FORECASTING MORTALITY BY CAUSES OF DEATHS COHERENT TO THE ALL-CAUSE MORTALITY FORECASTS USING THE LEE-CARTER MODEL

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Abstract

Mortality forecasts by cause of deaths are a powerful source of information on the future burden of disease. Despite its relevance, mortality forecasting by cause of death is still a major methodological challenge for demographers. Several studies have been developed to project mortality by a specific cause of death. Although these studies are of great relevance, they usually do not incorporate the demographic trends for total mortality in the analysis. The objective of this study is to propose an alternative method to forecast mortality by cause that is coherent to the total mortality forecasts, based on the Lee-Carter model. The model was tested using Brazilian mortality database for four causes of death: cardiovascular disease, neoplasms, external causes, and other diseases. Despite some limitations of the data, this alternative proved to be satisfactory for the mortality forecast by cause of deaths in the Brazilian context.

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1. INTRODUCTION

1.1. OBJECTIVES

The objective of this study is to propose a methodological alternative to forecast mortality by cause of death that is coherent to the all-causes mortality projection, based on the Lee-Carter model. We apply the proposed method to the Brazilian contexts focusing on four major causes of deaths (cardiovascular diseases, neoplasms, external causes, and other causes) and forecast age-specific mortality rates by causes from 2011 to 2030. We also compare our proposed methods to cause of death forecasts for each cause independently.

1.2. BACKGROUND

The continued decline in mortality means extended life expectancy, which is seen as a positive change of individuals and substantial social fulfillment, however leads to concerns about its implications for public and private old-age spending (Tuljapurkar & Boe, 1998; Lee and Mason, 2011; Lee, 2015). Since in populations with fertility already at very low levels, such changes in mortality might become responsible not only for increasing the proportion of older people, but also for the time spent by the elderly (Caselli & Vallin, 1990; Lee & Carter, 1992; Lee and Zhou, 2017; Murphy, 2017; Preston and Stokes, 2012). These changes tend to have a relevant impact on social security and private pension systems and private and public health programs, which have based their reserves on more modest life expectancies (Haberman & Russolilo, 2005; Lee, 2015).

Within this context, the role of mortality projection becomes increasingly relevant, as one of the leading reasons of these changes in the age structure of the world population is the continued decline in mortality (Caselli & Vallin, 1990; Wilmoth, 1998; 2000). This decline can be well predicted for considerably longer periods, given the regular age pattern of demographic variables and the often slow rate of change (Lee, 1998; Lee & Tuljapurkar, 2000). Still, demographic projections involve a great deal of uncertainty, which makes it necessary for any demographic projection methodology to provide indications of their associated uncertainty, the most important source of which is the future of vital rates (Lee, 1998). This is even more important in the case of causes of deaths. As mortality declined, there was an important change in the age pattern of mortality - to older ages - and the profile of causes of deaths - from infections to chronic and degenerative diseases (Horiuchi, 1999). Thus, there is more uncertainty involved in the future trends of mortality by cause. Also, changes in technology, behavior and social and economic dynamics might also impact how cause of death varies in the future, especially in the short-run.

Mortality forecasts by cause of deaths are a powerful source of information on the future burden of disease and therefore they are essential information for assessing population health as well as for economic, social and public health policies (Girosi and King 2003; Booth and Tickle, 2008). Despite its relevance, the mortality forecasting by cause is challenging. Several studies have been developed to project mortality by a specific cause of death (Boyle et. al., 2001; Moller et. al., 2002; Winkler et al., 2015; Gonzalez-Gonzalez et al., 2017; Chail et. al., 2019; Kjærgaard et. al., 2019; Reis, 2019) or a group of causes (Mathers and Loncar, 2006; Foreman et. al., 2017; Yun and Son, 2016). Although these studies are of great relevance, they usually do not incorporate the demographic trends for total mortality in the analysis. That is, the sum of the projected mortality rates for all causes is not always equal to the projected overall mortality.

In recent years, some studies have been developed with the purpose of projecting mortality by cause of death that guarantee the consistent with the forecast for total mortality. Park, Choi and Kim (2006) proposed a method to forecast the number of cause-age specific deaths through a two random process model. First, they used a time series model to forecast the total number of deaths and after that, they classified the deaths by cause using predicted probabilities from a multinomial regression.

Li et. al. (2019) proposed a method to reconcile the cause-specific projections to the total projections based on the Lee-Carter model. The method is based on the reconciliation approach to forecast multilevel time series. In other words, it is based on a bottom-up method that forecast the lower levels and then they add up to the upper levels. They argue that the method improves forecasts when compared to independent forecasts of causes of death. In general, previous approaches used multinomial logistic regressions or forecast each cause independently, but the final results were in general more pessimistic than the overall trend (Li, et.al, 2019; Wilmoth, 1995).

The Lee-Carter model (Lee and Carter, 1992) is the most widely used method for projecting total mortality in demography (Lee, 2019). However, the projection of cause mortality using the Lee-Carter model is not only inconsistent with total mortality but also tends to overestimate future mortality (Wilmoth, 1995; Li, 2019). In this context, our goal is to propose an adjustment to the original Lee-Carter model that allows the forecasting mortality by cause of death, which is simple, easy interpreted, is based on a few parameters and is strongly anchored in formal demographic relations.

1.3. WHY FORECAST AGE-SPECIFIC MORTALITY BY CAUSE IN BRAZIL?

Brazil is a good case to test the model. In Brazil, there was a considerable improvement in life expectancy at birth between 1990 and 2015, but with great heterogeneity between states (Borges, 2017). Reducing mortality from diarrhea, respiratory infections, and other infectious diseases, for example, has contributed to increased life expectancy in most states in the North and Northeast. Reducing mortality from cardiovascular disease, on the other hand, was the largest factor in the South, Southeast, and Midwest. In addition, deaths from external causes, especially among men, had a negative impact on life expectancy in several Brazilian states (Borges, 2017). França, et,al. (2017) examines levels and trends in cause mortality in Brazil and states between 1990 and 2015 using data from the Disease Burden project. Results indicate a generalized reduction in mortality levels occurred in Brazil from 1990 to 2015, particularly among children under 5 years. Significant changes in mortality rates occurred between communicable, maternal, neonatal, and nutritional disorders. The mortality profile has shifted to older ages with increasing noncommunicable diseases as well as premature deaths from violence.

Over the last century, Brazil has been experiencing a rapid epidemiological transition process, with the reduction of mortality from infectious diseases and increased mortality from chronic degenerative diseases. This process has accelerated over the last thirty years since the country has been going through several reforms in the health system, with the expansion of access to health services and the strengthening of primary health care. Although Brazil has presented several advances in the epidemiological transition process, it presents serious difficulties in complementing some phases of this transition, maintaining high rates of violent deaths and high rates of mortality by chronic diseases. In the context of important modifications, it is necessary to bring new evidence about the epidemiological profile of the Brazilian population in the future, which is fundamental for the planning of public health and social security policies (França, et.al, 2017; Borges, 2017).

2. METHODS

2.1. DATABASE

Mortality rates by year, cause, sex and age group were constructed from mortality information available in the Ministry of Health Mortality Information System (www.datasus.gov.br). The data is public available and considered of good quality. Causes of deaths are registered under ICD-IX from 1979 to 1995 and ICD-X from 1996 on. Population by age and sex are available from the National Statistical Office. We forecast age-specific mortality rates from 2011 to 2030 using data from 1979 to 2010. The period in which observed data overlaps with forecasted data (2011 to 2017) is used to analyze the prediction capacity of the model. Four causes of death are analyzed in this paper: Circulatory System Diseases, neoplasms, external causes, and other causes. These first three

causes, besides representing a significant share of deaths in Brazil, present very different temporal trajectories, thus contributing to the validation of the model.

2.2. LEE-CARTER MODEL

The Lee-Carter model (1992) uses only historical mortality trends for forecasting mortality, based on the estimation of three parameters: average mortality age profile, deviatitions by age from the average given the overall mortality level and the overall mortality level. The method combines a demographic model with time-series method of forecasting. The method involves modeling two-factors age and time - and uses matrix decomposition to extract a single time-varying index of the level of mortality, which is then forecast using a time-series model. The Lee-Carter method has been considered a powerful method to forecast mortality due to its precision and simple way to model age distribution of death rates (Lee and Carter, 1992; Lee and Miller, 2001; Lee, 2019; Booth, et.al, 2006).

In the original Lee-Carter model proposition, the age-specific mortality rates can be written as:

$$ln\left(m_{x,t}^{G}\right) = \alpha_x^G + \beta_x^G * K_t^G + \varepsilon_{x,t}^G \quad (1)$$

Where $ln\left(m_{x,t}^{G}\right)$ is the logarithm of mortality rate by all causes in age x at time t; α_x^G is the average age profile of mortality rates by all causes, that is, captures differences in rates by age,; β_x^G is the variation by age from the average level given the overall mortality level, that is, it captures differences in relative rates of change by age,; K_t^G is the overall mortality level at time t and captures changes in overall mortality.

2.3. LEE-CARTER MODEL FOR MORTALITY BY CAUSE OF DEATHS

Like Park, Choi and Kim (2006) and Li et. al. (2019), the methodological procedure proposed in this study to forecast mortality by causes of death is performed in two steps. First, the overall mortality level at time t (K_t^G) is calculated for the total mortality. After that, the age-specific mortality rates for each cause of death is associated with the overall mortality level. Thus, using the same idea from original Lee-Carter model, the age-specific mortality rates for a cause z can be written as:

$$ln\left(m_{x,t}^{z}\right) = \alpha_x^z + \delta_x^z * K_t^G + \varepsilon_{x,t}^z \quad (2)$$

Where $ln\left(m_{x,t}^{z}\right)$ is the logarithm of mortality rate by cause z in age x at time t; α_x^z is the age standard of mortality rate by cause c; δ_x^z is a term that relates the mortality rate by cause z in age x at time t with the overall mortality level at time t K_t^G.

The parameter δ_x^z can not be calculated via Lee-Carter as it takes into account both the effect of age deviation and the effect of cause deviation from the overall mortality level K_t^G. However, δ_x^z can be estimated using a linear regression model:

$$\hat{\beta}_x^G = \frac{cov(ln(m_{x,t}^G), K_t^G)}{var(K_t^G)} \text{ for total mortality} \quad (3)$$

$$\hat{\delta}_x^z = \frac{cov(ln(m_{x,t}^z), K_t^G)}{var(K_t^G)} \text{ for mortality by cause z} \quad (4)$$

$$\hat{\delta}_x^z = \hat{\beta}_x^G \frac{cov(ln(m_{x,t}^z), K_t^G)}{cov(ln(m_{x,t}^G), K_t^G)} \quad (5)$$

Intuitively, the parameter δ_x^z represents the deviation of mortality by cause z at age x from the overall mortality level. This parameter can be decomposed in two parts: the first term ($\hat{\beta}_x^G$) measures how much mortality at age x all-cause varies in relation to the overall level of mortality. The second term, the covariance ratio, represents the contribution of cause of death z to the deviation of mortality at age x from the average mortality level at period t.

3. PRELIMINARY RESULTS

This section presents the preliminary results of the mortality forecasts by cause Brazil between 1979 and 2030. Although the model estimates the mortality rates for all age groups simultaneously, we will present in this summary only the results for the individuals between 30 and 34 years old. This group was chosen because its results allow us to analyze the potentialities and limitations of the proposed model more clearly.

3.1. HISTORICAL TRENDS OF MORTALITY IN BRAZIL

Figures 1 and 2 show the mortality rates, in the natural logarithm scale, for females and males aged 30 to 34 years in Brazil, from 1979 to 2017. Cardiovascular diseases are one of the most important causes of death in Brazil. However, mortality from these causes has been falling substantially for both females and males over time. Neoplasms are also a major cause of death for both sexes, but they remain constant over time. External causes, in turn, are the leading cause of death among men aged 30 to 34 years, increasing over time. Among women, external causes have a minor impact on

mortality, falling over time. Finally, the other causes of death also fall progressively for men and women over time.

3.2. FORECASTING TOTAL MORTALITY

Figures 3, 4, and 5 (APPENDIX) show the parameter estimates of the all-causes mortality Lee-Carter model estimates. The parameter ax represents the age pattern of mortality between 1979 and 2010. In general, the observed age pattern is very close to that found by other studies applied to both Brazil and other regions, with high mortality in the early ages. Parameter ax also highlights male over-mortality among adult men. The parameter bx represents the temporal variation in relation to the age pattern of mortality between 1979 and 2010. Like the parameter ax, the parameter bx also presents behavior very similar to that found in other studies, with the most substantial gains in mortality occurring at young ages. Finally, the Kt represents the overall mortality level observed in Brazil from 1979 to 2010 and the projected overall mortality level from 2011 to 2030. In general, there is a reduction in the overall mortality level for the entire observed period, and by consequence, for the entire projection period. However, as the historical series of mortality for Brazil is small and with many disturbances over time, the confidence interval is relatively large.

3.3. ADJUSTING THE MODEL FOR CAUSE OF DEATHS

After estimating the parameters for the total mortality forecast, a linear regression model is estimated to obtain the δ_x^z for each cause of deaths. Figures 6 and 7 (APPENDIX) show the observed value of the natural logarithm of the mortality rate by cause, age group, sex and time and the predicted value of this same rate by the model. The red line is the symmetry line (45 degrees) in which the predicted value is equal to the adjusted value. All values are around the symmetry line with low dispersion, indicating that the estimated model is satisfactory for predicting mortality rates because of this. It is also important to note that the adjusted R^2 for all linear regression models is 99%. Figures 8 and 9 show the estimated δ_x^z values for each cause of death and their confidence interval.

3.4. FORECASTING MORTALITY BY CAUSE

Figures 10 and 11 (APPENDIX) show the mortality forecasting by cause of deaths for females and males, respectively. The light gray area represents the confidence interval (95%) of the estimated mortality due. The dark gray area represents the combination between this interval and the projected confidence interval of the Kt parameter (95%).

For females, the fit of the forecasting models for cardiovascular diseases and other causes is good and the predicted values are relatively close to the values observed for the period 2010-2017. However, the fit of the forecasting models for neoplasms and external causes is not good. since the mortality rates for these causes among females aged 30 and 34 do not show a clear temporal trend. For males, the fit of the forecasting models for cardiovascular diseases, external causes and other causes is good, but the adjustment for neoplasms is not satisfactory. It is important to note that the overall mortality has declined over time, while the mortality by external causes has been increasing for males between 30 and 34 years old. Therefore, the model fits well even when mortality from a cause does not follow the same trend as overall mortality.

4. DISCUSSION

Forecasting mortality by cause of death is still a major methodological challenge for demographers, but rapid changes in causes of death and its implication to the future of life expectancy increase the demand for this type of analysis (Caselli, Vallin and Marsilli, 2019). This study advances the literature on the subject by proposing a methodological alternative to the Lee-Carter model that allows the projection of mortality because it is consistent with the projection of total mortality. This alternative proved to be satisfactory for the mortality forecast by cause of deaths in the Brazilian context. However, it is important to note that this study is a work in progress, and some adjustments need to be made to improve the accuracy and quality of the estimates.

5. FUTURE DEVELOPMENTS

This summary presents the preliminary results of a work in progress. In the coming months some adjustments will be made: (a) estimation of the coherent Lee-Carter model for females and males; (b) Kt projection by other time series models that better fit in Brazilian database and thus reduce the uncertainty in projections; (c) estimation of the theta parameter by other regression methods in order to improve the estimates when mortality rates do not show a clear temporal trend; (d) creation of a digital directory with the mortality rates estimates for all age groups; (e) repository with R code for the proposed method; (f) improve the discussion and literature review.

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APPENDIX

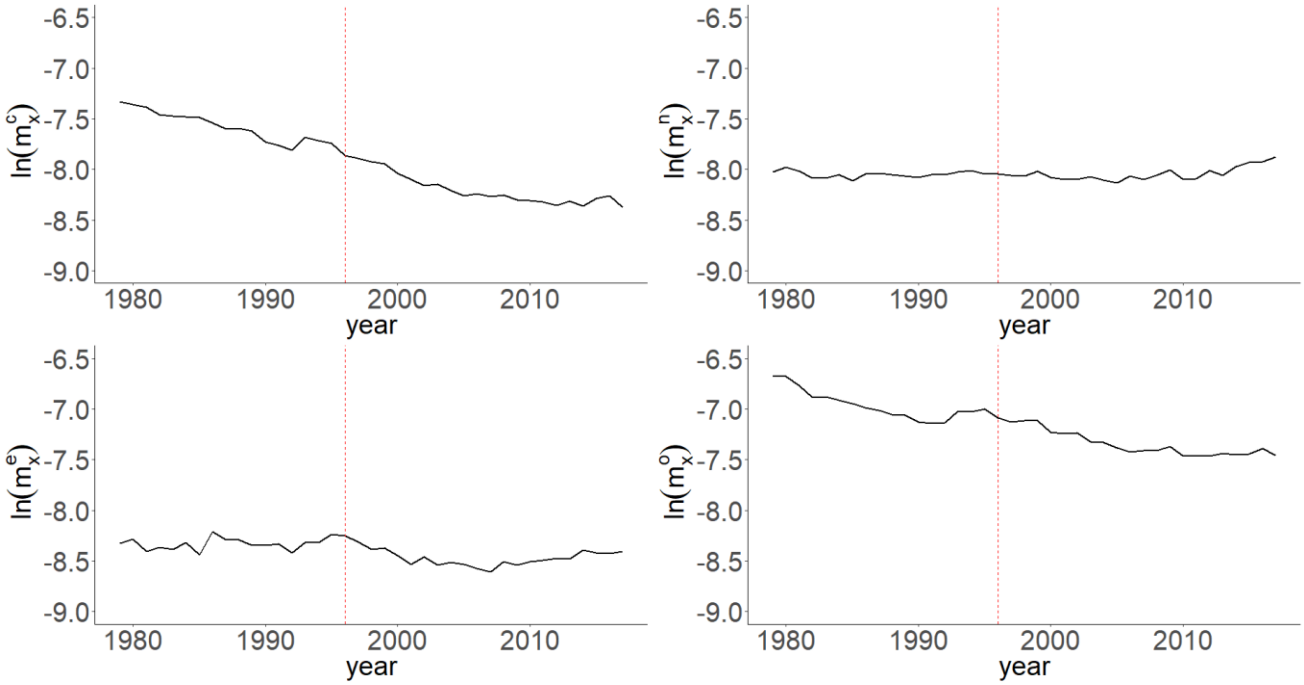

Figure 1 – Mortality rates by cause of death, in natural logarithm scale – Brazil, females, 35-39 years old (1979 – 2010)

Source: Mortality Information System of Brazilian Ministry of Health. Note: m_x^c is mortality rate by cardiovascular diseases, m_x^n is mortality rate by neoplasms, m_x^e is mortality rate by external causes and m_x^o is mortality rate by other causes.

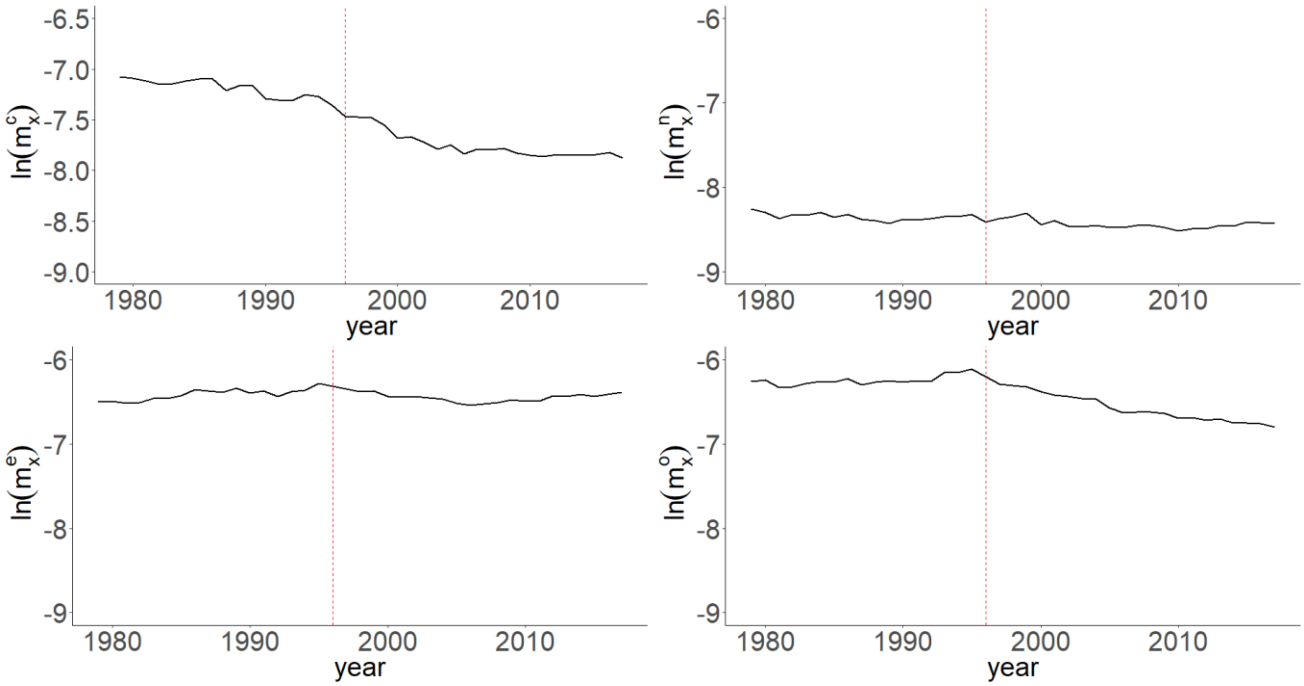

Figure 2 - Mortality rates by cause of death, in natural logarithm scale – Brazil, males, 35-39 years old (1979 – 2010)
Source: Mortality Information System of Brazilian Ministry of Health. Note: m_x^c is mortality rate by cardiovascular diseases, m_x^n is mortality rate by neoplasms, m_x^e is mortality rate by external causes and m_x^o is mortality rate by other causes.

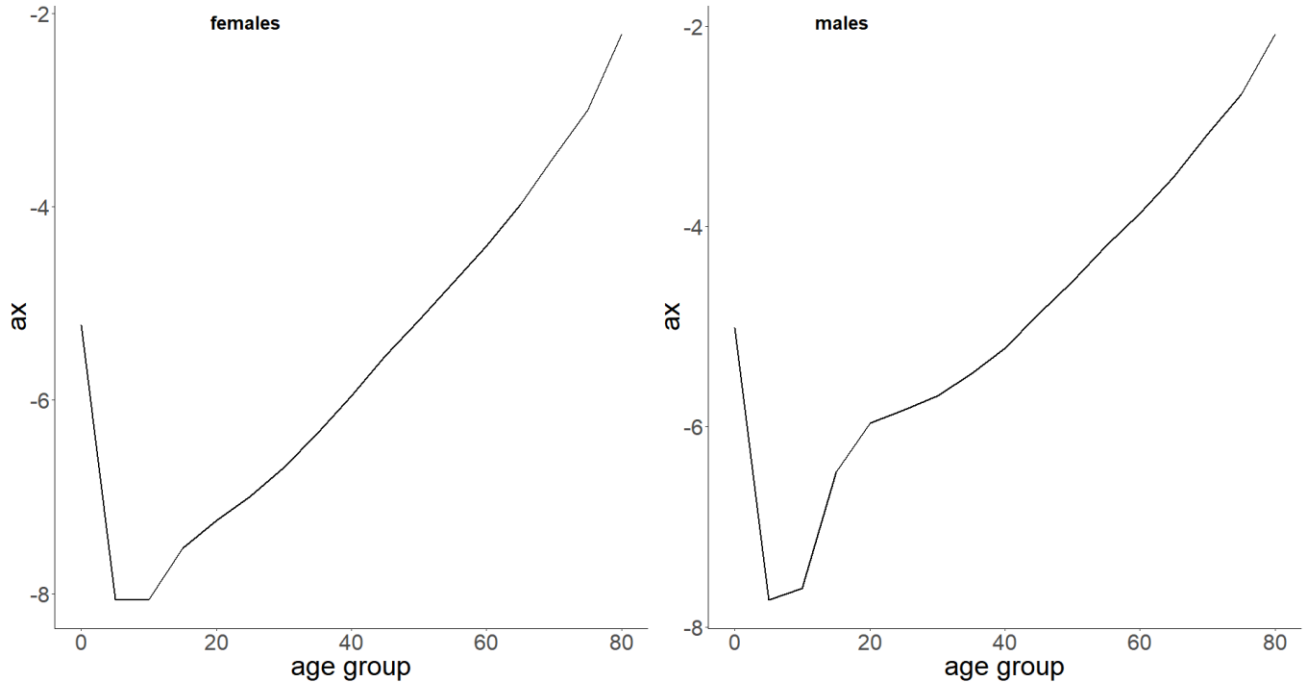

Figure 3 - Parameter α_x – Brazil, females and males (1979 – 2010)
Source: Mortality Information System of Brazilian Ministry of Health.

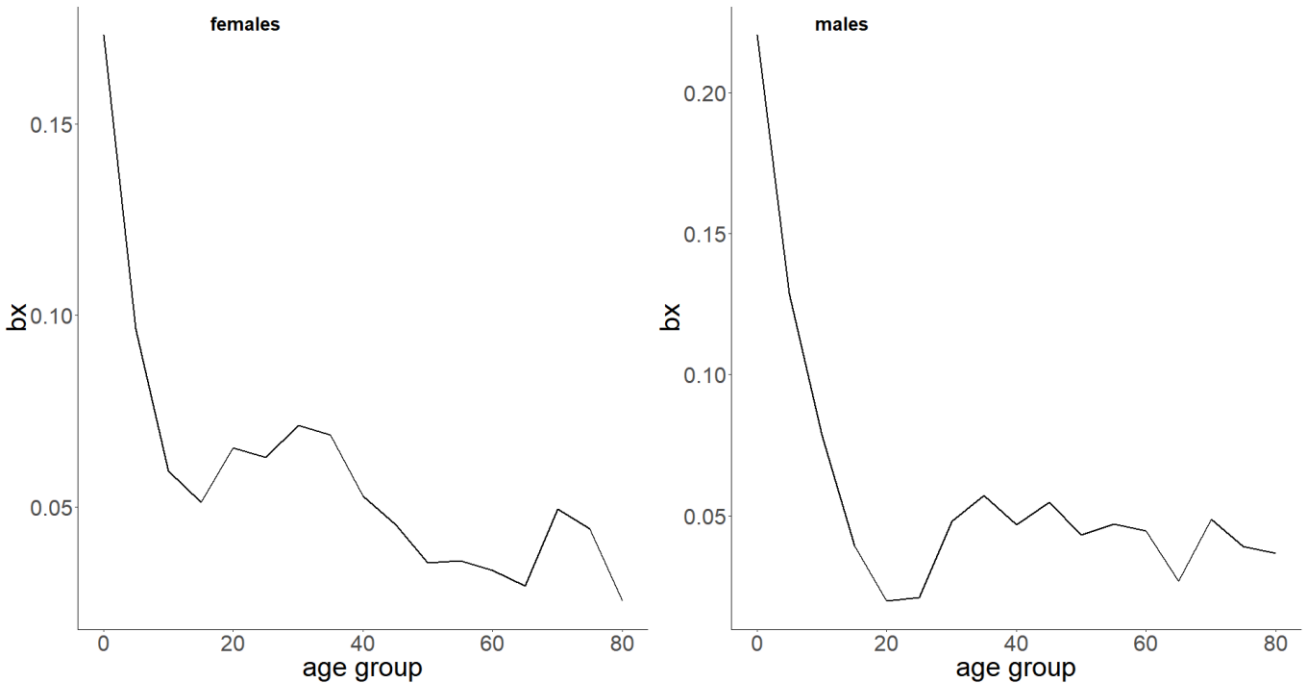

Figure 4 - Parameter β_x – Brazil, females and males (1979 – 2010)
Source: Mortality Information System of Brazilian Ministry of Health.

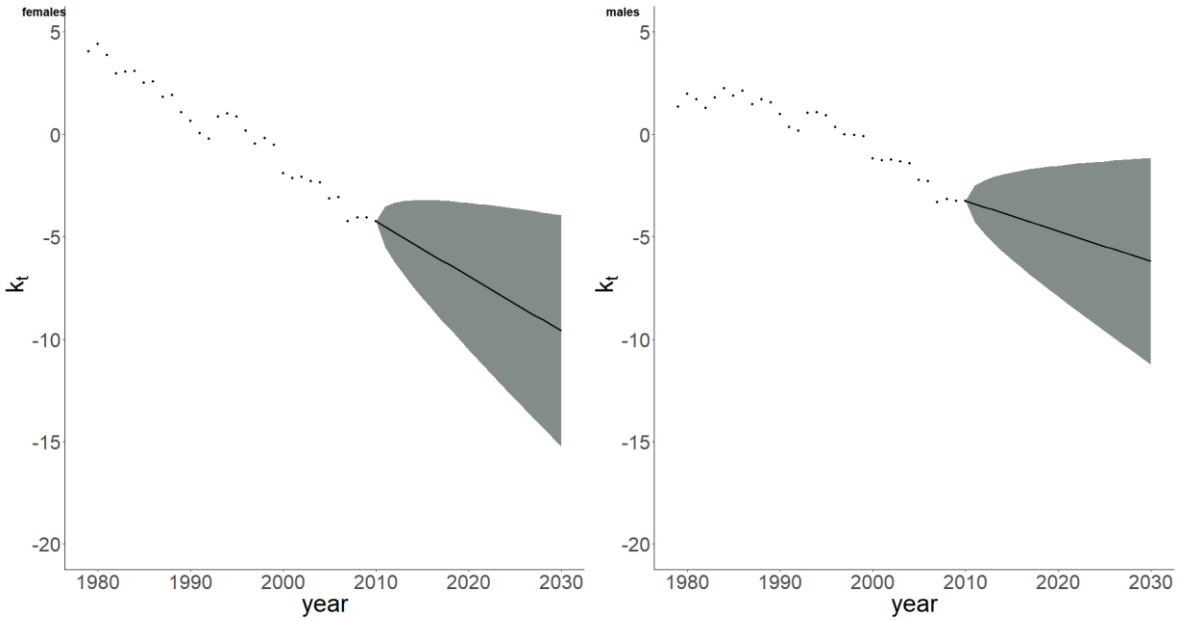

Figure 5 - Parameter K_T – Brazil, females and males - estimated and forecasted with a 95% confidence interval (1979 – 2030)
Source: Mortality Information System of Brazilian Ministry of Health.

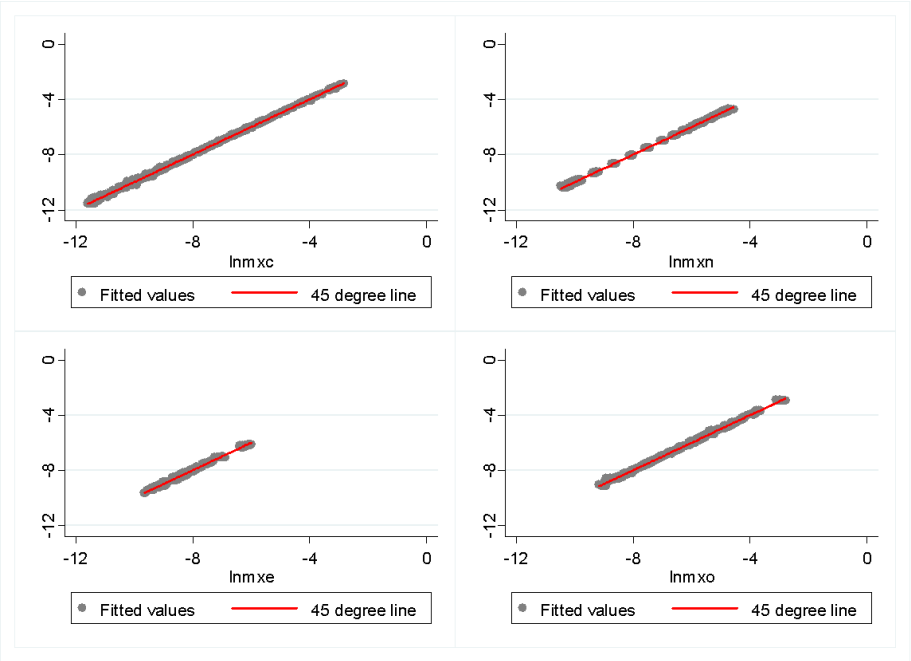

Figure 6 - Comparing the observed values with the fitted values of the regression model by cause of death – Brazil, females (1979-2010)

Source: Mortality Information System of Brazilian Ministry of Health. Note: m_x^c is mortality rate by cardiovascular diseases, m_x^b is mortality rate by neoplasms, m_x^e is mortality rate by external causes and m_x^o is mortality rate by other causes.

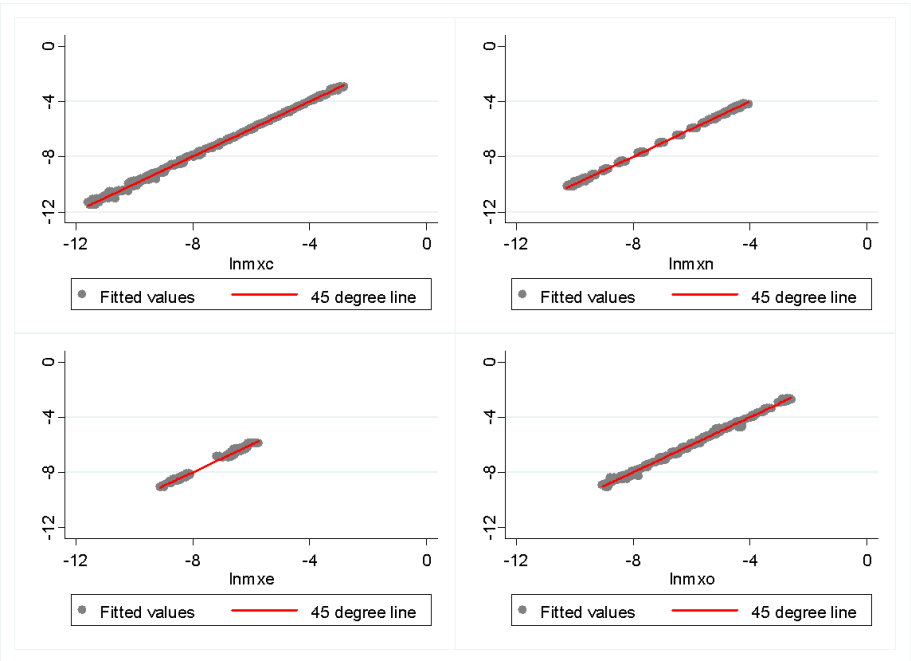

Figure 7 - Comparing the observed values with the fitted values of the regression model by cause of death – Brazil, males (1979-2010)

Source: Mortality Information System of Brazilian Ministry of Health. Note: m_x^c is mortality rate by cardiovascular diseases, m_x^b is mortality rate by neoplasms, m_x^e is mortality rate by external causes and m_x^o is mortality rate by other causes.

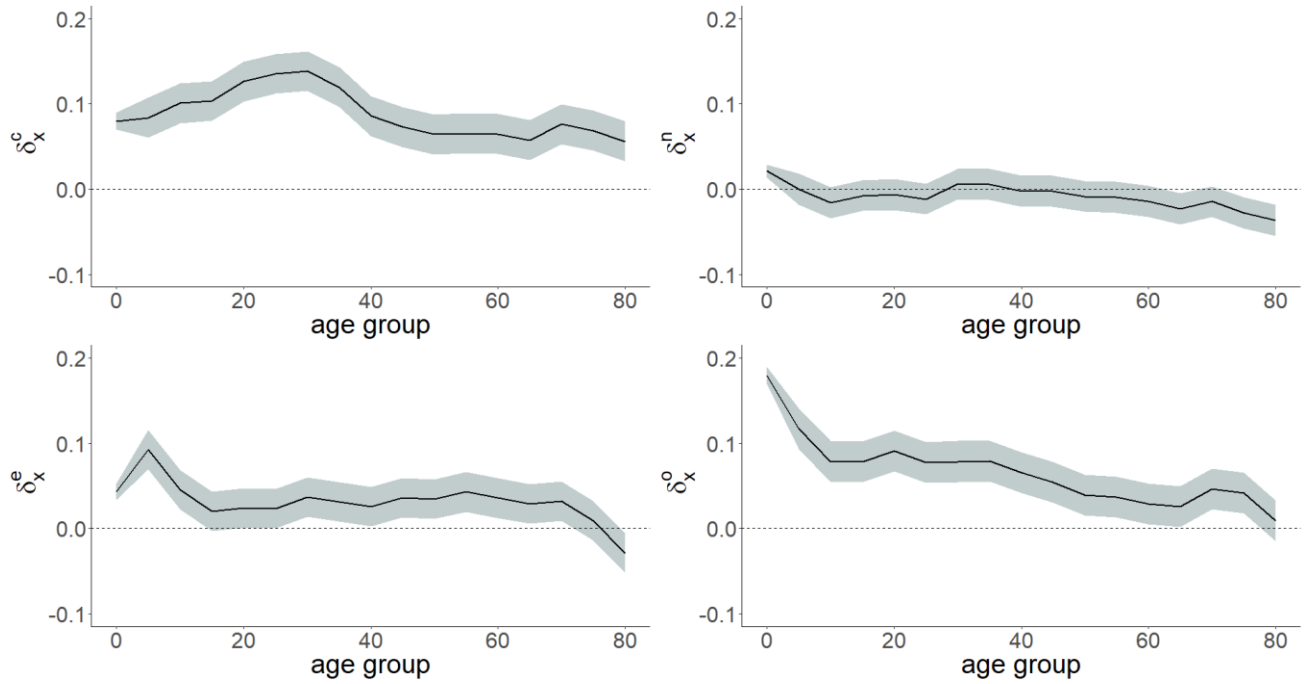

Figure 8 - Predicted parameter δ_x^z by cause of death with 95% confidence interval – Brazil, females (1979 – 2010)
Source: Mortality Information System of Brazilian Ministry of Health. Note: *c* represents cardiovascular diseases, *n* represents neoplasms, *e* represents external causes and *o* represents for other causes.

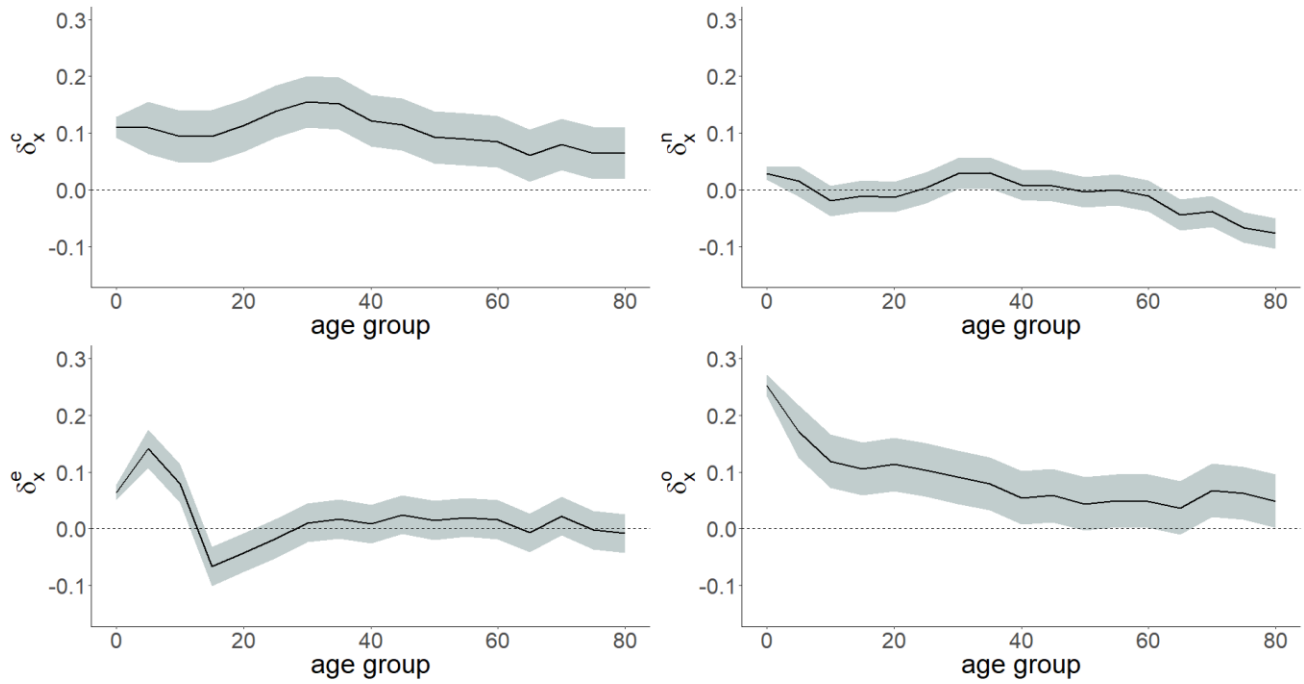

Figure 9 - Predicted parameter δ_x^z by cause of death with 95% confidence interval – Brazil, males (1979 – 2010)
Source: Mortality Information System of Brazilian Ministry of Health. Note: *c* represents cardiovascular diseases, *n* represents neoplasms, *e* represents external causes and *o* represents for other causes.

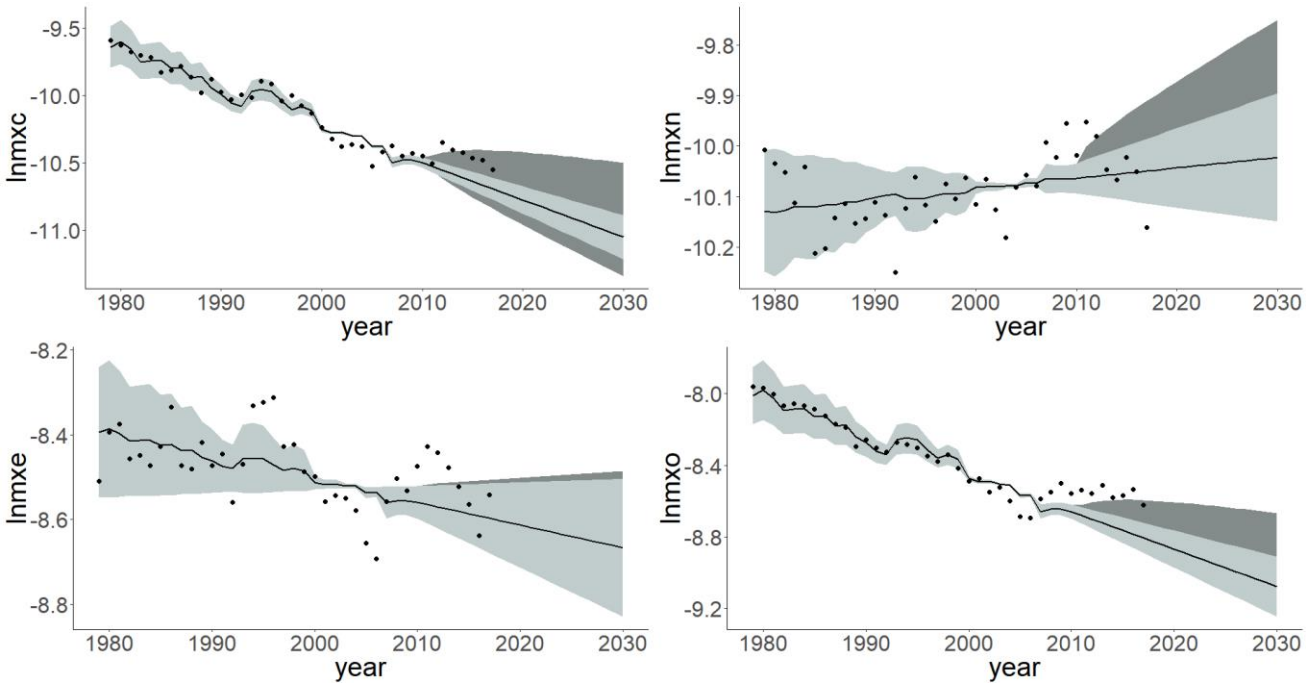

Figure 10 - Mortality rates by cause of death, in natural logarithm scale, with a 95% confidence interval – Brazil, females, 35-39 years old (1979 – 2030)

Source: Mortality Information System of Brazilian Ministry of Health. Note: m_x^c is mortality rate by cardiovascular diseases, m_x^b is mortality rate by neoplasms, m_x^e is mortality rate by external causes and m_x^o is mortality rate by other causes. The light gray area represents the confidence interval (95%) of the estimated mortality due. The dark gray area represents the combination between this interval and the projected confidence interval of the Kt parameter (95%).

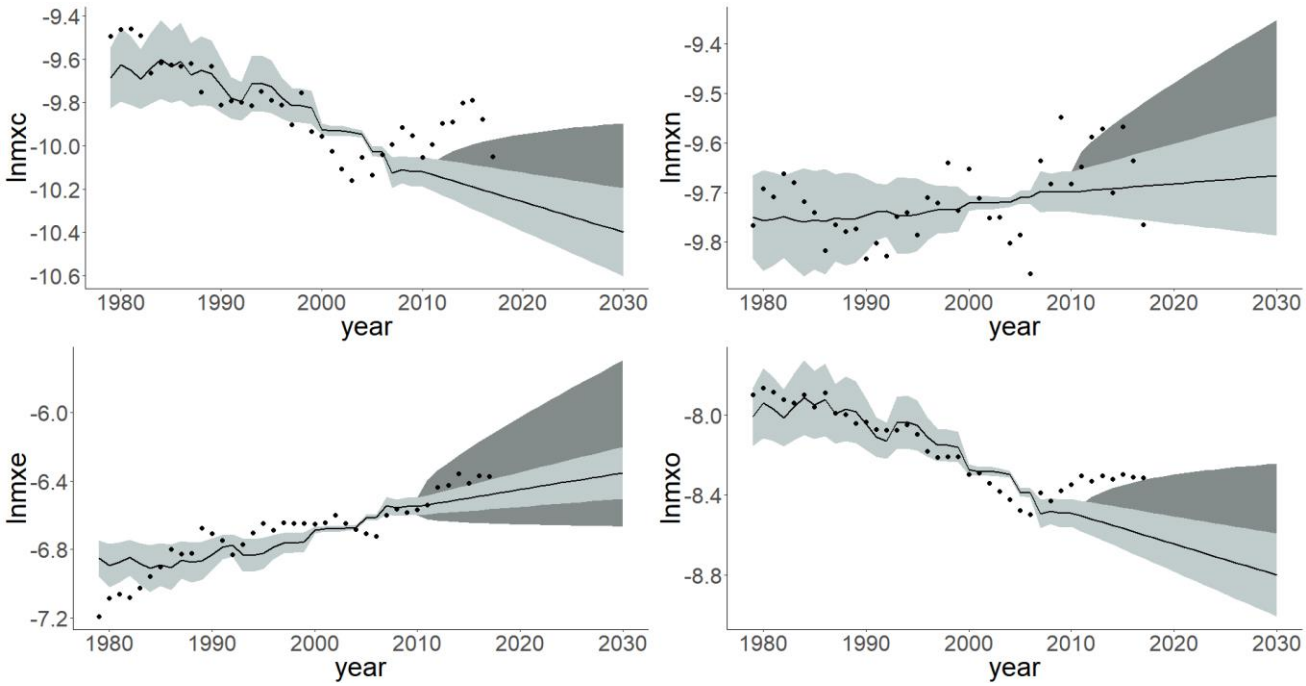

Figure 11 - Mortality rates by cause of death, in natural logarithm scale, with a 95% confidence interval – Brazil, males, 35-39 years old (1979 – 2030)

Source: Mortality Information System of Brazilian Ministry of Health. Note: m_x^c is mortality rate by cardiovascular diseases, m_x^b is mortality rate by neoplasms, m_x^e is mortality rate by external causes and m_x^o is mortality rate by other causes. The light gray area represents the confidence interval (95%) of the estimated mortality due. The dark gray area represents the combination between this interval and the projected confidence interval of the Kt parameter (95%).