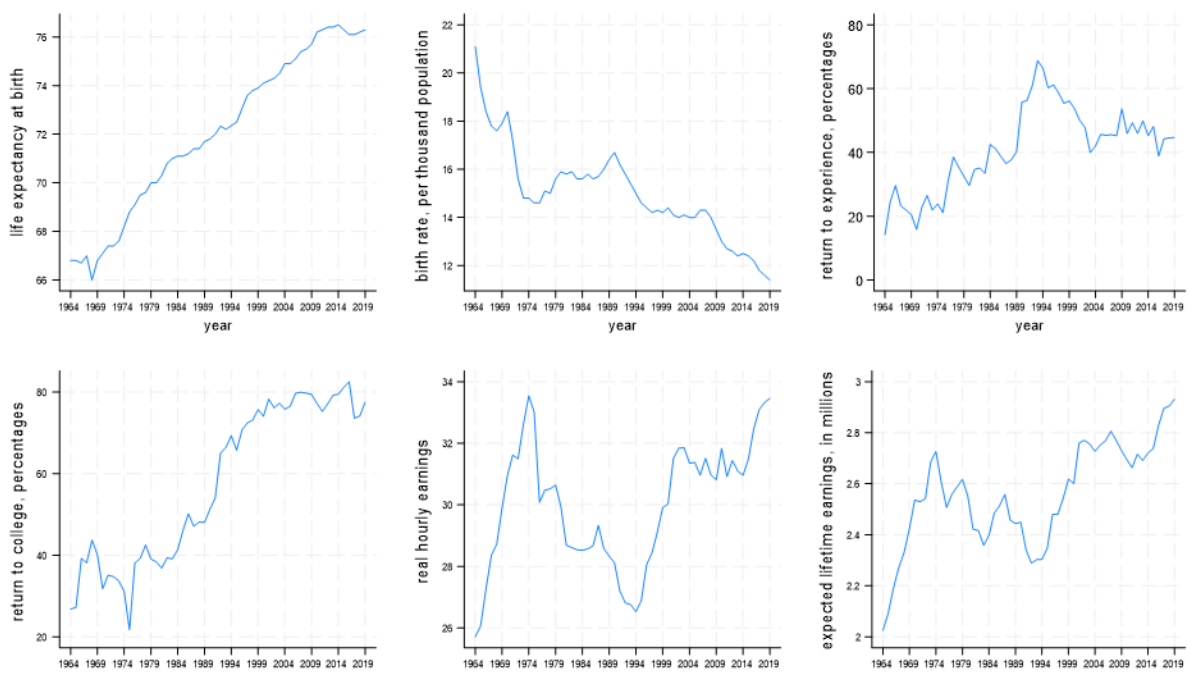

Figure 4: Impulse Response Function for Women's Model 3: Effects of Shocks to Life Expectancy, Returns to College, and Hourly Earnings on Expected Lifetime Earnings

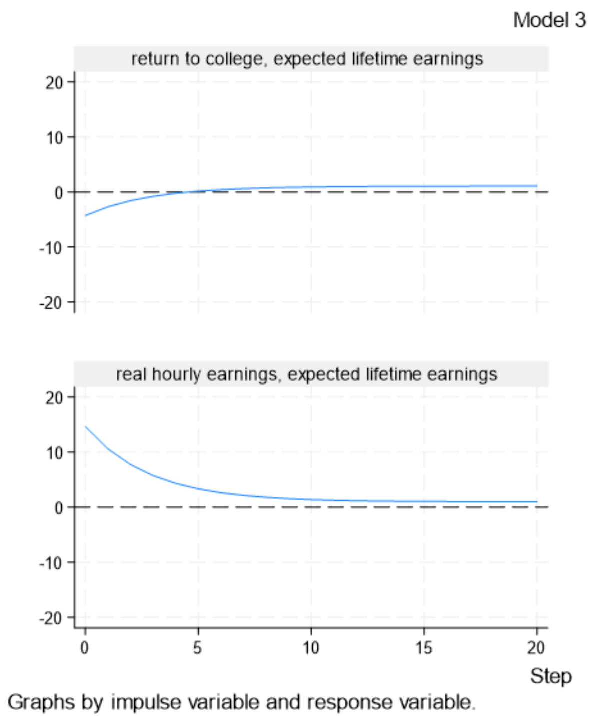

Figure 5: Impulse Response Function for Women's Model 4: Effects of Shocks to the Birth Rate, Returns to College, and Hourly Earnings on Expected Lifetime Earnings

Tables

Table 1: Descriptive Summary Statistics

Descriptive Summary Statistics, 1964-2019							
Variable	Obs	Mean	Std. Dev.	Min	Max	1964	2019
birth rate, women and men	56	15.005	1.955	11.4	21.1	21.1	11.4
Women							
life expectancy at birth (years)	56	78.378	2.277	73.7	81.4	73.7	81.4
returns to experience (%)	56	22.993	21.892	-14.384	58.056	-9.462	45.422
returns to college (%)	56	83.907	27.646	46.113	136.814	58.634	136.814
real hourly earnings (2019 $)	56	21.170	2.850	16.712	26.643	16.712	26.539
expected lifetime earnings (million 2019 $)	56	1.406	0.322	0.864	2.017	0.864	2.017
Men							
life expectancy at birth (years)	56	72.031	3.293	66	76.5	66.8	76.3
returns to experience (%)	56	41.067	13.202	14.225	68.796	14.225	44.644
returns to college (%)	56	57.413	19.259	21.691	82.559	26.793	77.506
real hourly earnings (2019 $)	56	29.981	2.024	25.715	33.541	25.715	33.458
expected lifetime earnings (million 2019 $)	56	2.557	0.202	2.025	2.931	2.025	2.931

Table 2: Unit Root Tests, Women

	Augmented Dickey-Fuller		Phillips-Perron		DF-GLS	
Variables	no trend	with trend	no trend	with trend	no trend	with trend
life expectancy at birth	-2.583	-1.625	-2.468	-1.468	0.914	-1.067
Δlife expectancy at birth	-3.851	-4.355	-7.057	-7.630	-3.853	-4.111
birth rate, women and men	-1.223	-2.851	-2.786	-3.687	0.409	-2.125
Δbirth rate, women and men	-5.045	-4.951	-5.093	-4.945	-1.699	-2.987
returns to experience	-0.891	-2.79	-1.130	-2.625	-0.050	-2.793
Δreturns to experience	-6.570	-6.522	-7.321	-7.251	-4.621	-5.870
returns to college	0.603	-2.207	0.390	-2.008	1.063	-1.602
Δreturns to college	-5.801	-6.184	-8.675	-8.969	-4.170	-5.334
real hourly earnings	-0.349	-1.642	-0.260	-1.537	0.726	-1.717
Δreal hourly earnings	-4.477	-4.477	-6.449	-6.405	-4.52	-4.522
expected lifetime earnings	0.325	-1.877	0.369	-1.653	1.721	-2.024
Δexpected lifetime earnings	-4.692	-4.729	-6.203	-6.195	-4.702	-4.709

Note: Critical values at 1, 5, 10 percent: without trend -3.6, -2.9, -2.6; with trend -4.2, -3.5, -3.2 (ADF, PPERRON)
For DF-GLS: without trend -2.6,-2.3 and -2.0; with trend -3.8, -3.2 and -2.9. Lag 1 included.

Table 3: Unit Root Tests, Men

	Augmented Dickey-Fuller		Phillips-Perron		DF-GLS	
Variables	no trend	with trend	no trend	with trend	no trend	with trend
life expectancy at birth	-1.229	-0.917	-1.056	-1.160	1.065	-1.377
Δlife expectancy at birth	-4.67	-4.872	-7.774	-7.872	-3.981	-4.445
birth rate, women and men	-1.223	-2.851	-2.786	-3.687	0.409	-2.125
Δbirth rate, women and men	-5.045	-4.951	-5.093	-4.945	-1.699	-2.987
returns to experience	-1.663	-1.534	-2.191	-1.933	-0.725	-1.507
Δreturns to experience	-5.605	-5.575	-8.201	-8.189	-2.607	-4.187
returns to college	-1.280	-1.751	-1.254	-2.071	-0.039	-1.914
Δreturns to college	-5.626	-5.521	-8.488	-8.478	-5.684	-5.654
real hourly earnings	-2.018	-2.100	-1.823	-1.876	-0.747	-1.805
Δreal hourly earnings	-4.324	-4.270	-5.700	-5.647	-4.231	-4.297
expected lifetime earnings	-2.045	-2.622	-2.095	-2.418	-0.302	-2.064
Δexpected lifetime earnings	-4.636	-4.570	-5.444	-5.396	-3.933	-4.431

Note: Critical values at 1, 5, 10 percent: without trend -3.6, -2.9, -2.6; with trend -4.2, -3.5, -3.2 (ADF, PPERRON)
For DF-GLS: without trend -2.6,-2.3 and -2.0; with trend -3.8, -3.2 and -2.9. Lag 1 included.

Table 4: Selection-order criteria

	Selection-order criteria, AIC					
	LL	LR	df	p	AIC	lag
Women						
Model 1	-133.051	520.06	16	0.000	5.887	1
Model 2	-140.552	45.913	16	0.000	7.406	3
Model 3	-371.777	529.04	16	0.000	15.068	1
Model 4	-377.707	39.293	16	0.001	16.527	3
Men						
Model 1	-199.632	32.178	16	0.009	9.063	2
Model 2	-215.094	36.828	16	0.002	9.657	2
Model 3	-438.138	472.32	16	0.000	17.621	1
Model 4	-440.733	43.303	16	0.000	18.336	2

Note: Significant AIC values are reported here.
The optimal lag is selected accordingly.

Table 5: Johansen test for cointegration

Johansen Test for Cointegration					
	Rank	parms	LL	eigenvalue	trace statistic
Women					
Model 1	0	8	-161.313		59.887
Model 2	0	40	-167.575		53.737
Model 3	1	15	-404.44	0.447	40.075
Model 4	1	47	-401.71	0.405	35.830
Men					
Model 1	0	24	-228.433		55.039
Model 2	0	24	-236.849		49.135
Model 3	0	8	-491.621		57.459
Model 4	0	24	-478.451		55.349

Note: 1 percent significance level reported. Models include a linear trend in the cointegrating equations and a quadratic trend in the undifferenced data.

Table 6: Vector error-correction models, alphas and betas

Vector error-correction models											
	equ.	life expectancy		birth rate		return college		hourly earnings		expected earnings	
		coef.	s.e.	coef.	s.e.	coef.	s.e.	coef.	s.e.	coef.	s.e.
alphas											
Model 3	1	0.076	0.059			-1.083	1.764	-0.683	0.124	-23.843	6.837
Model 4	1			-0.060	0.054	1.912	0.803	0.157	0.071	2.469	3.955
betas											
Model 3	1	1				0.007	0.007	0.897	0.206	-0.010	0.005
Model 4	1			1		-0.014	0.025	-1.089	0.864	0.018	0.020