Regime Switching in U.S. Mortality Trends: Evidence and Underlying Drivers

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Outline

Motivation

A Multi-Driver Regime-Switching Model

Concluding Remarks

Why Working-Age Mortality Trends Matter

Working-age mortality trends:
A leading indicator of social well-being.

- Mortality in working-age adults reflects **population health** and **economic resilience.**
- Persistent improvements were expected

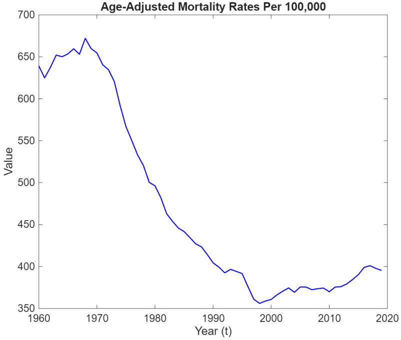
Why Working-Age Mortality Trends Matter

Working-age mortality trends:
A leading indicator of social well-being.

- Mortality in working-age adults reflects **population health** and **economic resilience.**
- Persistent improvements were expected
  - until the pattern changed.

A Century of Progress . . . Until 2000

Data: U.S. Total Population, Ages 25 to 64, Years 1960 to 2019



Observation

- Prior to 2000:
  Rapid improvements.
- 2000 to 2010:
  Slowing/flattening of improvement.
- Post 2010:
  From stagnation to deterioration.

The progress is disrupted.

The Puzzle

Expectation

Continuous improvement driven by medical advances, prevention, and socioeconomic gains.

Reality (2000-Current)

A plateau/slowdown or even deterioration in working-age mortality after 2000.

Why did the progress stall?

Recent Studies Point to “Deaths of Despair”

Selected references:

- Case & Deaton (2015)
  A marked increase in the U.S. all-cause mortality over 1999-2013, due to increasing death rates from drug and alcohol poisonings, and suicide.

- National Academies of Sciences, Engineering, and Medicine (2021)
  The increase in U.S. working age mortality that began in the 1990s for several specific causes of death (e.g., drug-and alcohol-related causes and suicide) is a major driver of the recent decline in life expectancy

- Ho & Hendi (2018)
  Declines in life expectancy in the U.S. during 2014-16 were more concentrated at younger ages (0-65 years), and drug overdose and other external causes of death played important roles in driving these declines.

- Many more: Ruhm (2018); Masters et al. (2018), . . .

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Recent Studies Point to "Deaths of Despair"

- "Death of Despair"
  - **Drug overdose**
  - **Alcohol-related mortality**
  - **Suicide**
- These causes expanded notably after the beginning of the 21st century and align with the timing of the slowdown.
- In recent years, several involution-like dynamics have emerged among high-income economies (U.S., Europe, etc.), which may further worsen the situation.

What is Missing?

- A **systematic modeling framework** that quantifies the shift in working-age mortality, linked to these risk factors.
- **Regime changes** (normal vs high-risk periods) are not explicitly captured in many models.
- Need to assess the **collective effect** of drug, alcohol, and suicide on the trend break.

Our Research Goal

- To develop a new model that explicitly captures **regime shifts** linked to *drug, alcohol, and suicide*; and
- To quantify the **collective impact** on working-age mortality over the past few decades.

So, How Do We Model This Shift?

Inputs	**Selection**	**Structure**
Mortality Data + Exogenous factors (socioeconomic, behavioral, . . .)	Backward Stepwise-AIC (retain strongest predictors)	Regime switching on drug/alcohol/suicide

A Multi-Driver Regime-Switching Model

Model Development Process

Notations

- Let us use $D_{x,t}$ and $E_{x,t}$ to denote the death counts and exposures for age x in year t, respectively.
- The raw central death rates $m_{x,t}$ is calculated by
$$m_{x,t} = \frac{D_{x,t}}{E_{x,t}}.$$
for $x = 1, \ldots, X$ and $t = 1, \ldots, T$.
- The (log) mortality improvement rates $y_{x,t}$ is defined by
$$y_{x,t} = \log\left(\frac{m_{x,t}}{m_{x,t-1}}\right) = \log(m_{x,t}) - \log(m_{x,t-1}) \qquad (1)$$
- Note: $y_{x,t} < 0$ refers to the case that mortality improves for individuals age x from year $t-1$ to year t, while $y_{x,t} > 0$ refers to the case of mortality deterioration.

The Model Development Process

- The proposed model is based on the Lee-Carter model, which models the log mortality rate via the following equation

$$\ln(m_{x,t}) = a_x + b_x k_t + e_{x,t}$$

where
  - a_x: the level of mortality at age x
  - b_x: the sensitivity of mortality at age x to changes in k_t
  - k_t: the dynamic of log mortality in year t
  - $e_{x,t}$: the error term

The Model Development Process

- We extend Lee-Carter model to include exogenous risk factors,

$$\ln(m_{x,t}) = a_x + b_x k_t + \sum_{i=1}^{K} \delta_x^{(i)} Z_t^{(i)} + e_{x,t}$$

  where
  - K: the number of exogenous variable in the model
  - $Z_t^{(i)}$: the i-th exogenous variable in year t
  - $\delta_x^{(i)}$: the sensitivity of changes in $Z_t^{(i)}$ at age x.
- Backward step-AIC method is used for risk factor selection.

The Multi-Driver Regime-Switching Model

- The multi-driver regime-switching model incorporates the regime-switching feature into the targeted risk factors

$$\ln(m_{x,t}) = a_x + b_x k_t + \sum_{i=1}^{K} \delta_x^{(i,r)} Z_t^{(i)} + e_{x,t}$$

where $r = 1, 2$, representing the two regimes. We let $\delta_x^{(i,1)} = \delta_x^{(i,2)}$ when a risk factor only carries one regime.

- The transition matrix is a 2-by-2 matrix

$$P = \begin{pmatrix} p_{11} & p_{12} \\ p_{21} & p_{22} \end{pmatrix}$$

where p_{ij} represents the transition probability that current regime is regime i and the next regime is regime j.

A Multi-Driver Regime-Switching Model

Parameter Estimation

Parameter Estimation

Potential Issue

- Potential issue: A large amount of parameters
  - A dataset that covers ages 25 to 64 ($X = 40$), years 1960 to 2019 ($T = 60$), and 11 risk factors ($K = 11$).
  - The number of parameters can be as large as 580 even for the non-regime-switching version.
- Methods to reduce the number of parameters:
  - The estimation is based on mortality improvement rates.
  - k_t follows a random walk with drift.
  - Third degree polynomial functions are used to govern the age-specific parameters
- The number of parameters reduces to around 50 in the above example.

Parameter Estimation

Based on Mortality Improvement Rates

- In differencing form, we have

$$y_{x,t} = \ln(m_{x,t}) - \ln(m_{x,t-1}) = b_x(k_t - k_{t-1}) + \sum_{i=1}^{K} \delta_x^{(i,r)} \left(Z_t^{(i)} - Z_{t-1}^{(i)} \right)$$

which simplifies to

$$y_{x,t} = b_x(d + \eta_t) + \sum_{i=1}^{K} \delta_x^{(i,r)} \left(Z_t^{(i)} - Z_{t-1}^{(i)} \right)$$

under the assumption that k_t follows a random walk,

$$k_t = d + k_{t-1} + \eta_t, \quad \text{where} \quad \eta_t \sim N(0, \sigma_k^2)$$

Parameter Estimation

Third Degree Polynomial for Age-Specific Parameters

- Furthermore, we assume that all age-specific variables (i.e., b_x and $\delta_x^{(i,r)}$) are governed by third-degree polynomial functions.
- For example,

$$b_x = \beta_0 + \beta_1 x + \beta_2 x^2 + \beta_3 x^3$$

- Under this assumption, the jagged patterns of the estimated age-specific variables are addressed, and the number of parameters is reduced dramatically at the expense of a slightly lower likelihood value.

Parameter Estimation

Likelihood Function

- Let $\vec{y}_t = (y_{1,t}, \ldots, y_{X,t})'$ and ρ_t denotes the regime in year t.
- The likelihood function can be expressed as the product of conditional density

  $$\mathcal{L}(\vec{\theta}) = f(\vec{y}_2|\vec{\theta}) \times f(\vec{y}_3|\vec{y}_2, \vec{\theta}) \times \cdots \times f(\vec{y}_T|\vec{y}_2, \vec{y}_3, \ldots, \vec{y}_{T-1}, \vec{\theta}),$$

  where

  $$f(\vec{y}_t|\vec{y}_2, \ldots, \vec{y}_{t-1}, \vec{\theta}) = \sum_{i=1}^{2}\sum_{j=1}^{2} f(\rho_{t-1} = i, \rho_t = j, \vec{y}_t|\vec{y}_2, \ldots, \vec{y}_{t-1}, \vec{\theta})$$

- We follow the procedure introduced in Hardy (2001) to compute $f(\rho_{t-1} = i, \rho_t = j, \vec{y}_t|\vec{y}_2, \ldots, \vec{y}_{t-1}, \vec{\theta})$ recursively.

Numerical Illustration

Numerical Illustration
Data

- Mortality data: U.S. total population for ages 25 to 64, years 1960 to 2019
- Eleven exogenous risk factors from years 1960 to 2019 covering various categories:
  - Category 1: Climate and Environmental
  - Category 2: Behavioral and Lifestyle
  - Category 3: Socioeconomic and Macroeconomic

Numerical Illustration

Exogenous Risk Factors

Category 1: Climate and Environmental	RF1	Cold Extreme
	RF2	Heat Extreme
	RF3	Pollutants (PM10)
	RF4	Pollutants (Nitrogen Oxides (NOx))
Category 2: Behavioral and Lifestyle	RF5	Drug Overdose (opioid and fentanyl)
	RF6	Suicide rate
	RF7	Alcohol consumption
	RF8	Heart disease mortality rate
Category 3: Socioeconomic and Macroeconomic	RF9	GDP growth rate
	RF10	Inflation rate
	RF11	Occupational safety

Numerical Illustration

Variable Selecrtion via Backward Step-AIC

Category 1: Climate and Environmental	RF1	Cold Extreme
	RF2	Heat Extreme
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	RF11	Occupational safety

A Comparison Between the Non-RS and RS Models

Model NRS0

- The Non-Regime Switching Model
- No Age-Specific Function

Model NRS1

- Non-Regime Switching Model
- Third Degree Poly-Age-Specific Function

Model MDRS

- Multi-Driver Regime Switching Model
- Third Degree Poly-Age-Specific Function

A Comparison Between the Non-RS and RS Models

	Non-Regime-Switching		Regime-Switching
	Model NRS0	Model NRS1	Model MDRS
Likelihood	5341.26	5314.37	5452.47
# of Parameters	363	39	53
AIC	-9956.52	-10550.74	-10798.93
Transition Prob.			$\begin{pmatrix} 0.7843 & 0.2157 \\ 0.6828 & 0.3172 \end{pmatrix}$

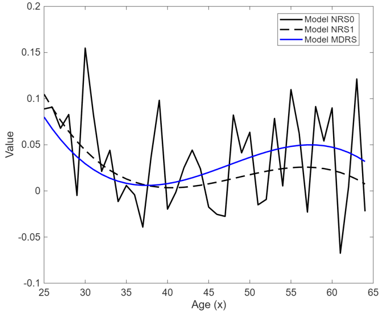
Numerical Illustration

Illustration on the Estimated δ_x

- For Non-Regime-Switching Risk Factors

Numerical Illustration

An example of the risk factor coefficients with no regime switching feature



RF2: Heat Extreme

- The jagged pattern is removed.
- The general trend is preserved.

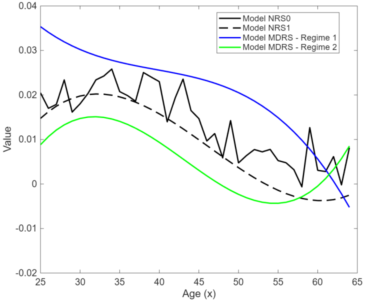
Numerical Illustration

Illustration on the Estimated δ_x

- For Regime-Switching Risk Factors

Numerical Illustration

Illustration on the Estimated δ_x - Regime Switching

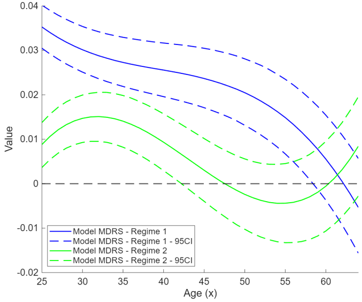


RF5: Drug Overdose

- Regime 1
  A higher impact is found among younger adults
- Regime 2
  Carries a smaller impact compared to regime 1, with a peak around 30 - 35

Numerical Illustration

Illustration on the Estimated δ_x - Regime Switching



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A Comparison Between the Non-RS and RS Models

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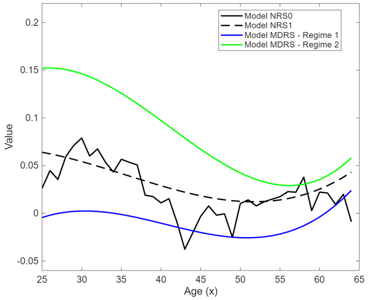

RF6: Suicide Rate

- Regime 1
  Insignificant across all working ages
- Regime 2
  A higher impact is found among younger adults

A Comparison Between the Non-RS and RS Models

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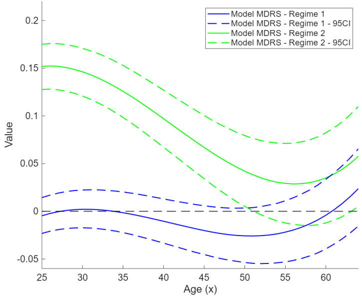

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A Comparison Between the Non-RS and RS Models

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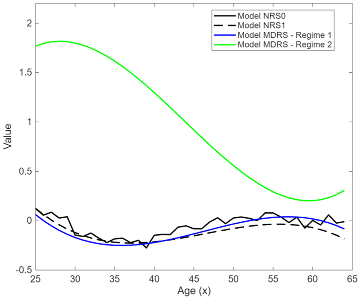

RF7: Alcohol Consumption

- **Regime 1**
  Insignificant across all working ages
- **Regime 2**
  A higher impact is found among younger adults

A Comparison Between the Non-RS and RS Models

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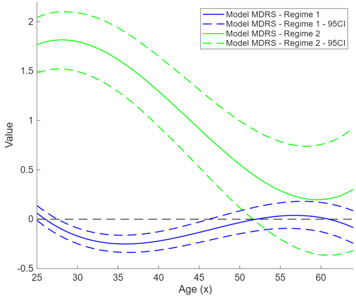


RF7: Alcohol Consumption

- Regime 1
  Insignificant across all working ages
- Regime 2
  A higher impact is found among younger adults

Numerical Illustration

Collective Impact of Drug Overdose, Suicide, and Alcohol Consumption

- In the proposed MDRS model, the three targeted risk factors (drug overdose, suicide, and alcohol consumption) switch regimes at the same pace.
- Their collective effects on mortality rates are assessed via

$$\frac{\hat{m}^*_{x,t} - \hat{m}_{x,t}}{\hat{m}_{x,t}}$$

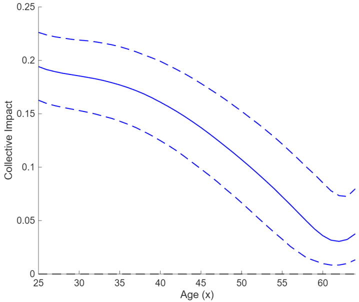
where $\hat{m}_{x,t}$ is the fitted mortality rates and

$$\hat{m}^*_{x,t} = \hat{m}_{x,t} \times exp\left(\sqrt{\vec{\delta_x}'\Sigma_Z\vec{\delta_x}}\right)$$

is the fitted mortality rates with a collective one-sigma change in the three targeted risk factors

Numerical Illustration

Collective Impact of Drug Overdose, Suicide, and Alcohol Consumption

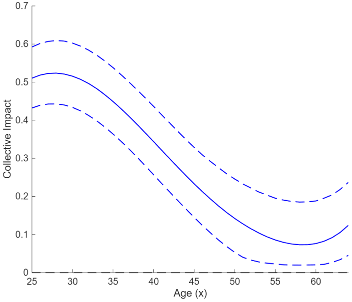


Regime 1

- The major driving force is drug overdose.
- A downward trend is observed.
- Younger adults (age <35) mortality rates can increase by 15%-25% if a one-sigma collective change occurs in drug/suicide/alcohol.

Numerical Illustration

Collective Impact of Drug Overdose, Suicide, and Alcohol Consumption



Regime 2

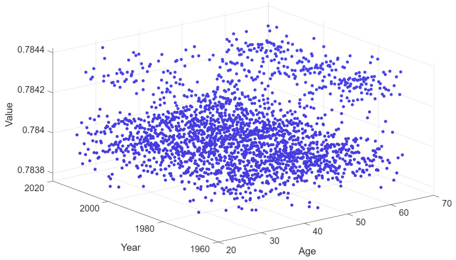
- The major driving force is suicide and alcohol consumption.
- A general downward trend with a peak around 25-30.
- Younger adults (age <35) mortality rates can increase by 40%-60% if a one-sigma collective change occurs in drug/suicide/alcohol.

Robustness Check

- The jackknife method is used to assess the robustness of the model.
- Implementing the jackknife method:
  - leaves out one observation at a time from the dataset,
  - refits the model, and
  - examines how the estimates change.
- It is closely related to the Leave-One-Out (LOO) method: LOO assesses predictive performance, while Jackknife focuses on the stability of the parameter estimates.

Robustness Check

Illustration



- Model MDRS: $\hat{p}_{11} = 0.7843$
- Jackknife Est.: $\hat{p}_{11} = 0.7841$
- Jackknife Var.: 7.3925×10^{-4}
- Relative Change:

$$\frac{\sqrt{7.3925 \times 10^{-4}}}{|0.7841|} = 3.47\%$$

Concluding Remarks

- We have developed a multi-driver regime-switching Lee-Carter model with age polynomials.
- The proposed model quantifies the post-2000 slowdown and post-2010 deterioration via regime shifts that are linked to the drug-alcohol-suicide impact
- A one-sigma collective change in drug-alcohol-suicide may lift young-adult mortality by 15-25% (Regime 1) and 40-60% (Regime 2).

Future Work

- Asynchronous regime-switching:
  A multi-chain regime architecture where each targeted risk factor evolves under its own transition matrix

References

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Questions and Answers