

An investigation of period and cohort effects in adult mortality across 31 countries

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13th International Longevity Risk and Capital Markets Solutions Conference, Taiwan

September 22, 2017



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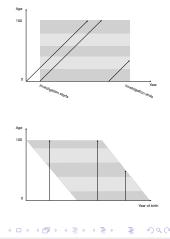
We fitted an age-cohort model with period effects using Bayesian maximum a posteriori estimation to mortality data of men and women in 31 countries. We find:

- Diminishing variance of period effects in almost all countries
- Very high correlation in estimated period effects between men and women in the same country
- Very high correlation in cohort mortality shocks between men and women in the same country
- Cohort mortality seems to be influenced by both cultural and geographical effects; period shocks seem to be largely geographical

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Motivation

- Period analysis vs cohort analysis
- McCarthy (2017) argues that using cohort and age as primary variables, with period effects secondary, may have significant advantages
 - There is a natural link to survival distributions
 - Cohort effects are as good at capturing a constant time trend
 - Cohort effects are persistent across age
 - The variance of cohort effects does not appear to be diminishing
- He proposed an age-cohort model with random period effects estimated using BMAP that allows us to separate period and cohort effects



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Here, we apply this model to male and female mortality data from 31 countries to:

- Identify international trends in period and cohort mortality
- Better understand common drivers of period and cohort mortality shocks
- Assist countries in understanding how best to diversify their mortality shocks (whether through capital markets or otherwise)
- (Will also serve to validate the model itself)



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		Model			
Mod	el				

An age-cohort model of mortality (based on CBD, 2006)

$$log(m_{x,c}) = \alpha_c + \beta_c \frac{x - k_1}{k_2} + \gamma_t + \epsilon_{x,c}$$

where $m_{X,C}$ = observed central rate of death;

$$x = \text{ age and } k_1 \text{ and } k_2 \text{ are chosen constants such that } \frac{x - k_1}{k_2} \in [-1, 1];$$

c = cohort;

t = period = x + c;

 α_{C} = the average level of cohort effects for cohort c throughout their lives;

 β_{C} = the slope of cohort effects for cohort c throughout their lives;

$$\gamma_t \sim N(0, \sigma_{\gamma}^2)$$
, i.e. the period random effects

 $\epsilon_{X,C} \sim N(0, \sigma_{\epsilon}^2 \omega_{X,C}), \text{ where } \omega_{X,C} = \frac{1}{D_{X,C}} \text{ and } D_{X,C} \text{ is the number of deaths in cohort c and age } x;$

estimated using BMAP with prior distribution

$$\begin{bmatrix} \alpha_{C} \\ \beta_{C} \end{bmatrix} = \theta_{C}, \text{ where } (\theta_{C} - \theta_{C-1}) \text{ follows a lag-1 VAR}, \\ \text{meaning } (\theta_{C} - \theta_{C-1}) = \mu + \Delta(\theta_{C-1} - \theta_{C-2}) + \nu_{C} \text{ and } \nu_{C} \sim MW(0, \Sigma)_{2} \text{ for } \Sigma = 0 \text{ fo$$

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BMAP estimation steps

Step 1: Estimate $\hat{\alpha}_c$ and $\hat{\beta}_c$ cohort by cohort using ML

Step 2: Use $\hat{\alpha}_c$ and $\hat{\beta}_c$ to estimate VAR coefficients for prior distribution

Step 3:

Use Bayes' theorm, the estimated prior and the likelihood function of the data to generate the posterior distribution

Step 4: Obtain point estimates $\hat{\alpha}_c$ and $\hat{\beta}_c$ as the joint mode of the posterior distribution

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Image: A matrix and a matrix

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		Data		
Datc	k			

- The Human Mortality Database (HMD mortality.org) Countries include: Australia, Japan, Slovakia, Austria, Finland, Slovenia, France, Spain, Belgium, Germany, Sweden, Bulgaria, Greece, Netherlands, Switzerland, Canada, Hungary, New Zealand, Taiwan, Chile, Norway, UK, Croatia, Ireland, Poland, USA, Croch Popublic, Israel, Portugal, Dopmark
 - Poland, USA, Czech Republic, Israel, Portugal, Denmark, Italy
- Male and female; ages from 35 to 100 (This allows us to run the model 31 countries × 2 sexes times independently.)
- Periods (*t*): 1900 2015
- Cohorts (c): 1800 1975

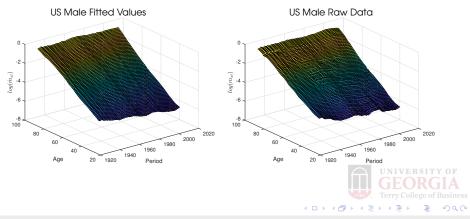
(Countries have different available data length.)



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Model performance

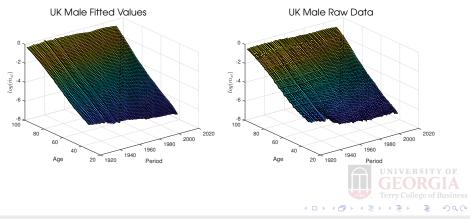
Fitted v. Raw - US Male



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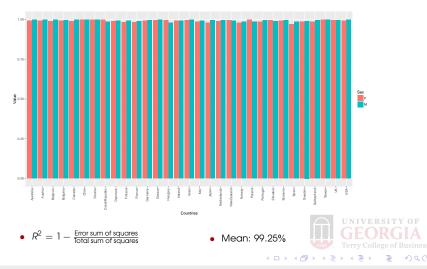
Model performance

Fitted v. Raw - UK Male



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Model performance - R^2



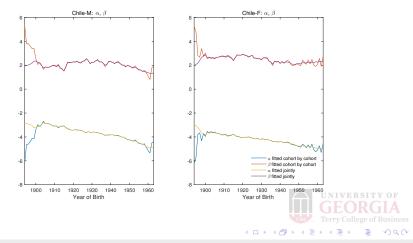
Estimation results

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		Estimation results		

Estimates

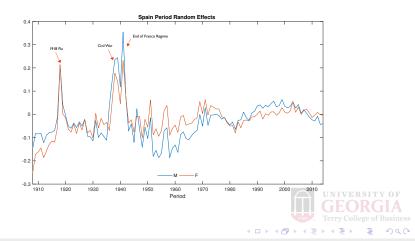
Cohort Level and Slope (α and β)



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Period Effects (γ)



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Which countries share similar mortality characteristics?

• Sets of cohort and period parameter estimates:

 $\{\hat{\alpha}_{i,s,c}, \hat{\beta}_{i,s,c}, \hat{\gamma}_{i,s,t}\}$ $i \in \{1, ..., 31\}$ $s \in \{M, F\}$ $c \in \{1800, ..., 1975\}$ $t \in \{1900, ..., 2015\}$

- What are their statistical properties?
- Do they contain information about international mortality patterns?

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Summary Introduction Model Data Estimation results Cohort effects Period effects Conclusion

Statistical properties of the cohort effects

- Strong evidence of unit roots in $\{\hat{\alpha}_{i,s,c}, \hat{\beta}_{i,s,c}\}$
- $\{\Delta \hat{\alpha}_{i,s,c}, \Delta \hat{\beta}_{i,s,c}\}$ generally follow AR(1) processes:

$$\Delta \hat{\alpha}_{i,s,c} = \mu_{i,s}^{\alpha} + \Phi_{i,s}^{\alpha} \Delta \hat{\alpha}_{i,s,c-1} + \epsilon_{i,s,c}^{\alpha}$$

$$\Delta \hat{\beta}_{i,s,c} = \mu_{i,s}^{\beta} + \Phi_{i,s}^{\beta} \Delta \hat{\beta}_{i,s,c-1} + \epsilon_{i,s,c}^{\beta}$$

Define cohort mortality shocks as:

$$U_{i,s,c}^{\alpha} = \Delta \hat{\alpha}_{i,s,c} - \hat{\mu}_{i,s}^{\alpha} - \hat{\Phi}_{i,s}^{\alpha} \Delta \hat{\alpha}_{i,s,c-1}$$

$$U_{i,s,c}^{eta} = \Delta \hat{eta}_{i,s,c} - \hat{\mu}_{i,s}^{eta} - \hat{\Phi}_{i,s}^{eta} \Delta \hat{eta}_{i,s,c-}$$



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Statistical properties of the cohort mortality shocks within country

- Strong positive correlation between shocks for males and females
- Strong negative correlation between u^α and u^β: cohort mortality shocks affect mortality at younger ages more than at older ages

$$\frac{\frac{1}{n}\sum_{c} Corr(u_{s_{1},c}^{i}, u_{s_{2},c}^{i})}{j = \alpha, s_{2} = M} \quad i = \alpha, s_{1} = F \quad i = \beta, s_{1} = M \quad i = \beta, s_{1} = F$$

$$\frac{j = \alpha, s_{2} = M}{j = \alpha, s_{2} = F} \quad 0.585 \quad 1$$

$$j = \beta, s_{2} = M \quad -0.408 \quad -0.275 \quad 1$$

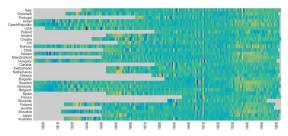
$$j = \beta, s_{2} = F \quad -0.414 \quad -0.284 \quad 0.938$$

$$\bigcup_{i=1}^{n} \bigcup_{i=1}^{n} \bigcup_{i=1}^{\dots$$

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Statistical properties of the cohort mortality shocks between countries

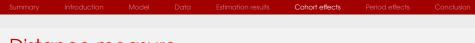
- Strong historical component in u^{lpha} but not so much in u^{eta}
- 1918 flu epidemic, WWI, WWII all exerted permanent effects on cohort mortality in many countries



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• How can we identify countries that are more and less similar?

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Distance measure

Correlation distance between countries i and j

$$d(x, y)_{i,j} = 1 - corr(u_{i,y}^{x}, u_{j,y}^{x})$$

where $x \in \{\alpha, \beta\};$ $y \in \{M, F\}$



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Distance measures

Distance Matrix

The pairwise correlation gives us a distance matrix:

	Australia	Japan	Slovakia	Austria	
Australia	0	0.922	0.778	0.729	
Japan	0.922	0	1.178	0.702	
Slovakia	0.777	1.177	0	0.800	
Austria	0.729	0.702	0.800	0	
Finland	0.910	0.995	0.711	0.778	
Slovenia	0.830	0.788	0.600	0.616	
France	0.833	0.810	0.657	0.653	
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But how to interpret this in an accessible way?

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Cluster analysis

Methods of grouping data given a distance matrix

- Principal component analysis allows us to infer a map given a distance matrix
 - The first k eigenvalues of the Gram matrix give the best _ k-dimensional approximation to the map (we use two)
- Hierarchical clustering
 - Cluster by "cluster distances"
 - Start with each point as a cluster
 - Group the closest pairs \rightarrow calculate the pairwise cluster distances
 - Group again... \rightarrow cluster dendrogram



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Clustering - cohort mortality shocks (u^{α} and u^{β})

We calculate an aggregate cohort mortality shock distance measure between countries i and j as:

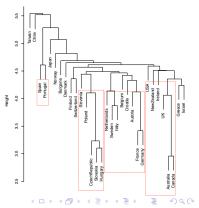
$$S_{i,j} = d(\alpha, M)_{i,j} + d(\alpha, F)_{i,j} + d(\beta, M)_{i,j} + d(\beta, F)_{i,j}$$

Seem to be both cultural and regional components

- Anglosphere falls into a single group
- The other groupings appear to be more geographical
 - Western Europe
 - Eastern Europe
 - Scandinavia (plus Bulgaria and Switzerland)
 - Iberian peninsula

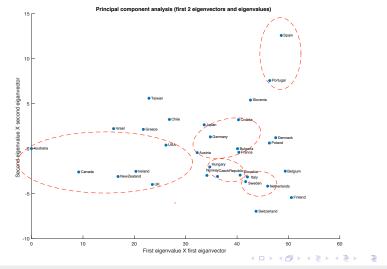
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Hierachical clustering - aggregate cohort mortality shocks by country

Clustering - cohort mortality shocks (u^{α} and u^{β})



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Statistical properties of the period effects

- These were estimated as random effects $\sim N(0, \sigma_{\gamma}^2)$
- We find no evidence of unit roots, but we do find significant first-order autocorrelation (on average $\Phi \approx 0.4$, but with significant variation from country to country)
- Rather than estimating residuals as we did in the cohort analysis, to maintain consistency with our estimation assumption, we set:

$$U_{i,s,t}^{\gamma} = \hat{\gamma}_{i,s,t}$$

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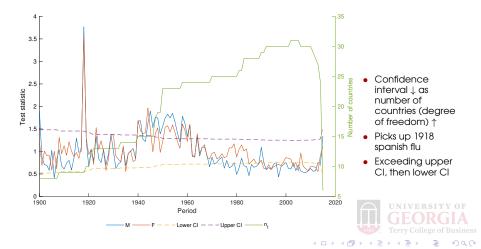
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Statistical properties of the period mortality shocks within country

- Very high correlation between males and females (average \approx 0.767)
- But, strong evidence that the variance of these shocks has declined
- Hypothesis test:
 - Null: The variance of period effects before and after 1960 is the same.
 - Test statistic: $F_{i,s} = \frac{var(\hat{\gamma}_{i,s,t \le 1960})}{var(\hat{\gamma}_{i,s,t > 1960})} \sim F(n_1, n_2)$, where n_1 is the number of periods before 1960 and n_2 the number after
 - Of the 24 countries with enough data, 21 reject for men and TY OF 17 for women, often with negligable p-values

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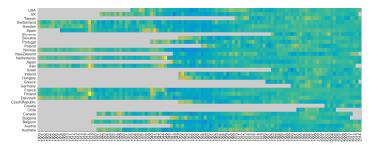
Summary Introduction Model Data Estimation results Cohort effects Period effects Conclus Testing for diminishing period effects across countries



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Statistical properties of the period mortality shocks across countries

Various historical events can be identified, as well as broad patterns



- 1918 flu epidemic
- World War II
- Dutch Hongerwinter
- Decline in importance of period effects

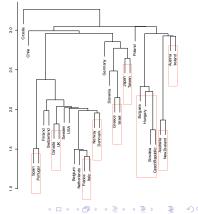
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Clustering - period mortality shocks (γ)

Cultural effects seem less important, geographic poximity seems to matter more

- Anglosphere no longer falls into a single group
- Most groupings are geographical



Hierarchical Clustering (Correlation Distance)

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- Very high correlation in cohort mortality shocks between men and women in the same country
- Cohort mortality seems to be influenced by both cultural and geographical effects; period shocks seem to be largely geographical

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				Conclusion
Q&	А			

Thank you!



David G. McCarthy and Polin Wang