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Doi: <https://doi.org/10.15517/psm.v22i1.58896>

Volumen 22, número 1, Art. Cient. Julio-diciembre 2024



Población y Salud en Mesoamérica

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Cómo citar este artículo:

Oviedo, C. and Silva Urrutia, E. (2024). Life expectancy loss by education level and sex: the impact of COVID-19 in the US (2020) and their forecasts. *Revista Población y Salud en Mesoamérica*, 22(1). <https://doi.org/10.15517/psm.v22i1.58896>



ISSN-1659-0201 <http://ccp.ucr.ac.cr/revista/>

Revista electrónica semestral
[Centro Centroamericano de Población](#)
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Life expectancy loss by education level and sex: the impact of COVID-19 in the US (2020) and their forecasts

Pérdida de esperanza de vida por nivel educativo y sexo: El impacto de la COVID-19 en Estados Unidos (2020) y sus pronósticos

Carlos Oviedo¹, Eliud Silva Urrutia²

Abstract: Objective: Stratified life expectancy loss by education levels and sex helps measure particular mortality impacts during a catastrophic event. We propose a statistical approach to estimate them using the US case during the COVID-19 pandemic in 2020. **Method:** First, we estimate life expectancies according to available data, including those years when catastrophic events occur. Second, we use them to calculate a valid multivariate time series VAR(p) model, omitting the respective catastrophic(s) year(s). Through the model, we generate forecasts, which are compared with estimated data, and afterward, the life expectancy losses are quantified as their differences. **Results:** Less than four times the life expectancy losses with low education compared to the high education group. Our projections also indicate that life expectancies with almost all education falls outside the forecast intervals. **Conclusion:** The more educated the population is, the less life expectancy is lost. Women always outlive men within each education stratum. Long-term estimates continue to underscore gender disparities in life expectancy.

Keywords: life expectancy loss; VAR model; multivariate forecasts; education level.

Resumen: Objetivo: La pérdida de esperanza de vida estratificada por niveles educativos y sexo ayuda a medir impactos de mortalidad específicos durante un evento catastrófico. Proponemos un enfoque estadístico para estimarlos en un año. **Método:** Primero, se estiman esperanzas de vida según los datos disponibles, incluyendo aquellos años cuando ocurren eventos catastróficos. Segundo, se usan para calcular un modelo de series temporales multivariadas VAR(p), omitiendo el(los) año(s) catastrófico(s) respectivo(s). A través del modelo, se generan pronósticos, que se comparan con los datos estimados, y luego se cuantifican las pérdidas de esperanza de vida como sus diferencias. **Resultados:** Se aplica nuestra propuesta empleando el caso de Estados Unidos durante la pandemia de COVID-19 en 2020. Se tienen poco más de cuatro veces la pérdida de esperanza de vida con baja educación en contraste con el estrato de alta educación. Las proyecciones indican que las esperanzas de vida con casi todos los niveles de educación caen fuera de los intervalos de pronóstico. **Conclusión:** Cuanto más educada es la población, menos esperanza de vida se pierde. Las mujeres siempre sobreviven más que los hombres dentro de cada estrato educativo. Las estimaciones a largo plazo continúan destacando las disparidades de género en la esperanza de vida.

Palabras clave: pérdida de esperanza de vida; modelo VAR; pronósticos multivariados; nivel educativo.

Received: 22 feb, 2024 | **Corrected:** 16 oct, 2024 | **Accepted:** 25 oct, 2024

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1. Introduction

Demographically speaking, life expectancy is a well-known index that summarizes mortality across time. According to Yusuf et al. (2014), life expectancy can help compare mortality by regions, cities, or countries and the same place over time. A derived index, such as the life expectancy at a given age, has the same properties but is more specific. An extensive revision of the use of life expectancy index and its management is illustrated in Luy et al., 2020.

An interesting point is to analyze life expectancy at a given age (life expectancy, from now on) by education level. According to Raghupathi et al. (2020), there is evidence from 26 OECD countries for 1995–2015 that adults with higher education levels have better health and lifespans than less educated populations. Additionally, this research indicates that obtaining tertiary education is essential in shaping life expectancy. A step ahead is measuring stratified life expectancy losses given a catastrophic event, like the COVID-19 pandemic, in a particular context.

This paper proposes a statistical strategy for measuring stratified life expectancy losses. It is addressed by utilizing available data to estimate the inputs for a multivariate time series VAR(p) model, also used for forecasting. Then, the differences between forecasts and the inputs in the respective years provide life expectancy losses. Given the quality information from the US, we focus on this case through education level and sex, taking into account official data from 2000 to 2020.

Indeed, several previous research papers have highlighted, on the one hand, the positive effects of education on achieved life expectancy and, on the other hand, their losses after the COVID-19 pandemic almost systematically around the globe. However, no one has proposed how to quantify stratified life expectancy losses after any catastrophic event, which we consider to be a contribution.

We acknowledge the limitations of the data. For instance, the definition of high, medium, and low education could have changed over time and among countries. This change may make it difficult to compare data from different periods. That is why it was necessary to standardize the information using the most disaggregated data. We also recognize that applying the present approach could be impossible or too hard, especially in developing countries where the quality of information should be improved.

2. Background

Meara et al. (2008) analysed trends in life expectancy and mortality by education and then estimated which diseases were causing differential mortality trends. Similarly, they studied educational differences in mortality and life expectancy between non-Hispanic blacks and whites between 1980 and 1990 in the US. All advances in life expectancy occurred among the better-educated groups, except for the black group. Only two educational groups were considered: the low level comprised people with 12 years or less of education, while the high level included people with at least 13 years.

The authors calculated life expectancy by education, race, and sex. One outstanding result was that life expectancy increased significantly in the most educated groups, and no significant changes were found for the other group.

In the Norwegian context, changes in life expectancy by education level have been identified between 1961 and 2009. Distinct patterns emerged based on sex, with three educational levels considered: primary, secondary, and tertiary. The results show that life expectancy increased across all education levels, but the gap between those with primary and tertiary education widened. Notably, the gain in life expectancy for individuals with lower education was delayed by ten years compared to those with higher education (Steingrimsdóttir et al., 2012).

Beltrán-Sánchez and Drumond (2013) made estimates of the transition probabilities between disability states, life expectancy, and how years of disability are influenced by age, sex, and education. They focused on Sao Paolo, Brazil, and urban areas of Mexico in 2013. Interpolative Markov chains and longitudinal data are employed to achieve this. So, they point out significant results indicating substantial educational variations in the occurrence and recovery from disability across the countries. Further analysis revealed that older adults in Mexico experienced lengthier periods of disability-free life when compared to their counterparts in São Paulo, regardless of their educational levels. The discussion highlights the prevalence of educational disparities in disability rates in São Paulo and urban areas of Mexico.

One objective of the US regarding health is to improve life expectancy (Kaplan et al., 2014). The authors argue the existence of the most vital relationship between that framework's educational level and life expectancy. They also point out that addressing the health gap linked to lower education could extend life expectancy by as much as ten years. However, they affirm that proof of the positive health outcomes from efforts to enhance educational level is still an outstanding challenge.

The correlation between life expectancy and educational attainment in the Netherlands has been highlighted by Van Baal et al. (2016). They proposed and applied a method for forecasting life expectancy by educational level in populations aged 65 and older. Their findings indicate that life expectancy increases with higher education levels, and the gaps between educational groups are expected to widen over time.

Bilal et al. (2019) examine the differences in life expectancy and how they relate to socioeconomic variables, including education, in six of the biggest Latin American cities. The cities were Buenos Aires, Argentina; Belo Horizonte, Brazil; Santiago, Chile; San José, Costa Rica; Mexico City, Mexico; and Panama City, Panama. By using a Bayesian model to estimate mortality rates, they compute the average life expectancy at birth by sex and sub-city as well as the difference between the ninth and first decile of life expectancy. They found that life expectancy at birth varied significantly with education years for men and women for all the analyzed cities.

A recent study used a decomposition analysis to examine the contribution of changes in educational attainment to the increase in life expectancy in Italy, Denmark, and the US (Luy et al., 2019). The

authors found that, in the US, changes in educational attainment contributed to the rise in life expectancy at birth of 0.7 years. This finding is consistent with other studies that have found that people with higher levels of education tend to live longer than people with lower levels of education. People with higher levels of education are more likely to have access to quality healthcare, adopt healthy behaviors, and have higher incomes, which allow them to live in more favourable conditions.

Employing the three-layer Li and Lee model, among other results, Nusselder et al. (2022) provide forecasts of life expectancies for low, mid, and high education by sex education in the Netherlands. In this paper the authors give evidence of increases in life expectancy between age 35 and 85 for all education groups. Likewise, their results suggest that inequalities in the mortality index between high and low education will be almost equivalent during 2018-2048. Another interesting finding is that the educational inequalities will continue or increase by sex for the three decades projected.

Gómez Ugarte and García Guerrero (2023) addressed a set of estimates of life expectancy and life span for the Mexican population amid a national health system with inequalities. They consider some socioeconomic factors that impact mortality, such as income and education. For the estimates, they study the variables of education level, occupation, and access to social security. Regarding mortality and education, they found that increasing educational levels and health coverage positively impact life expectancy. Likewise, the population without formal education has the worst life expectancy.

3. Resultados

3.1 Model

We have six time series, three education levels by two sexes. So, to represent their behavior, the selected model was the Autoregressive Vector of order p , VAR(p) (for details, see Haslbeck et al., 2021). It can generally be considered an extension in vector terms of the AR(p) univariate models (Box et al., 2015). A significant difference between univariate and multivariate models is that the latter considers the modeling of the eventual relationship across time in the different series contained in the vectors. In this way, we do not want to prove any relative theory to the phenomenon but only consider the underlying data dynamic.

Without loss of generality, let $\{Y_{(t,M)}\}$ and $\{X_{(t,M)}\}$ be two-time series representing high and low educational attainment for men and similarly $\{Y_{(t,W)}\}$ and $\{X_{(t,W)}\}$ for women; these can be modeled simultaneously using a VAR(p) model. It is particularly interesting because the interdependence between the education levels is also implicit in the mentioned model. In this way, a VAR(p) is defined by a system in which the regressors are the lagged values of them, that is

$$\begin{aligned}
 Y_{t,M} &= c_1 + \alpha_{11}Y_{t-1,M} + \alpha_{12}Y_{t-2,M} + \dots + \alpha_{1p}Y_{t-p,M} + \beta_{11}X_{t-1,M} + \beta_{12}X_{t-2,M} + \dots + \\
 &\beta_{1p}X_{t-p,M} + \gamma_{11}Y_{t-1,W} + \gamma_{12}Y_{t-2,W} + \dots + \gamma_{1p}Y_{t-p,W} + \delta_{11}X_{t-1,W} + \delta_{12}X_{t-2,W} + \dots + \\
 &\delta_{1p}X_{t-p,W} + \varepsilon_{1t} \\
 X_{t,M} &= c_2 + \alpha_{21}Y_{t-1,M} + \alpha_{22}Y_{t-2,M} + \dots + \alpha_{2p}Y_{t-p,M} + \beta_{21}X_{t-1,M} + \beta_{22}X_{t-2,M} + \dots + \\
 &\beta_{2p}X_{t-p,M} + \gamma_{21}Y_{t-1,W} + \gamma_{22}Y_{t-2,W} + \dots + \gamma_{2p}Y_{t-p,W} + \delta_{21}X_{t-1,W} + \delta_{22}X_{t-2,W} + \dots + \\
 &\delta_{2p}X_{t-p,W} + \varepsilon_{2t} \\
 Y_{t,W} &= c_3 + \alpha_{31}Y_{t-1,W} + \alpha_{32}Y_{t-2,W} + \dots + \alpha_{3p}Y_{t-p,W} + \beta_{31}X_{t-1,W} + \beta_{32}X_{t-2,W} + \dots + \\
 &\beta_{3p}X_{t-p,W} + \gamma_{31}Y_{t-1,M} + \gamma_{32}Y_{t-2,M} + \dots + \gamma_{3p}Y_{t-p,M} + \delta_{31}X_{t-1,M} + \delta_{32}X_{t-2,M} + \dots + \\
 &\delta_{3p}X_{t-p,M} + \varepsilon_{3t} \\
 X_{t,W} &= c_4 + \alpha_{41}Y_{t-1,W} + \alpha_{42}Y_{t-2,W} + \dots + \alpha_{4p}Y_{t-p,W} + \beta_{41}X_{t-1,W} + \beta_{42}X_{t-2,W} \dots + \\
 &\beta_{4p}X_{t-p,W} + \gamma_{41}Y_{t-1,M} + \gamma_{42}Y_{t-2,M} + \dots + \gamma_{4p}Y_{t-p,M} + \delta_{41}X_{t-1,M} + \delta_{42}X_{t-2,M} \dots + \\
 &\delta_{4p}X_{t-p,M} + \varepsilon_{4t}
 \end{aligned}$$

where ε_{it} and ε_{jt} are assumed to be random errors, and the errors can be correlated, that is, $\text{cov}(\varepsilon_{it}, \varepsilon_{jt}) \neq 0$ for $i \neq j$ and $i, j = 1, 2, 3, 4$. Additionally, estimating parameters of a VAR(p) model requires selecting the number of lags p , which can be defined from different criteria, such as the Akaike Information Criterion (AIC), the Schwartz Information Criterion (SIC), or the Hannan–Quinn Information Criterion. From them, the last was the considered here.

The residual assumptions for the VAR(p) model are normality and white noise patterns. For the estimates in this paper, normality is verified through the Jarque-Bera test, while the white noise is by the Portmanteau (Q) test. The significance of the estimated coefficients and the functional relationship for every equation are verified by the t and F tests, respectively. The inverted roots of the characteristic polynomial linked to the estimated model should be less than one for assessing a stationary model. Both R^2 and adjusted R^2 are also informative regarding the model's convenience.

The selected estimated VAR(p) model helps to forecast in given years. They are compared with estimates corresponding to the chosen years, then life expectancy losses are calculated. Likewise, we assume that the impact of the catastrophic event could be transitory for any year. In this way, the strength of educational and health institutions of the corresponding country makes life expectancies recover their original projected path. We consider this assumption too realistic in developed countries but not developing ones. That is why we illustrate its application for the US case during the COVID-19 pandemic.

3.2 Data

The case to present our approach was the US in 2020. So, the demographic data utilized in this study were taken from harmonized databases. Population data were retrieved from the Integrated Public Use Microdata Series (IPUMS, 2023). Meanwhile, mortality statistics were extracted from the US Centers for Disease Control and Prevention (CDC) reports. The sample selection focused on individuals aged 30, considering that most have completed their formal education by this age in the US, as Luy et al. (2019) suggested.

Regarding education levels, we consider low, medium, and high. So, the following definitions, suggested by Luy et al. (2019), were adopted: "low education includes the International Standard Classification of Education (ISCED-97) levels 0 (pre-primary education), 1 (primary education or first stage of basic education), and 2 (lower secondary education); medium education includes the levels of 3 (upper secondary education) and 4 (post-secondary non-tertiary education); high education refers to the levels of 5 (first stage of tertiary education) and 6 (second stage of tertiary education)".

Life expectancies were calculated for each subgroup from 2000 to the most recent available year, 2020. This temporal approach facilitated a thorough assessment of trends over two decades, offering a whole perspective on life expectancy dynamics within different population strata. To ensure that our estimates were accurate, we successfully reproduced those from 1990 and 2010, as elaborated by Luy et al. (2019). Afterward, we forecast from 2019 to 2030 and estimate the excess mortality in 2020.

4. Results

Before discussing the results, it is worth saying that in 2015, life expectancy in the US declined for the first time in more than twenty years (Harper et al. 2021). Life expectancy fell from 78.9 years in 2014 to 78.6 years in 2017, then recovered in 2018 to 78.7. The female population typically has had a greater life expectancy than males, with a systematic gap of roughly six years. The COVID-19 pandemic harmed life expectancy in the US. In fact, Silva et al. (2023) estimated that between 2020 and 2022, US life expectancy dropped by 3.08 years during the COVID-19 pandemic.

The following table summarizes life expectancy estimates across the different groups by education level and sex from 2000 to 2020. Additionally, the index was also calculated for the total population. Over time, there has been a general upward trend in life expectancy across all educational levels. It is appreciated that the index experiments fell in 2020, independent of educational attainment.

Table 1. Life expectancy at age 30 and over by education level and sex, the US
2000-2020

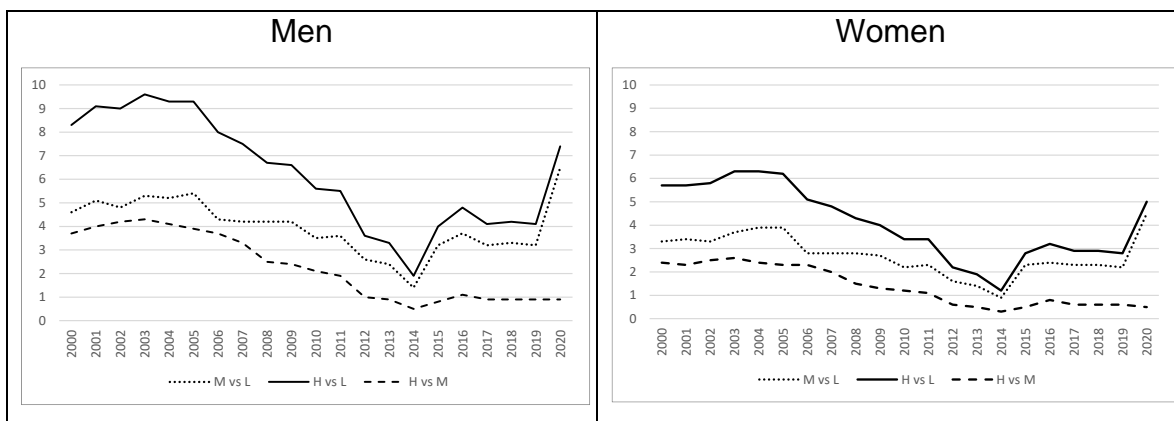
| Year | Men | | | Women | | | Total | | |
|------|------|------|------|-------|------|------|-------|------|------|
| | L | M | H | L | M | H | L | M | H |
| 2000 | 41.3 | 45.9 | 49.6 | 47.1 | 50.4 | 52.8 | 44.1 | 48.3 | 51.0 |
| 2001 | 40.6 | 45.7 | 49.7 | 46.7 | 50.1 | 52.4 | 43.6 | 48.1 | 50.8 |
| 2002 | 40.9 | 45.7 | 49.9 | 46.8 | 50.1 | 52.6 | 43.7 | 48.1 | 51.1 |
| 2003 | 42.3 | 47.6 | 51.9 | 47.9 | 51.6 | 54.2 | 45.0 | 49.8 | 52.9 |
| 2004 | 43.9 | 49.1 | 53.2 | 49.0 | 52.9 | 55.3 | 46.4 | 51.2 | 54.1 |
| 2005 | 45.5 | 50.9 | 54.8 | 50.3 | 54.2 | 56.5 | 47.9 | 52.7 | 55.5 |
| 2006 | 48.3 | 52.6 | 56.3 | 52.8 | 55.6 | 57.9 | 50.5 | 54.3 | 57.0 |
| 2007 | 49.3 | 53.5 | 56.8 | 53.5 | 56.3 | 58.3 | 51.4 | 55.1 | 57.5 |
| 2008 | 51.3 | 55.5 | 58.0 | 54.9 | 57.7 | 59.2 | 53.1 | 56.8 | 58.6 |
| 2009 | 51.5 | 55.7 | 58.1 | 55.2 | 57.9 | 59.2 | 53.4 | 56.9 | 58.6 |
| 2010 | 53.2 | 56.7 | 58.8 | 56.3 | 58.5 | 59.7 | 54.8 | 57.7 | 59.2 |
| 2011 | 53.7 | 57.3 | 59.2 | 56.6 | 58.9 | 60.0 | 55.2 | 58.2 | 59.5 |
| 2012 | 56.6 | 59.2 | 60.2 | 58.6 | 60.2 | 60.8 | 57.6 | 59.7 | 60.5 |
| 2013 | 57.1 | 59.5 | 60.4 | 59.0 | 60.4 | 60.9 | 58.1 | 60.0 | 60.6 |
| 2014 | 59.2 | 60.6 | 61.1 | 60.3 | 61.2 | 61.5 | 59.8 | 60.9 | 61.3 |
| 2015 | 57.9 | 61.1 | 61.9 | 59.5 | 61.8 | 62.3 | 58.8 | 61.5 | 62.1 |
| 2016 | 56.9 | 60.6 | 61.7 | 59.1 | 61.5 | 62.3 | 58.1 | 61.1 | 62.0 |
| 2017 | 57.8 | 61.0 | 61.9 | 59.4 | 61.7 | 62.3 | 58.7 | 61.4 | 62.1 |
| 2018 | 57.7 | 61.0 | 61.9 | 59.4 | 61.7 | 62.3 | 58.6 | 61.4 | 62.1 |
| 2019 | 57.8 | 61.0 | 61.9 | 59.5 | 61.7 | 62.3 | 58.7 | 61.4 | 62.1 |
| 2020 | 53.4 | 59.9 | 60.8 | 56.4 | 60.9 | 61.4 | 54.8 | 60.5 | 61.1 |

Note: L-Low, M-Medium, H-High.

Notably, men with low education experienced an increase from 41.3 years in 2000 to 53.4 years in 2020. Meanwhile, those women in the same education level and period passed from 47.1 to 56.4, respectively. As expected, given the impact of the COVID-19 pandemic, all cases have outstanding falls in 2020. As a matter of fact, the most dramatic loss of life expectancies was recorded for a population with low education. In that case, the index is equivalent to those from 2011, a setback of close to nine years.

The gender gap in life expectancy is evident, with women consistently outliving men across all educational levels. However, it is notorious that the gap appears to fluctuate over time, with periods of convergence and divergence around 2014 and 2020, respectively. Educational attainment plays a crucial role in life expectancy, with individuals in the high education category consistently experiencing longer life expectancies than their counterparts in the low and medium education categories. Comparing education levels by pairs, the women's gaps have less variability, as noted in the following figure.

Figure 1. Gaps between different educational attainments by sex, the US 2000-2020



Note: L-Low, M-Medium, H-High.

The life expectancies by sex taken from Table 1 are the inputs to estimate a VAR(p) model. The estimated model provides a comprehensive insight into the relationship between endogenous time series named as (sex-education level): Men-Low (ML_t), Men-Medium (MM_t), Men-High (MH_t), Women-Low (WL_t), Women-Medium (WM_t), and Women-High (WH_t). Likewise, a constant was also included in the multivariate model. It is clear that the statistical significance of these variables is a critical point in understanding their impact on life expectancy estimates and forecasts. According to the Hannan–Quinn Information Criterion, the appropriate model order was $p = 1$.

The model performance is suitable, as evidenced by the high adjusted R-squared values, suggesting a strong ability to explain the variability in life expectancy across the chosen variables. Additionally, the F-statistic and associated p-values underscore the overall significance of the models in capturing the observed data. Further validation of the models includes an examination of the characteristic polynomial inverted roots, all of which are less than 1, indicating their stability. Normality and white noise tests on residuals support the adequacy of the model. The coefficients reveal (see Table 2) that ML_t , MM_t , WL_t , and WM_t are statistically explained by MH_{t-1} , all of them with a positive impact. Conversely, MH_t and WH_t display significance through ML_{t-1} , MH_{t-1} , with a positive impact, and WL_{t-1} , with a negative impact. The constants also resulted significant for the WH_t equation.

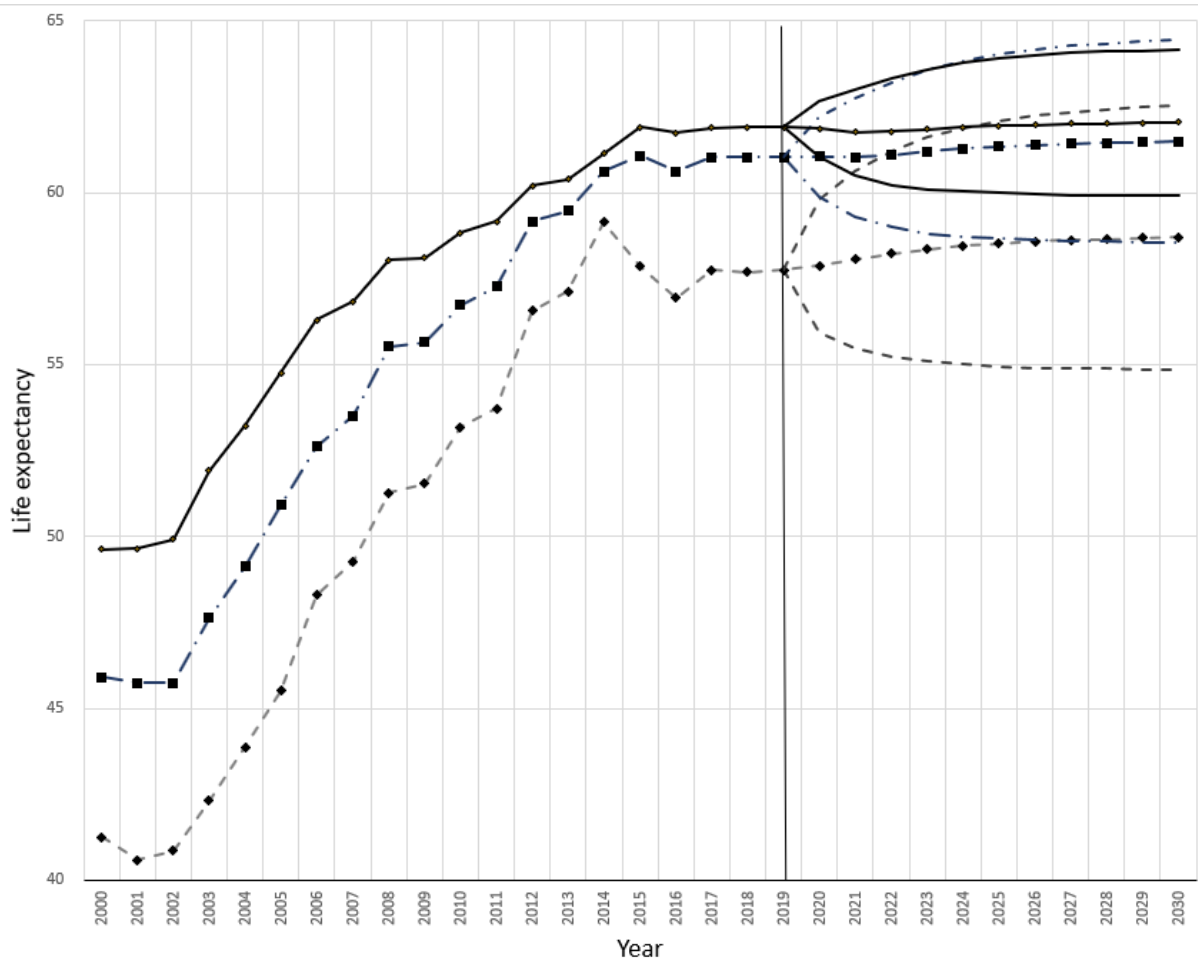
Table 2. Estimates of the VAR(1) model.

| Variables | ML _t | Sig. | MM _t | Sig. | MH _t | Sig. | WL _t | Sig. | WM _t | Sig. | WH _t | Sig. |
|-------------------------|-----------------|------|-----------------|------|-----------------|------|-----------------|------|-----------------|------|-----------------|------|
| ML _{t-1} | 0.25 | | 1.75 | | 1.99 | * | 0.10 | | 1.40 | | 1.68 | * |
| MM _{t-1} | 0.13 | | -2.82 | * | -3.13 | | -0.28 | | -2.21 | | -2.27 | |
| MH _{t-1} | 3.63 | . | 3.15 | * | 3.45 | *** | 2.66 | . | 2.50 | ** | 2.57 | *** |
| WL _{t-1} | 0.60 | | -1.58 | | -2.08 | * | 0.62 | | -1.30 | | -1.80 | * |
| WM _{t-1} | -1.11 | | 3.05 | | 2.77 | | -0.63 | | 2.09 | | 1.71 | |
| WH _{t-1} | -2.92 | | -2.63 | | -2.32 | | -1.84 | | -1.74 | | -1.32 | |
| Const | 26.12 | | 6.13 | | 19.52 | | 22.75 | | 17.87 | | 27.98 | . |
| RSE | 1.05 | | 0.62 | | 0.41 | | 0.75 | | 0.41 | | 0.31 | |
| R ² | 0.98 | | 0.99 | | 0.99 | | 0.98 | | 0.99 | | 0.99 | |
| Adjusted R ² | 0.97 | | 0.98 | | 0.97 | | 0.98 | | 0.98 | | 0.91 | |
| F | 108.60 | | 227.30 | | 304.80 | | 118.80 | | 292.30 | | 648.80 | |
| p-value | 0.00 | | 0.00 | | 0.00 | | 0.00 | | 0.00 | | 0.00 | |

Sig. codes: 0 "****", 0.001 "***", 0.01 "**", and 0.05 ".".

The valid model is consequently used to make forecasts. So, life expectancy projections by education levels and sex from 2020 to 2030 were estimated. These projections and forecasting intervals at 95% offer valuable insights into the potential trajectories of life expectancy. Over the years, these values experienced an upward trajectory for both men and women. The projections showcase a continuation of these trends, with expected increases in life expectancy across education strata.

Figure 2. Men's life expectancy forecasting at age 30 and over by education.



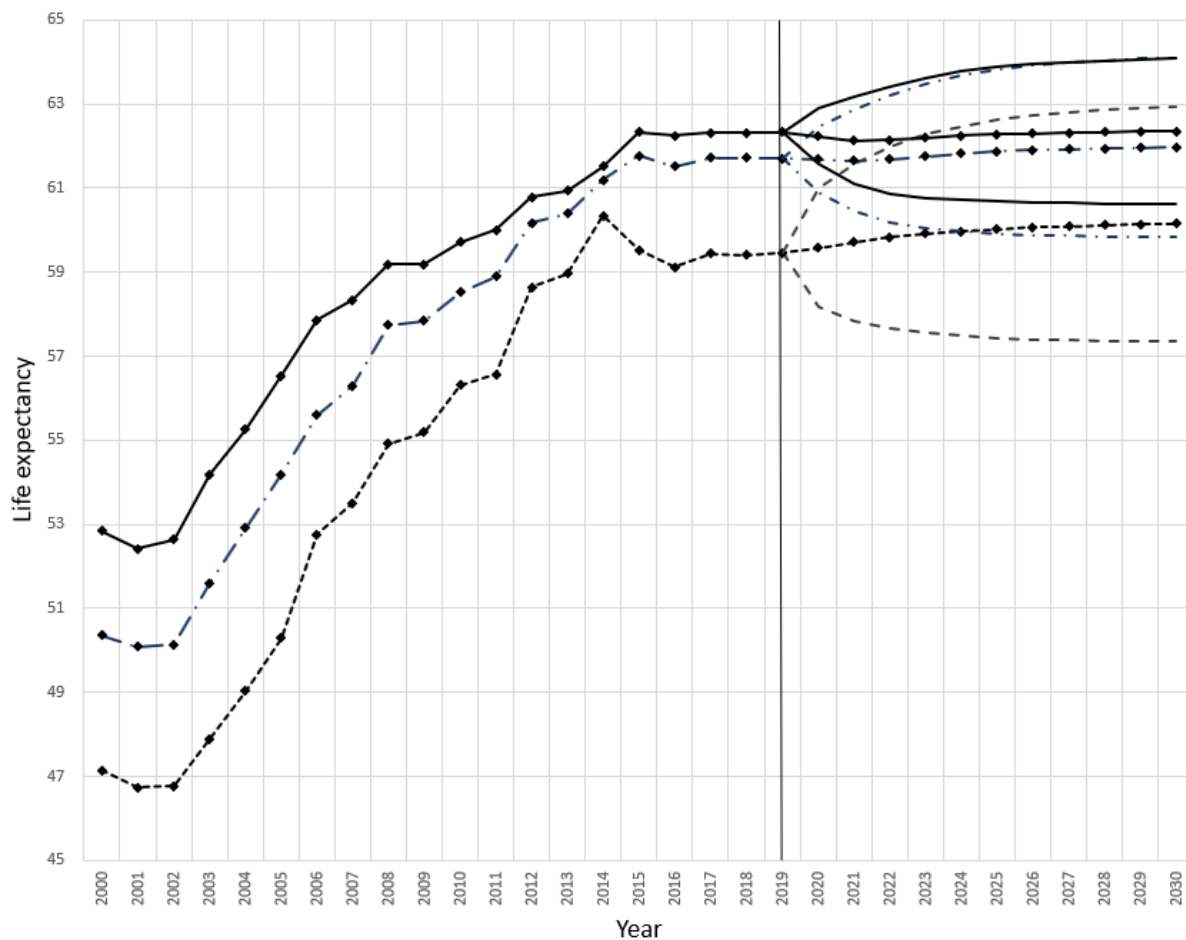
Solid line: Men-High (MH), Dotted line: Men-Low (ML), and Dot and dash line: Men-Medium (MM).

The life expectancy projections 2020 exhibit a distinctive pattern within the different educational levels. Notably, the calculated life expectancies fall below the forecasted lower limits for individuals with low education (ML) and high education (MH). This discrepancy underscores a significant impact, primarily attributed to the unprecedented challenges posed by the COVID-19 pandemic, which led to a substantial increase in mortality rates and subsequently influenced life expectancy. Conversely, for those with medium education (MM), the estimate is slightly above the calculated lower limit.

In 2020, the forecasted life expectancy for men with low education was 57.9 years, reflecting a considerable improvement compared to 2000. The forecasting interval, ranging from 55.9 to 59.8, emphasizes the inherent uncertainty in long-term projections. As we move into the subsequent years, the predictions anticipate further gains in life expectancy. The forecasted values and the minimum and maximum bounds of the forecasting intervals provide a nuanced understanding of the potential range of outcomes.

The women’s projections for 2020 to 2030 present a nuanced scenario. In 2020, the forecasted life expectancy for women with low education (WL) was 59.6 years, slightly below the observed value of 61.7 years in 2019. This discrepancy could be attributed to the impact of the COVID-19 pandemic, increasing mortality rates that affected women with lower educational attainment disproportionately. The projected values for 2020 fall within the forecasting interval. Women with medium education (WM) exhibit a more optimistic outlook, with the forecasted values consistently surpassing the observed and lower limit values. It suggests a more resilient pattern, potentially indicating a more effective response to external shocks such as the pandemic within this education stratum.

Figure 3. Women’s life expectancy forecasting at age 30 and over by education.



Solid line: Women-High (WH), Dotted line: Women-Low (ML), and Dot and dash line: Women-Medium (MM).

The impact of the COVID-19 pandemic on life expectancy projections appears to have manifested differently for men and women. Despite facing a global health crisis in 2020, women across education levels exhibited a certain resilience, with projections either meeting or slightly surpassing observed life expectancies. It suggests that women, particularly those with medium education (WM), may have demonstrated a capacity to navigate the challenges posed by the pandemic more adeptly than their male counterparts. Women with medium education (WM) consistently exhibited projections above observed and lower limit values, indicating protection conferred by educational achievements. In the following Table, there is a summary of life expectancy loss by sex in 2020.

Table 3. Life expectancy loss by sex, the US 2020.

| Year | Men | | | Women | | |
|-------------------------|--------------|----------------|--------------|--------------|----------------|--------------|
| | Low | Medium | High | Low | Medium | High |
| Estimate | 53.4 | 59.9 | 60.8 | 56.4 | 60.9 | 61.4 |
| Forecasts | 57.9 | 61.1 | 61.9 | 59.6 | 61.7 | 62.2 |
| 95% prediction interval | (55.9, 59.8) | (59.88, 62.22) | (61.1, 62.7) | (58.2, 61.0) | (60.91, 62.47) | (61.6, 62.9) |
| Life expectancy loss | 4.5 | 1.2 | 1.1 | 3.2 | 0.8 | 0.8 |

It is outstanding how little more than four times the life expectancy losses in men with low education is in contrast with the high education group, suggesting a disproportionate impact. A similar proportion also occurs for females under similar comparison. Our projections also indicate that the respective life expectancy of men and women with almost all education falls outside the forecast intervals. Long-term estimates continue to underscore gender disparities in life expectancy. Despite overall improvements, women consistently outlive men across all education strata. This persistent difference emphasizes the need for tailored health interventions for gender-specific health determinants and vulnerabilities.

5. Discussion

As mentioned earlier, the VAR(p) model is not commonly used in demographic studies. In fact, none of the reviewed papers addressing this issue have employed it. A key advantage of the VAR(p) model is that it accounts for inter-temporal relationships, enabling more accurate joint estimates and forecasts. In this case, life expectancy in the US is examined, considering variations across academic levels and sexes. Additionally, the 95% confidence intervals for the forecasts help identify significant differences between the point estimates of each time series, while also providing likely ranges for

future estimates. In brief, our life expectancy estimates based on educational levels are in line with previous research: the more educated population has a higher life expectancy, particularly women. This result is also maintained in the forecasts.

The VAR(1) model estimates reveal several significant relationships between life expectancy by education level for both men and women. The key variable MH_{t-1} (Men-High) consistently shows a strong positive influence across various life expectancy outcomes. Specifically, the lagged value of MH has a positive and significant effect of 3.63 on ML_t (Men-Low), 3.45 on MH_t (Men-High), 2.66 on WL_t (Women-Low, weak significance), 2.50 on WM_t (Women-Medium), and 2.57 on WH_t (Women-High). This indicates that an increase in life expectancy for men with higher education levels leads to an increase in life expectancy across other groups, including men with lower education levels and women across all educational levels. For instance, a one-year increase in life expectancy for Men-High leads to a 3.63-year increase for Men-Low and similar increases for the other groups.

In contrast, MM_{t-1} (Men-Medium) has a negative and significant effect of -2.82 on MM_t (Men-Medium), suggesting that an increase in the life expectancy of men with medium education in the previous period leads to a 2.82-year decrease in the life expectancy for the same group. This points to a self-correcting mechanism in life expectancy for men with medium education, where gains in one period are followed by declines in the next. Additionally, WL_{t-1} (Women-Low) has a negative and significant effect of -1.80 on WH_t (Women-High), suggesting that an increase in life expectancy for women with lower education reduces the life expectancy of women with higher education levels by 1.80 years, highlighting an inverse relationship between these two groups.

Ceteris paribus, these findings suggest that, holding other factors constant, improvements in life expectancy for highly educated men (MH_{t-1}) have a broad, positive effect across all groups. On the other hand, fluctuations in the life expectancy of men with medium education (MM_{t-1}) show a self-regulating behavior, while the negative relationship between life expectancy for women with low education (WL_{t-1}) and women with high education (WH_t) suggests a more complex interaction between these groups. The results emphasize the critical role of education in determining life expectancy, with men in higher education levels driving positive outcomes across the population, while other dynamics between education levels introduce variability in life expectancy trends.

6. Conclusions

The analysis provides crucial insights into historical trends, the impact of the COVID-19 pandemic in 2020 through forecasting intervals, and the subsequent projections. Over 2000-2019, life expectancies for both men and women exhibited a positive trajectory, reflecting overall improvements. Women consistently demonstrated higher life expectancies than men for all

education levels, emphasizing sex disparities. Although generalized, the COVID-19 impact in 2020 has notorious differences in educational attainment and sex.

The resilience of women overall exhibited a more resilient outlook, showing more adaptability to catastrophic events such as pandemics. This resilience suggests that educational attainment may play a role in mitigating the impact of external shocks on life expectancy. A comparative analysis revealed nuanced differences between men and women, emphasizing the importance of considering gender-specific factors in understanding life expectancy figures.

In brief, individuals with higher educational attainment consistently exhibit higher life expectancies in the US in all years. Likewise, the more educated the population is, the less life expectancy is lost. Women always outlive men within each education stratum. So, assessing the impact of educational level and gender on life expectancy in the U.S. during the COVID-19 pandemic provides valuable insights. As the future line of research, it could be interesting to decompose these estimates and forecasts by race, migration patterns, and other social variables. To do that, we consider that a critical point in making the required estimates and the model is having good-quality information.

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