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1 War, hunger, and aging curves — Full Results

Generated: 2026-02-14 21:50 UTC

2 Methods

2.1 Study question

We test how **war** (conflict intensity) and **hunger** (food insecurity indicators) perturb the shape of age-specific adult mortality curves. In stable settings, adult mortality hazard increases approximately exponentially with age (Gompertz law). Crisis settings may instead add an age-independent hazard (Makeham term), introduce a young-adult “hump” (violence signature), or potentially change the adult aging slope.

2.2 Mortality data (outcome)

We use **UN World Population Prospects (WPP) 2024** age-specific death rates (**mx**) by country, year, sex, and age. These are used as a standard approximation to the hazard within age bins.

Implementation: `scripts/30_export_wpp_from_r.R` exports `data/raw/wpp_mx.csv` (and `data/raw/wpp_mx.parquet` if the R `arrow` package is installed) with columns `iso3`, `year`, `sex`, `age`, `mx`.

2.3 Conflict intensity (war covariate)

We use **UCDP Battle-Related Deaths (BRD)** as annual battle deaths by country-year. We aggregate battle deaths to country-year and scale by population to obtain `battle_deaths_per_100k`.

Implementation: place the downloaded BRD CSV/XLSX into `data/raw/ucdp/` and run `scripts/20_prepare_udcp.py`.

2.4 Hunger / food insecurity (hunger covariates)

We fetch two World Bank WDI indicators: - `SN.ITK.DEFC.ZS`: prevalence of undernourishment (PoU, %) - `SN.ITK.MSFI.ZS`: prevalence of moderate or severe food insecurity (FIES, %)

Population for normalization is `SP.POP.TOTL`.

Implementation: `scripts/10_fetch_wdi.py`.

2.5 India SRS (optional add-on)

Separately from the cross-country war/hunger panel, we can apply the same “aging curve decomposition” idea to India’s **SRS Abridged Life Tables (2018–22)** at the state/UT level and by residence: - Input: `SRS-Abridged_Life_Tables_2018-2022.pdf` (repo root) - Extraction: `scripts/05_extract_srs_life_tables.py → data/intermediate/srs_abridged_life_tables_2018_22.csv` - The abridged tables provide `nqx` over age intervals (e.g., 20–25). We derive a hazard proxy for closed intervals: - `mx`

approx –

$\ln(1 - nqx)/n$ (where `n` is the interval width) - The open-ended 85+ interval has `nqx` shown as ... in the PDF, so `mx` is left missing.

We then fit the same GM/GMH models per `area × residence × sex` and compute **Urban – Rural** deltas: - Fit + deltas: `scripts/55_fit_srs_models.py → data/processed/srs_params.parquet, data/processed/srs_urban_rural_deltas.parquet, reports/figures/srs/, reports/tables/srs_*.csv`

2.6 Extra APIs (optional)

If your environment has internet access, there are optional fetchers for additional national series: - World Bank WDI (life expectancy + mortality): `scripts/11_fetch_wdi_extra.py` - WHO GHO (OData): `scripts/12_fetch_who_gho.py`

2.7 Mortality models

2.7.1 Gompertz–Makeham (adult fit)

On adult ages 40–89 we fit: $\mu(x) = c + ae^{bx}$ where: - b is the aging slope ($MRDT = \ln(2)/b$), - a shifts the Gompertz component, - c is an age-independent extrinsic hazard (Makeham).

2.7.2 Young-adult hump extension (war signature)

To capture disproportionate young-adult violent mortality, we extend: $\mu(x) = c + ae^{bx} + h \exp\left(-\frac{(x-\mu_h)^2}{2\sigma_h^2}\right)$ with fixed hump center/width ($\mu_h = 28$, $\sigma_h = 10$) and estimated amplitude $h \geq 0$.

2.7.3 Estimation

We fit parameters by non-linear least squares minimizing the log-scale residual: $\log(mx) - \log(\mu(x; \theta))$ with positivity enforced by log-parameterization.

2.8 Event windows

For each case country we define: - pre: t0-5 ... t0-1 - crisis: t0 ... t1 - post: t1+1 ... (if available)

Controls are selected a priori in `config/project.yml`.

2.9 Outputs

- **Panel (base):** `data/processed/panel_base.parquet`
- **Fitted params:** `data/processed/params.parquet`

- Fit QC: data/processed/fit_qc.parquet
- WDI extra series (optional): data/intermediate/wdi_extra.parquet
- WHO GHO series (optional): data/intermediate/who_gho.parquet
- SRS (India) extracted table: data/intermediate/srs_abridged_life_tables_2018_22.csv
- SRS (India) fitted params: data/processed/srs_params.parquet
- SRS (India) Urban–Rural deltas: data/processed/srs_urban_rural_deltas.parquet
- SRS (India) figures: reports/figures/srs
- Figures: reports/figures
- Tables: reports/tables

2.10 India (SRS) Add-on

This repo can also fit GM/GMH on India's SRS abridged life tables (2018–22) by `area × residence × sex`.

Run:

```
python3 scripts/05_extract_srs_life_tables.py
python3 scripts/55_fit_srs_models.py
```

Key outputs:

- data/intermediate/srs_abridged_life_tables_2018_22.csv (tidy extraction + derived mx)
- data/processed/srs_params.parquet and reports/tables/srs_params.csv
- data/processed/srs_urban_rural_deltas.parquet and reports/tables/srs_urban_rural_deltas.csv
- Figures: reports/figures/srs

2.10.1 SRS Figures

2.11 Fit Summary

- Fits: **680** (rows in data/processed/params.parquet)
- Converged: **680** (100.0%)

2.11.1 Convergence Rate (sample)

iso3	sex	converged_rate
BGR	Female	1
BGR	Male	1
JOR	Female	1
JOR	Male	1
MAR	Female	1
MAR	Male	1
OMN	Female	1
OMN	Male	1
POL	Female	1
POL	Male	1
ROU	Female	1
ROU	Male	1
SYR	Female	1
SYR	Male	1
TUN	Female	1
TUN	Male	1
UKR	Female	1
UKR	Male	1

iso3	sex	converged_rate
YEM	Female	1
YEM	Male	1

2.12 Event-Window Summary (Cases)

case_group	iso3	sex	param	crisis_minus_pre
SYR_2011	SYR	Female	b	-0.004431
SYR_2011	SYR	Female	c	0.0002054
SYR_2011	SYR	Female	h	6.859e-05
SYR_2011	SYR	Female	mrdt	0.2909
SYR_2011	SYR	Male	b	-0.0137
SYR_2011	SYR	Male	c	-0.0001834
SYR_2011	SYR	Male	h	0.004174
SYR_2011	SYR	Male	mrdt	1.035
UKR_2022	UKR	Female	b	-0.003541
UKR_2022	UKR	Female	c	9.131e-05
UKR_2022	UKR	Female	h	-1.343e-05
UKR_2022	UKR	Female	mrdt	0.3101
UKR_2022	UKR	Male	b	-0.01378
UKR_2022	UKR	Male	c	8.71e-12
UKR_2022	UKR	Male	h	0.001508
UKR_2022	UKR	Male	mrdt	1.91
YEM_2015	YEM	Female	b	-0.0005103
YEM_2015	YEM	Female	c	-1.803e-05
YEM_2015	YEM	Female	h	-8.238e-05
YEM_2015	YEM	Female	mrdt	0.03672
YEM_2015	YEM	Male	b	-0.005231
YEM_2015	YEM	Male	c	-0.0005862
YEM_2015	YEM	Male	h	0.001992
YEM_2015	YEM	Male	mrdt	0.4172

Full CSV: `reports/tables/event_summary.csv`

2.13 Figures

2.13.1 YEM_2015 — YEM

2.13.1.1 Female

2.13.1.2 Male

2.13.2 SYR_2011 — SYR

2.13.2.1 Female

2.13.2.2 Male

2.13.3 UKR_2022 — UKR

2.13.3.1 Female

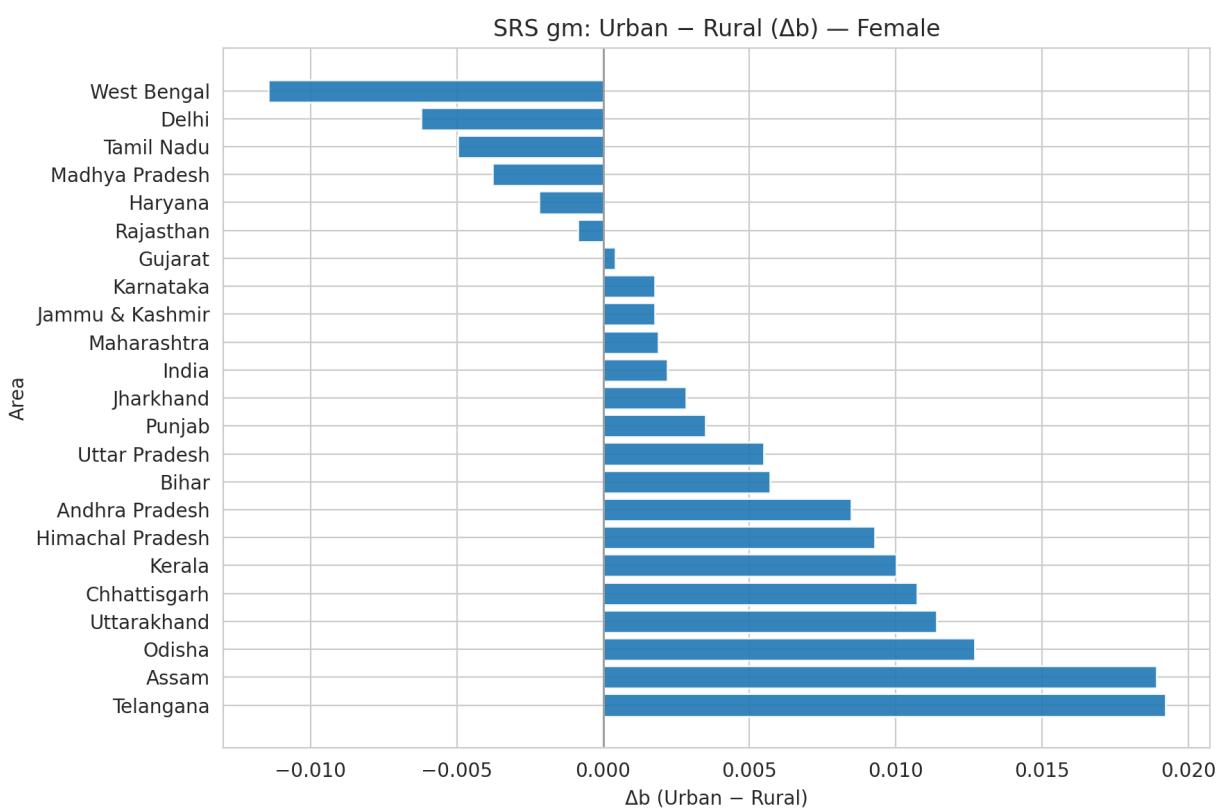


Figure 1: delta_b_urban_minus_rural_gm_Female

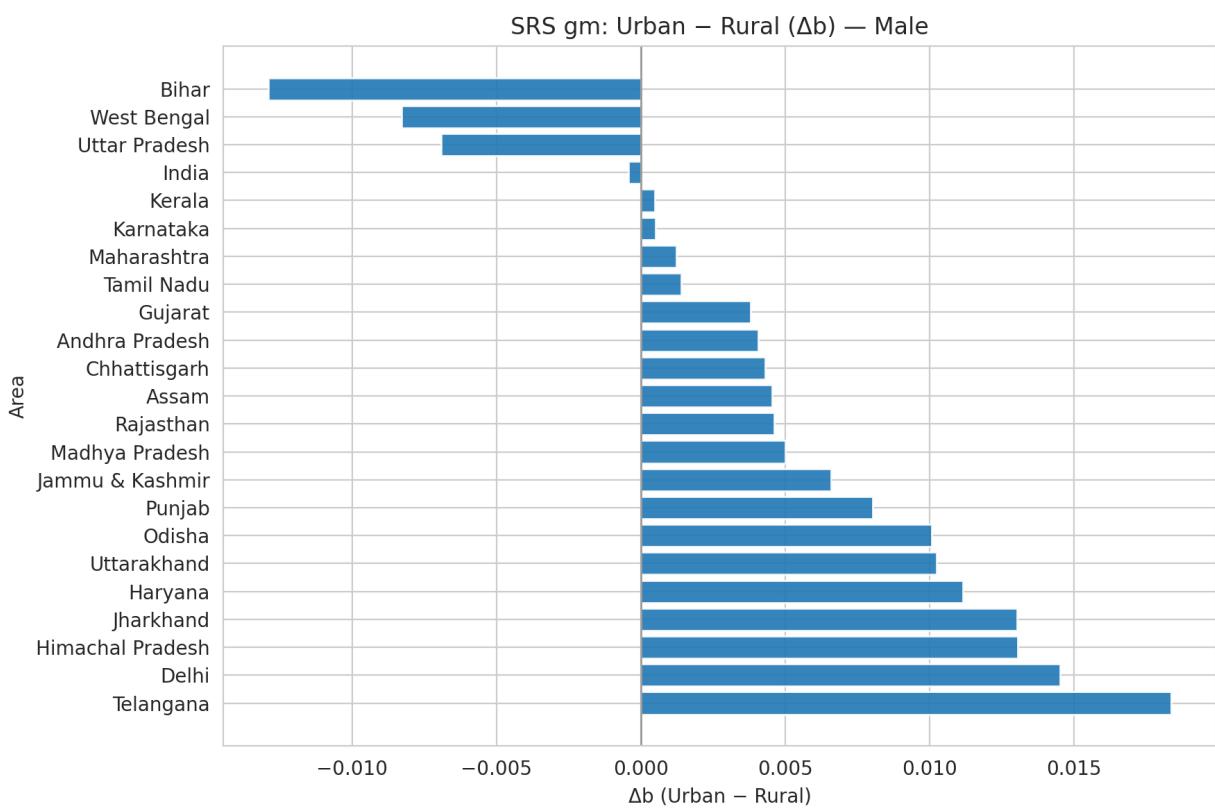


Figure 2: delta_b_urban_minus_rural_gm_Male

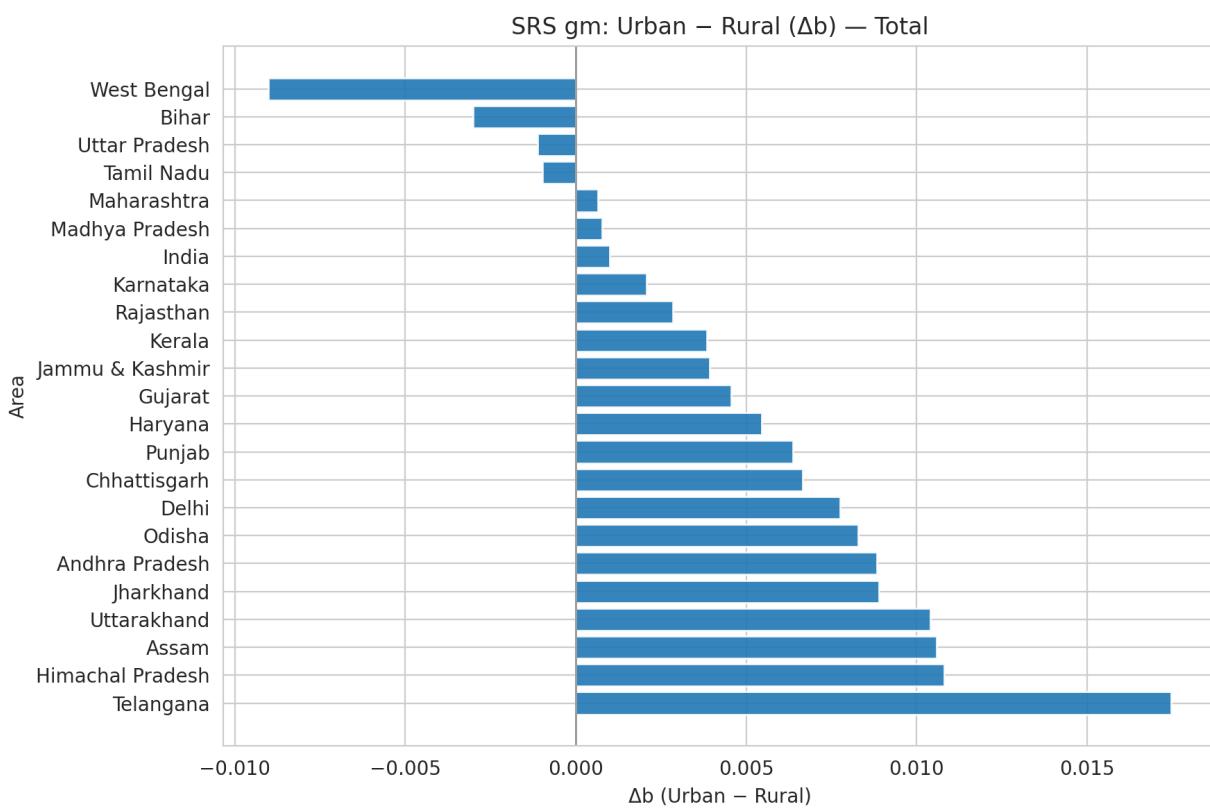


Figure 3: delta_b_urban_minus_rural_gm_Total

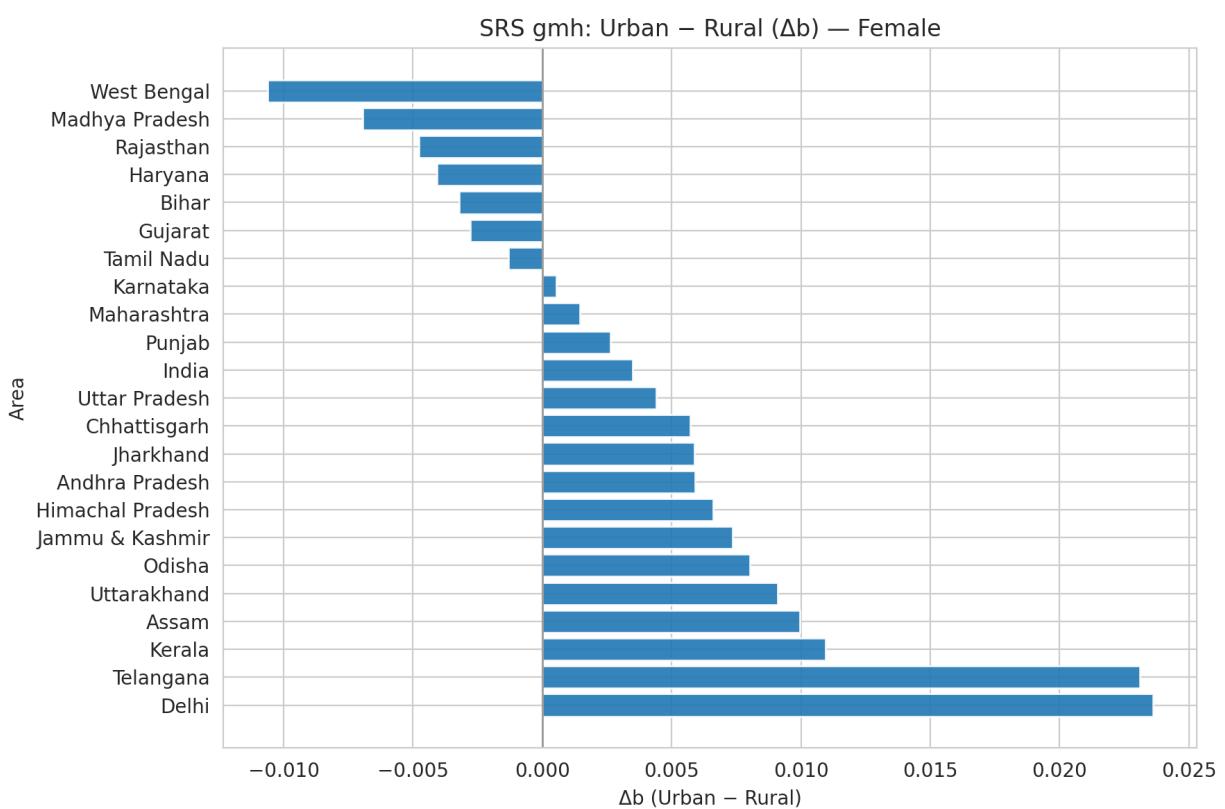


Figure 4: delta_b_urban_minus_rural_gmh_Female

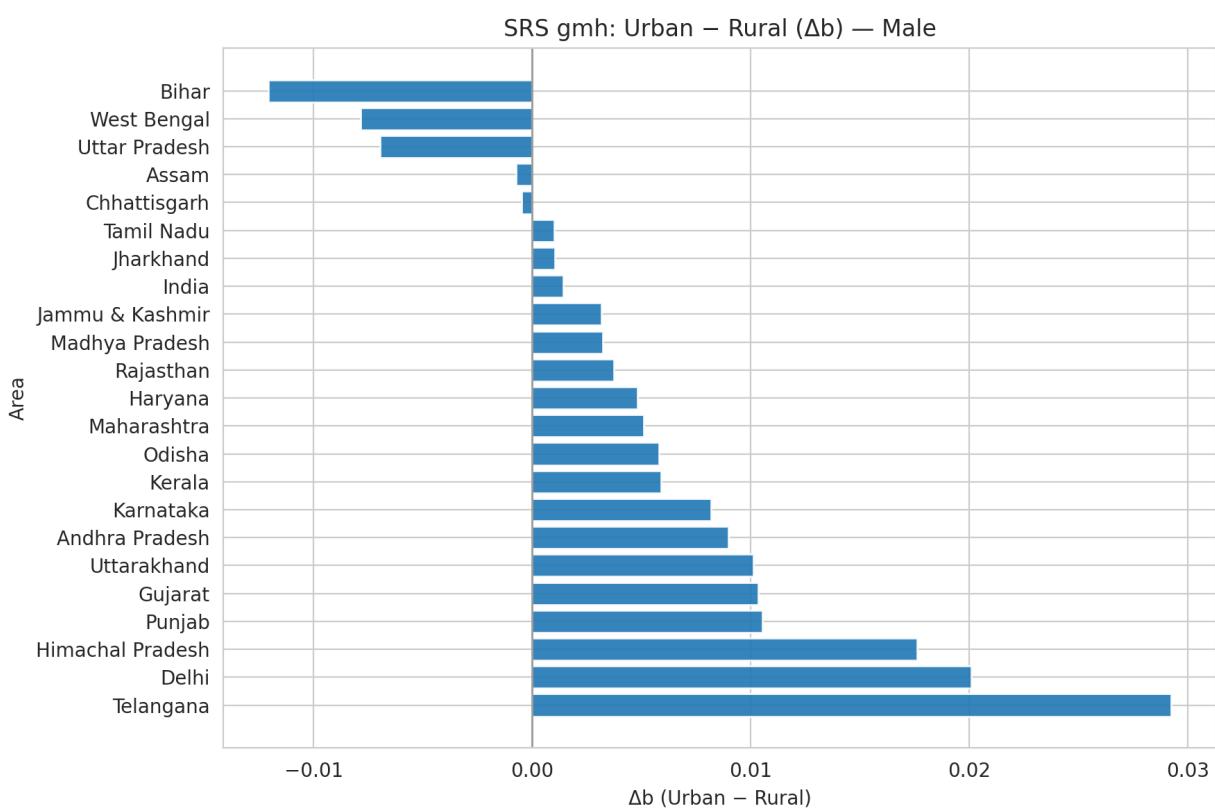


Figure 5: delta_b_urban_minus_rural_gmh_Male

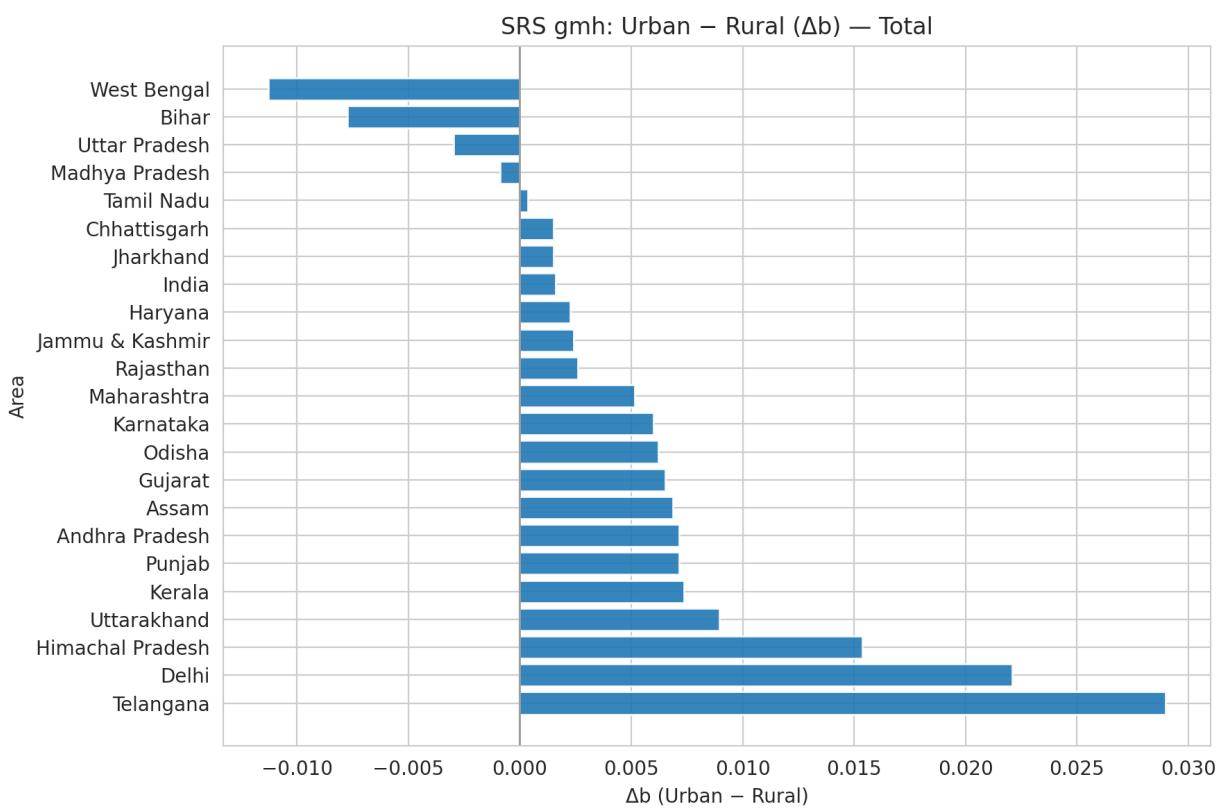


Figure 6: delta_b_urban_minus_rural_gmh_Total

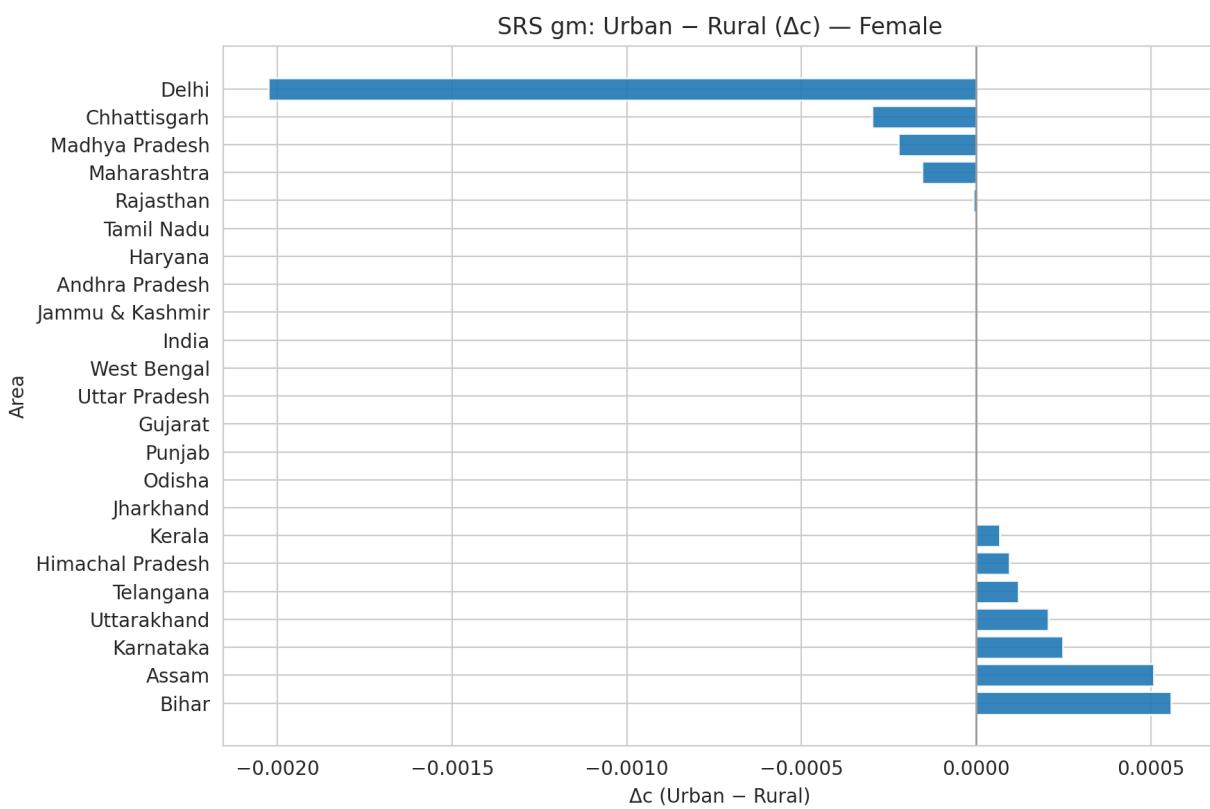


Figure 7: delta_c_urban_minus_rural_gm_Female

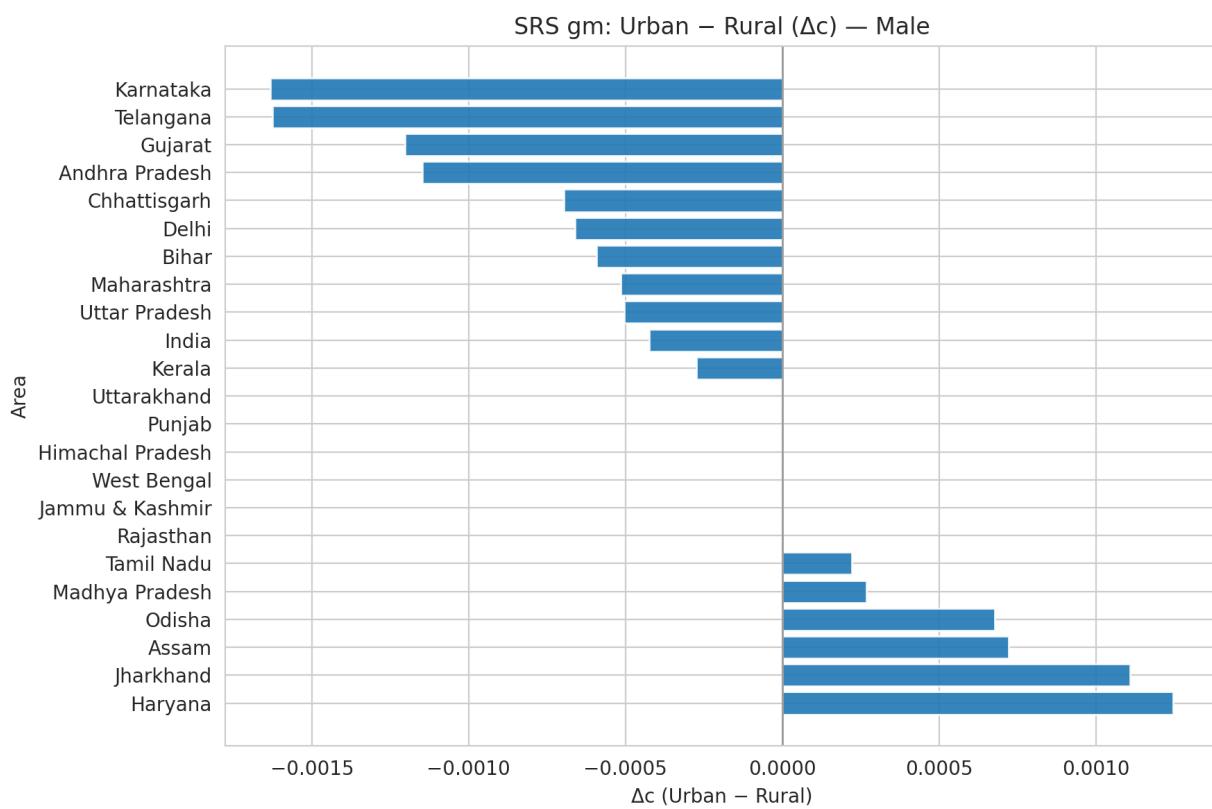


Figure 8: delta_c_urban_minus_rural_gm_Male

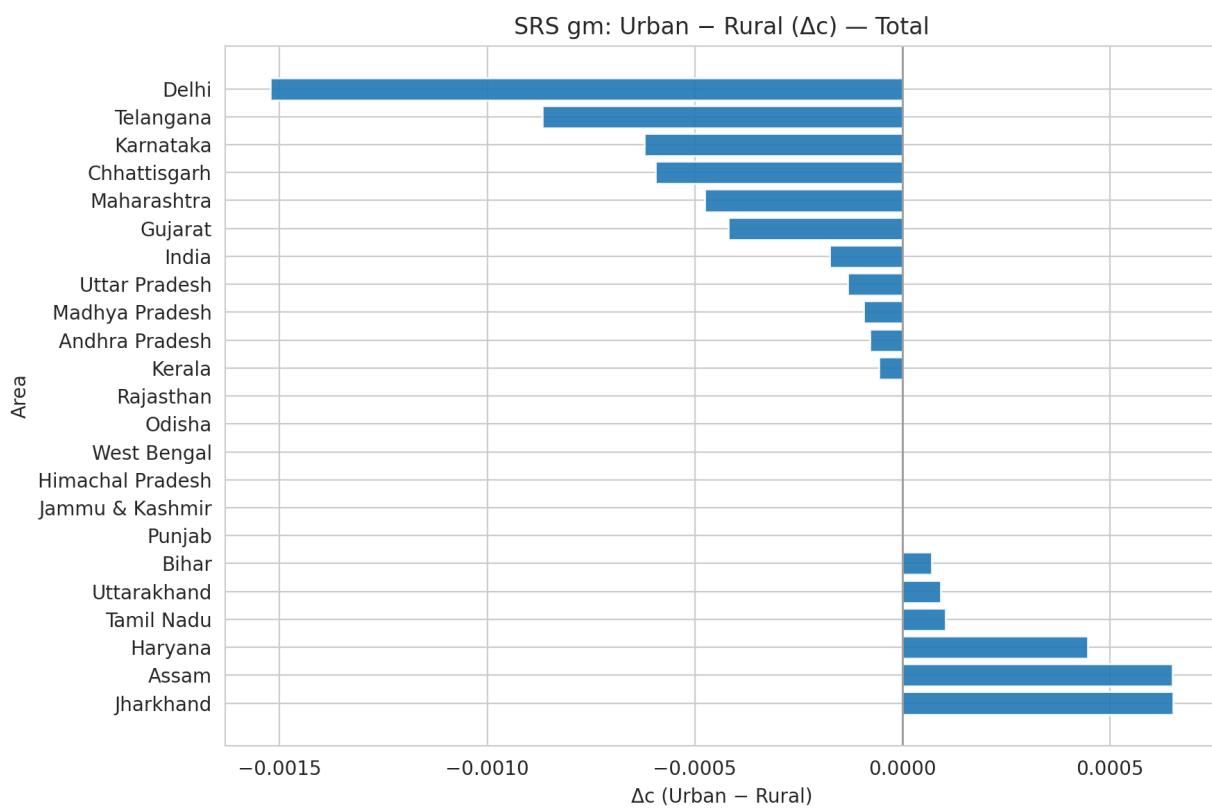


Figure 9: delta_c_urban_minus_rural_gm_Total

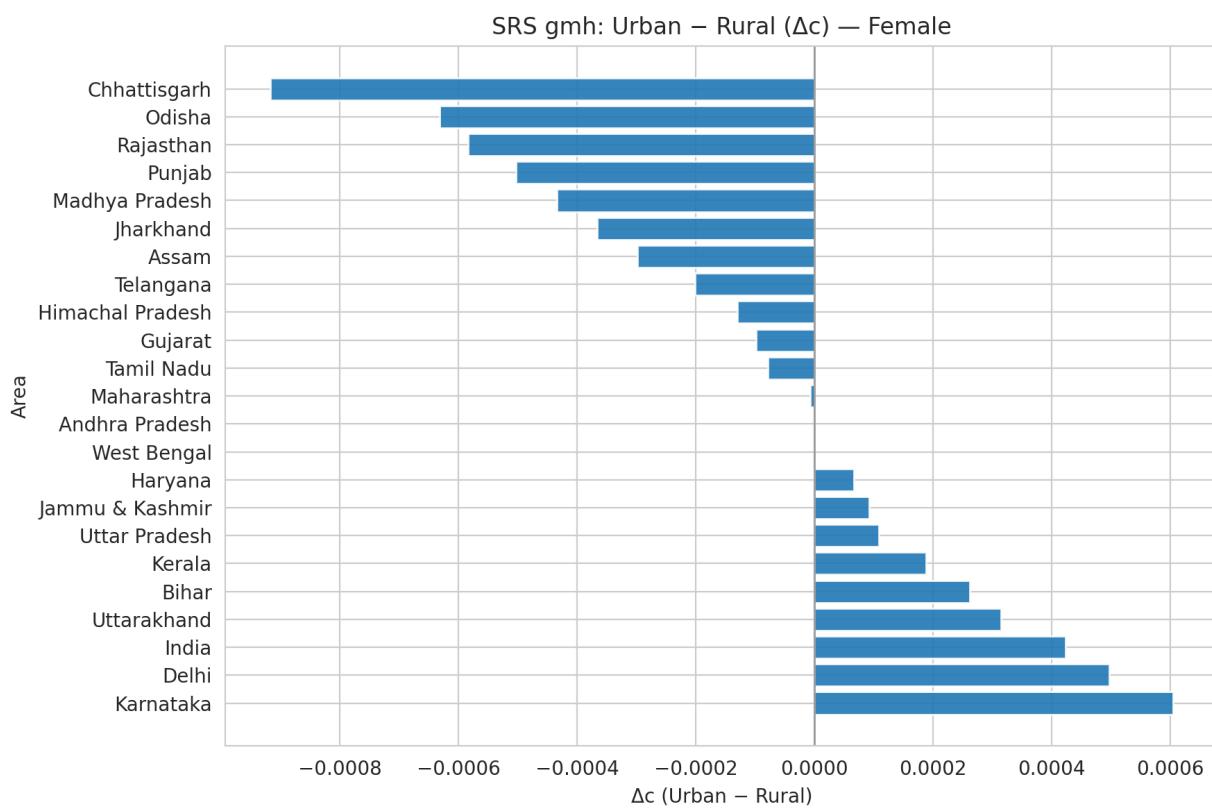


Figure 10: delta_c_urban_minus_rural_gmh_Female

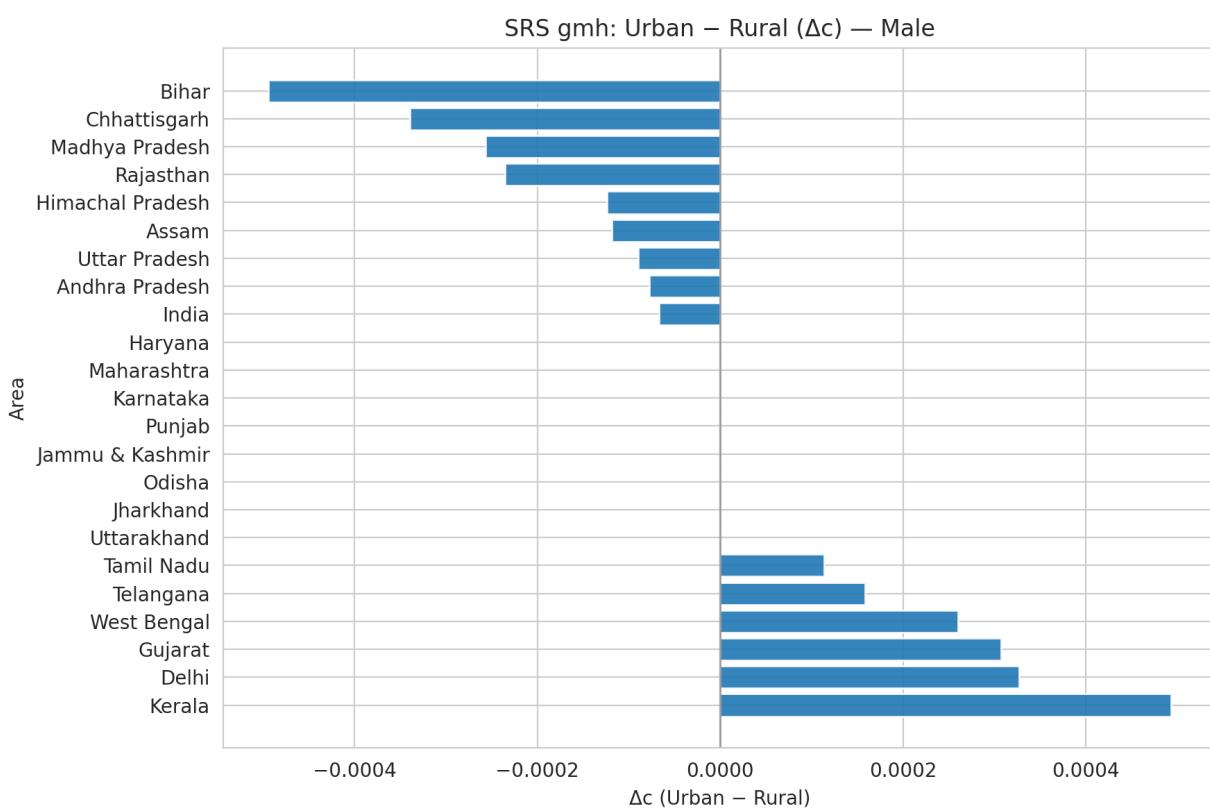


Figure 11: delta_c_urban_minus_rural_gmh_Male

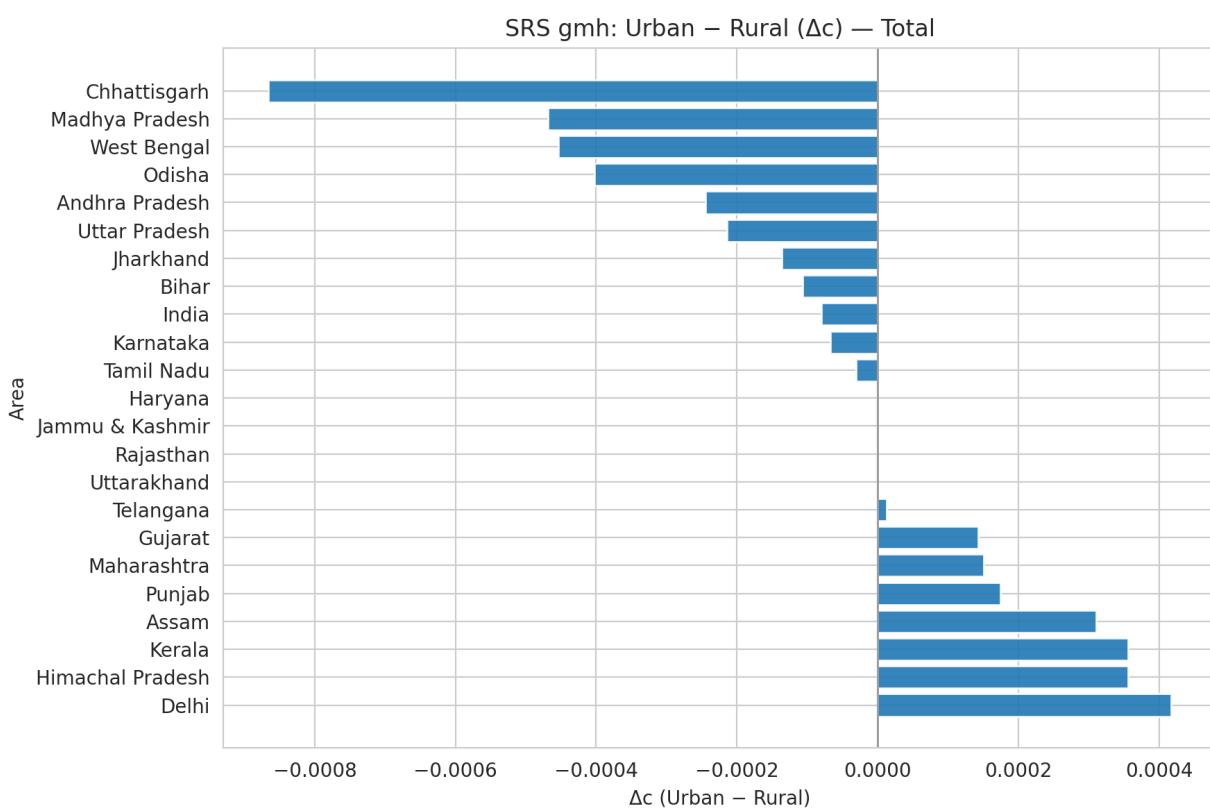


Figure 12: delta_c_urban_minus_rural_gmh_Total

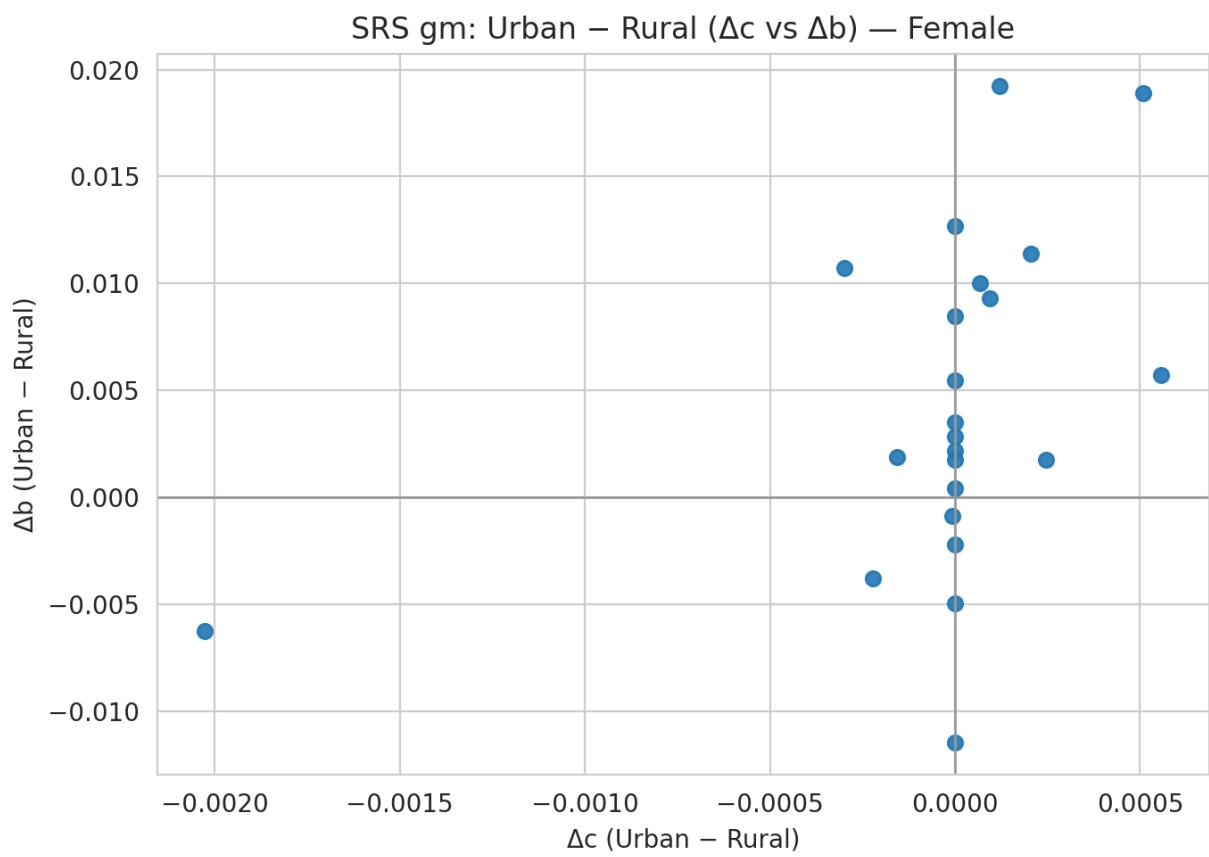


Figure 13: delta_cb_urban_minus_rural_gm_Female

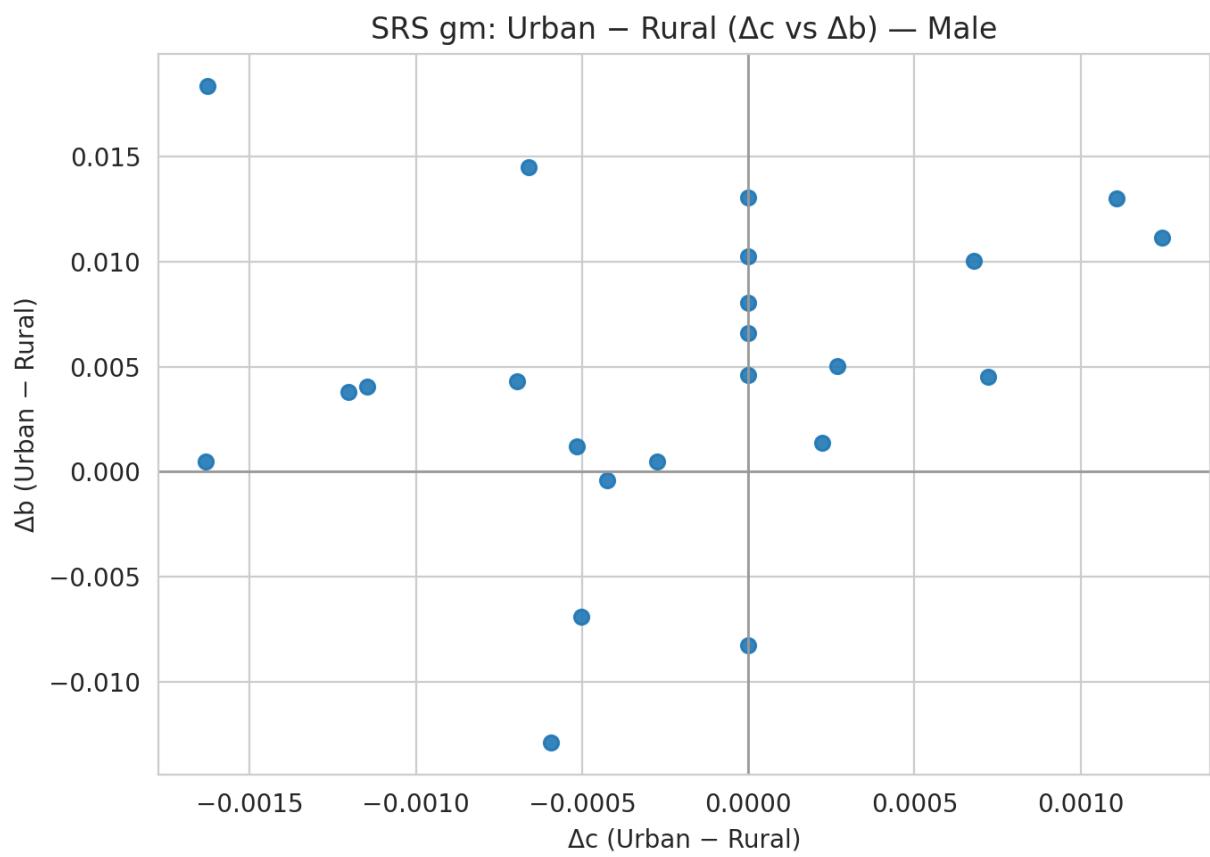


Figure 14: delta_cb_urban_minus_rural_gm_Male

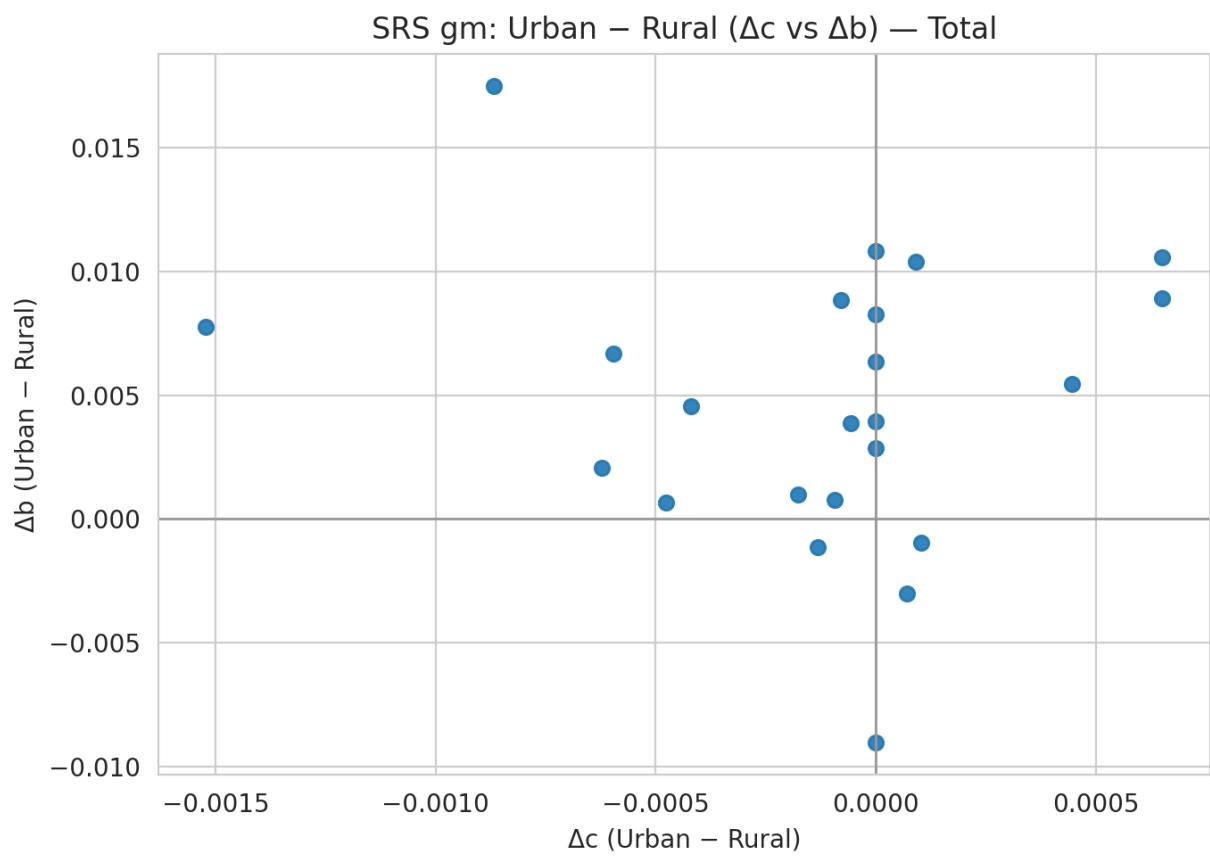


Figure 15: delta_cb_urban_minus_rural_gm_Total

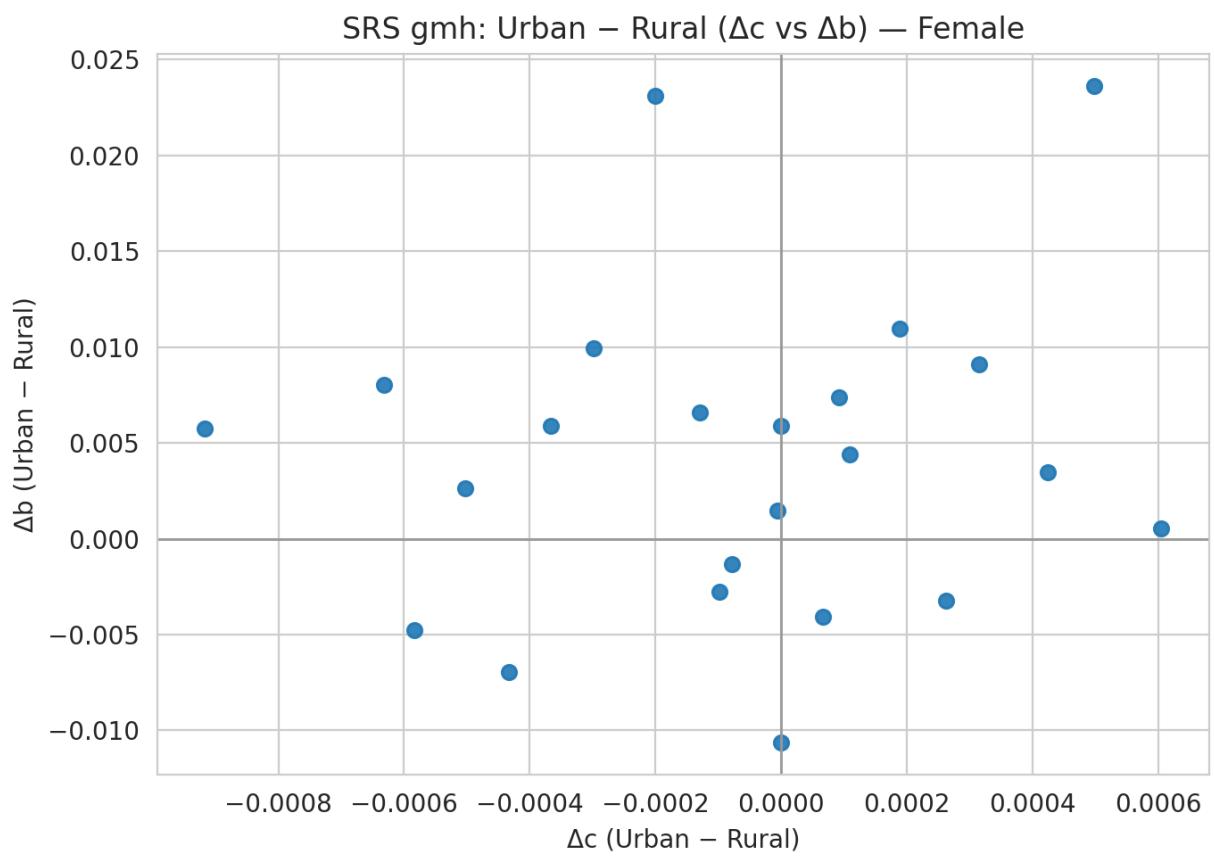


Figure 16: delta_cb_urban_minus_rural_gmh_Female

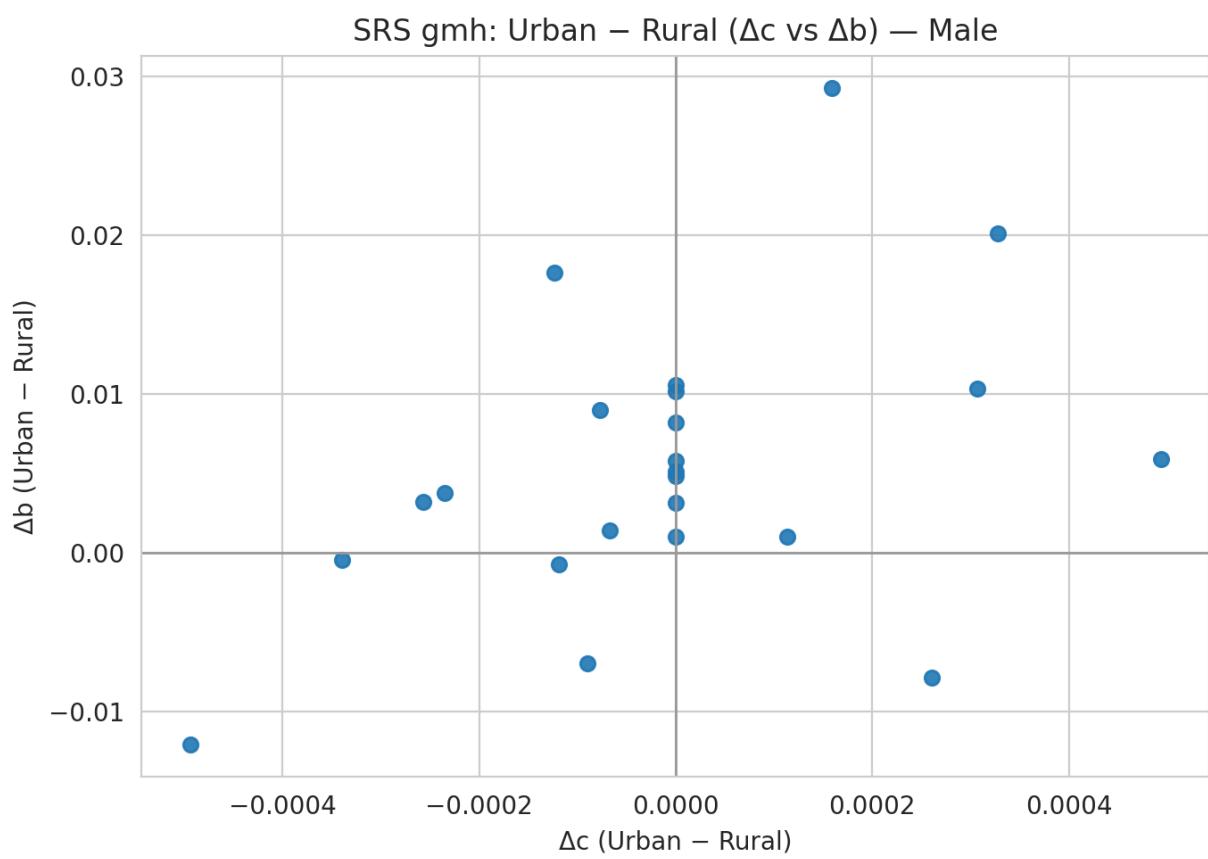


Figure 17: delta_cb_urban_minus_rural_gmh_Male

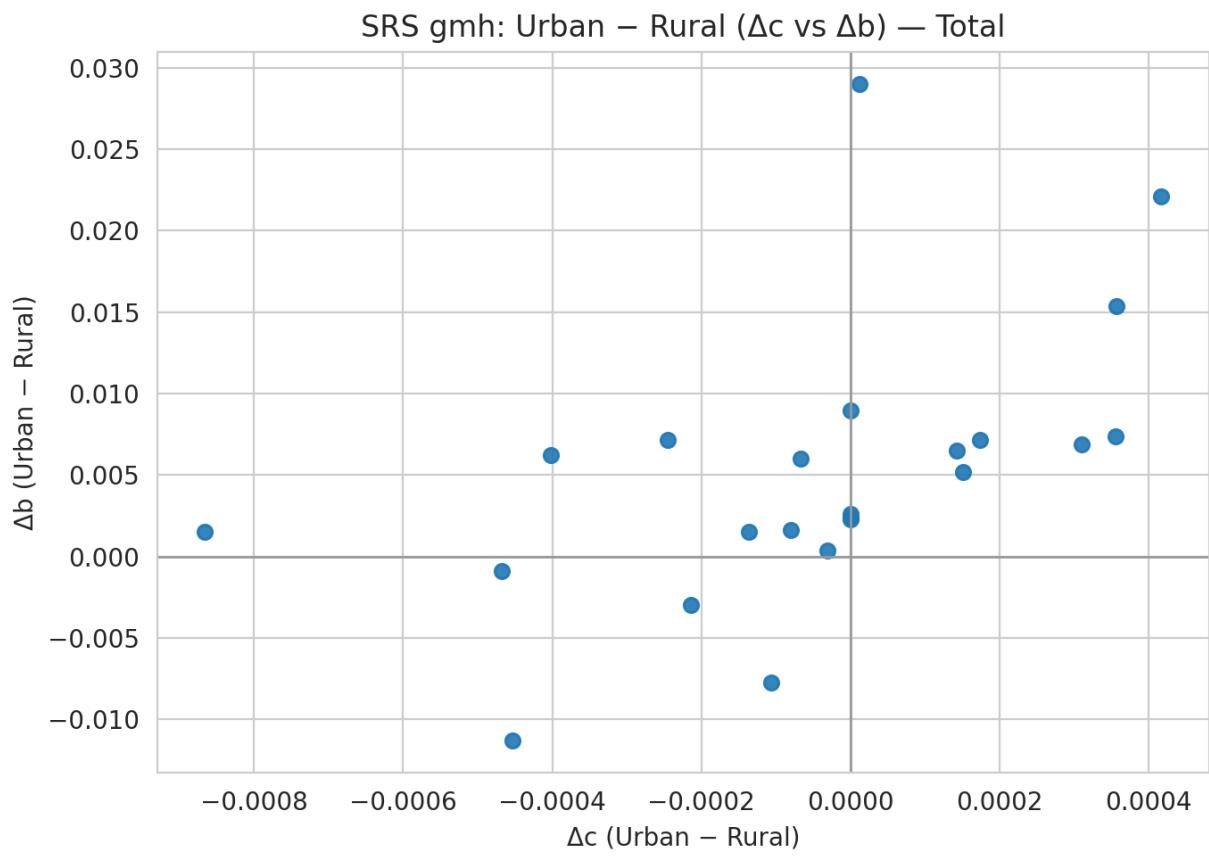


Figure 18: delta_cb_urban_minus_rural_gmh_Total

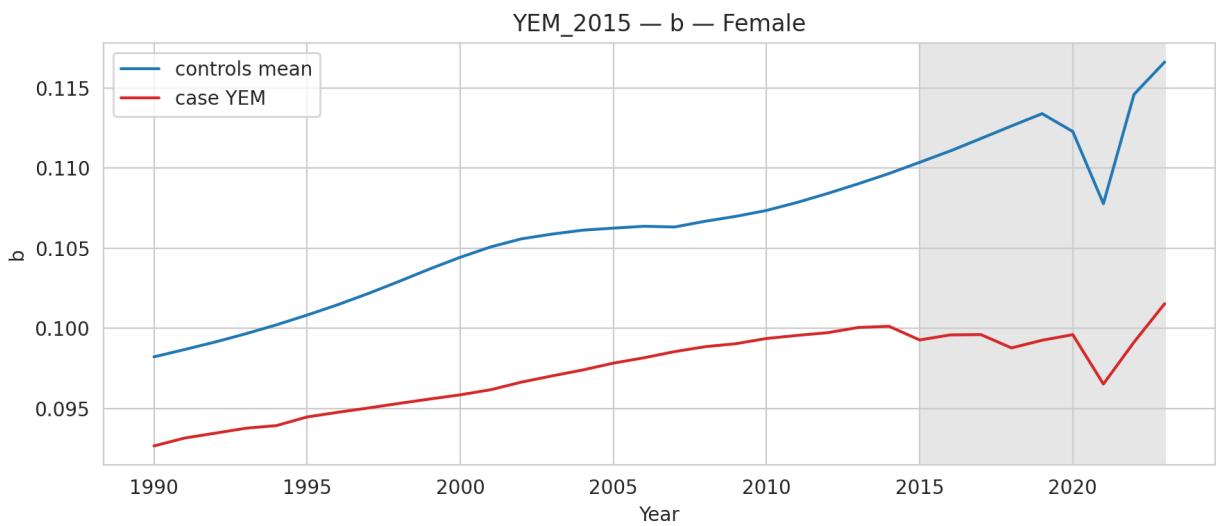


Figure 19: YEM_2015_YEM_Female_timeseries_b

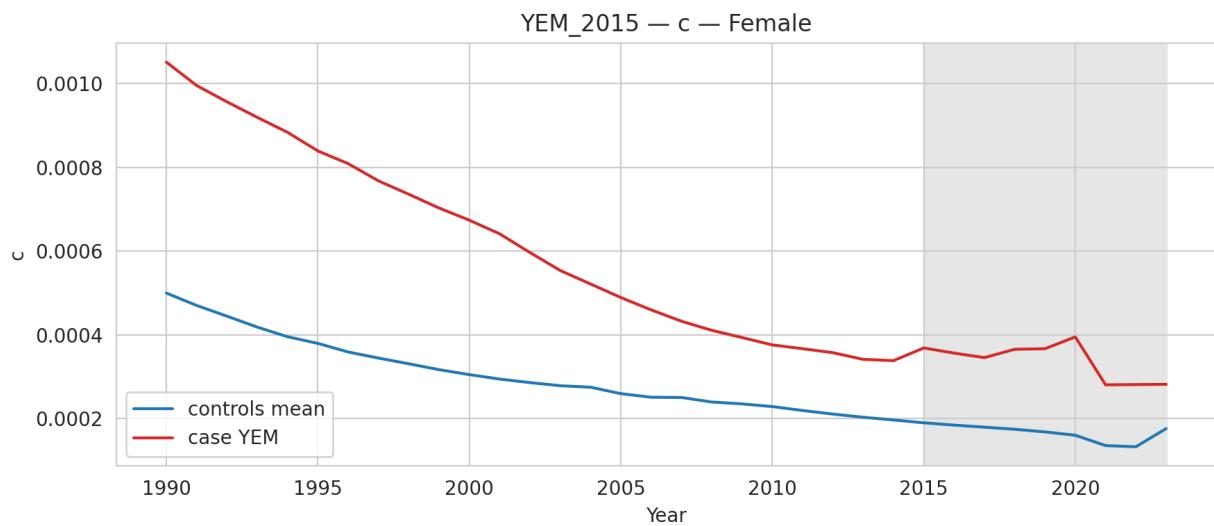


Figure 20: YEM_2015_YEM_Female_timeseries_c

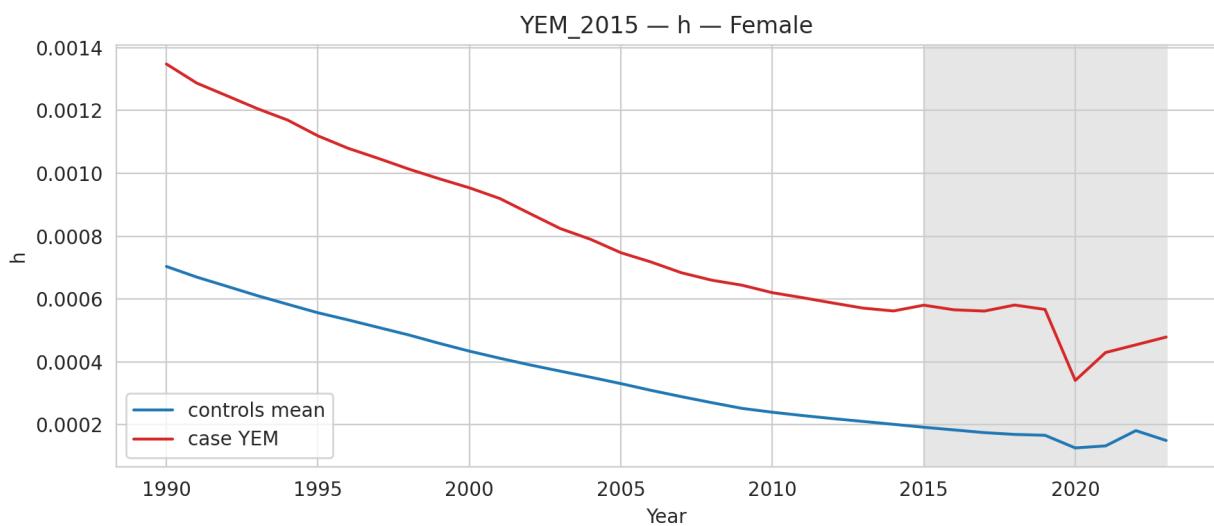


Figure 21: YEM_2015_YEM_Female_timeseries_h

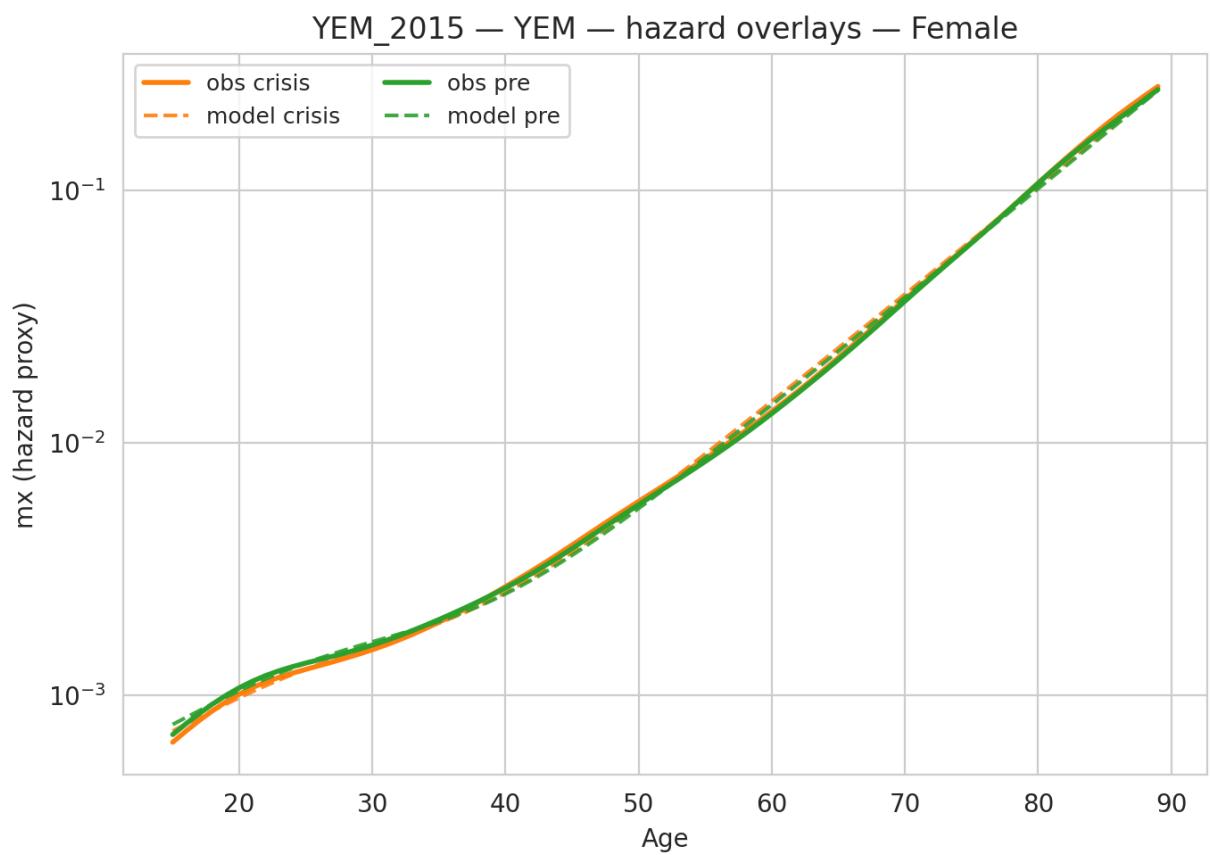


Figure 22: YEM_2015_YEM_Female_hazard_overlays

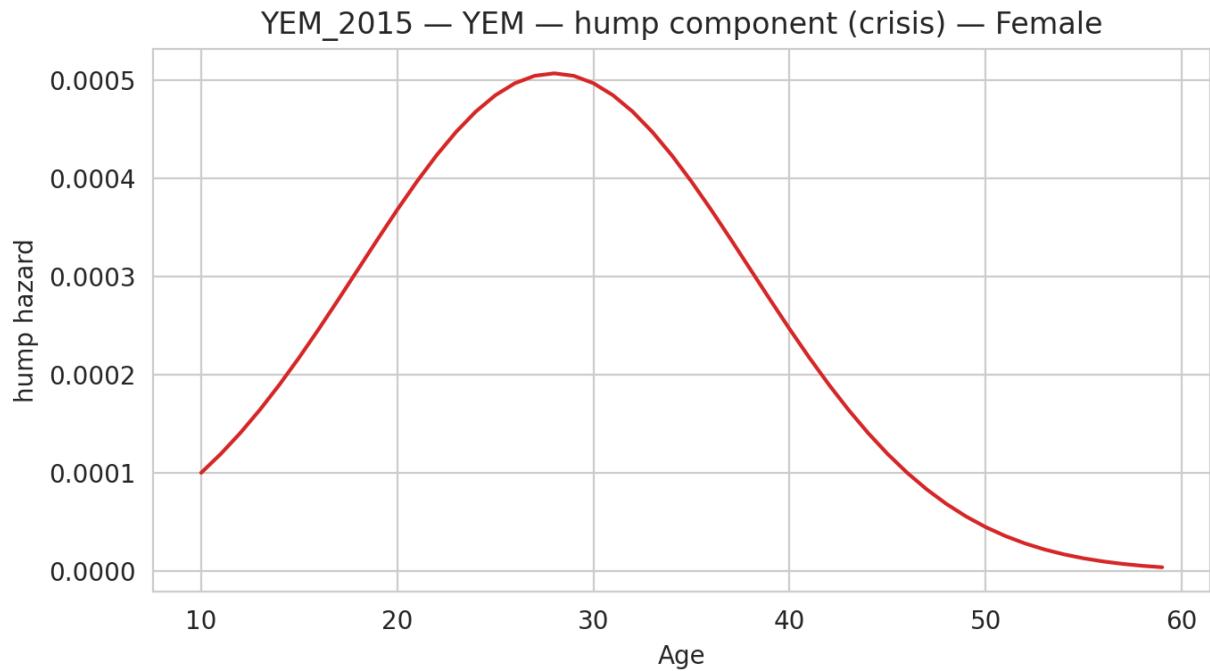


Figure 23: YEM_2015_YEM_Female_hump_component

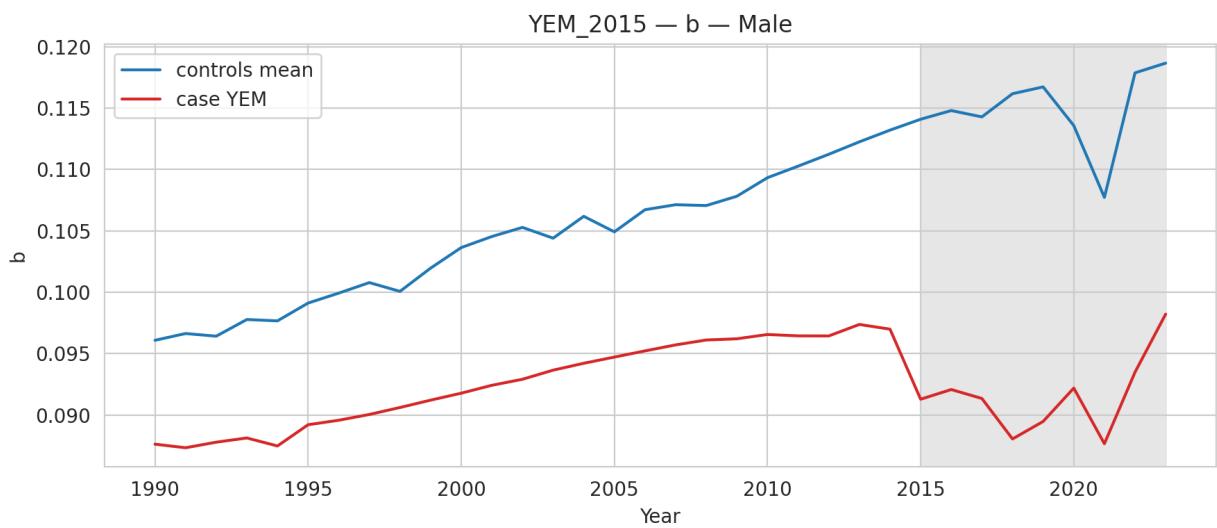


Figure 24: YEM_2015_YEM_Male_timeseries_b

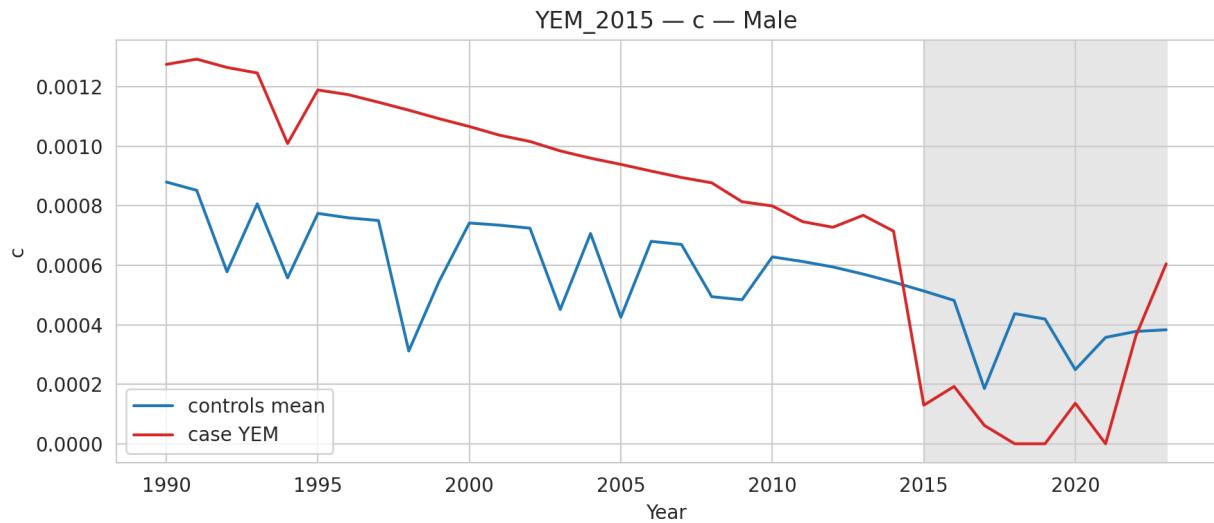


Figure 25: YEM_2015_YEM_Male_timeseries_c

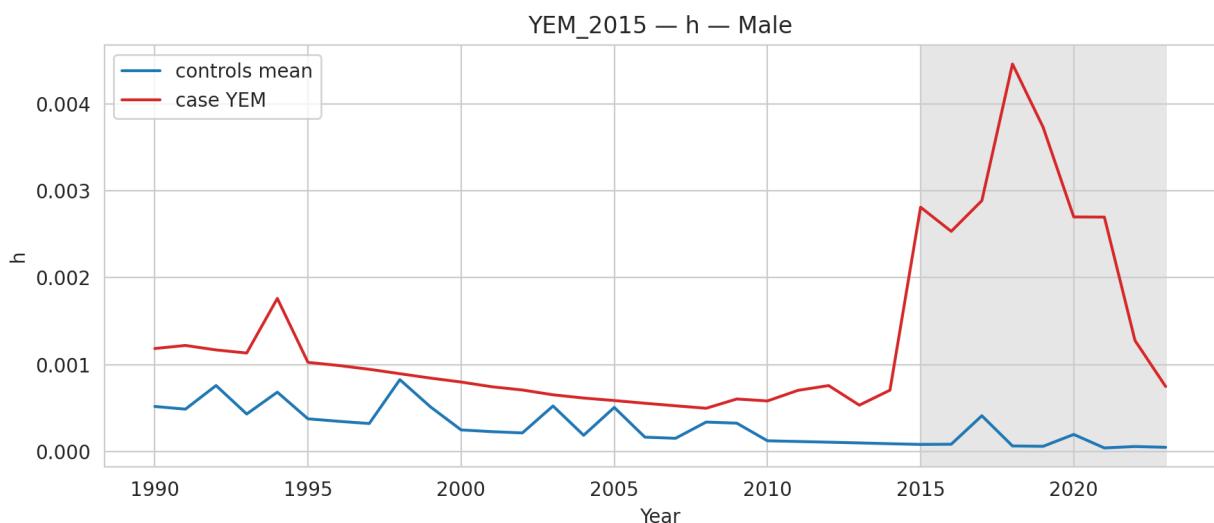


Figure 26: YEM_2015_YEM_Male_timeseries_h

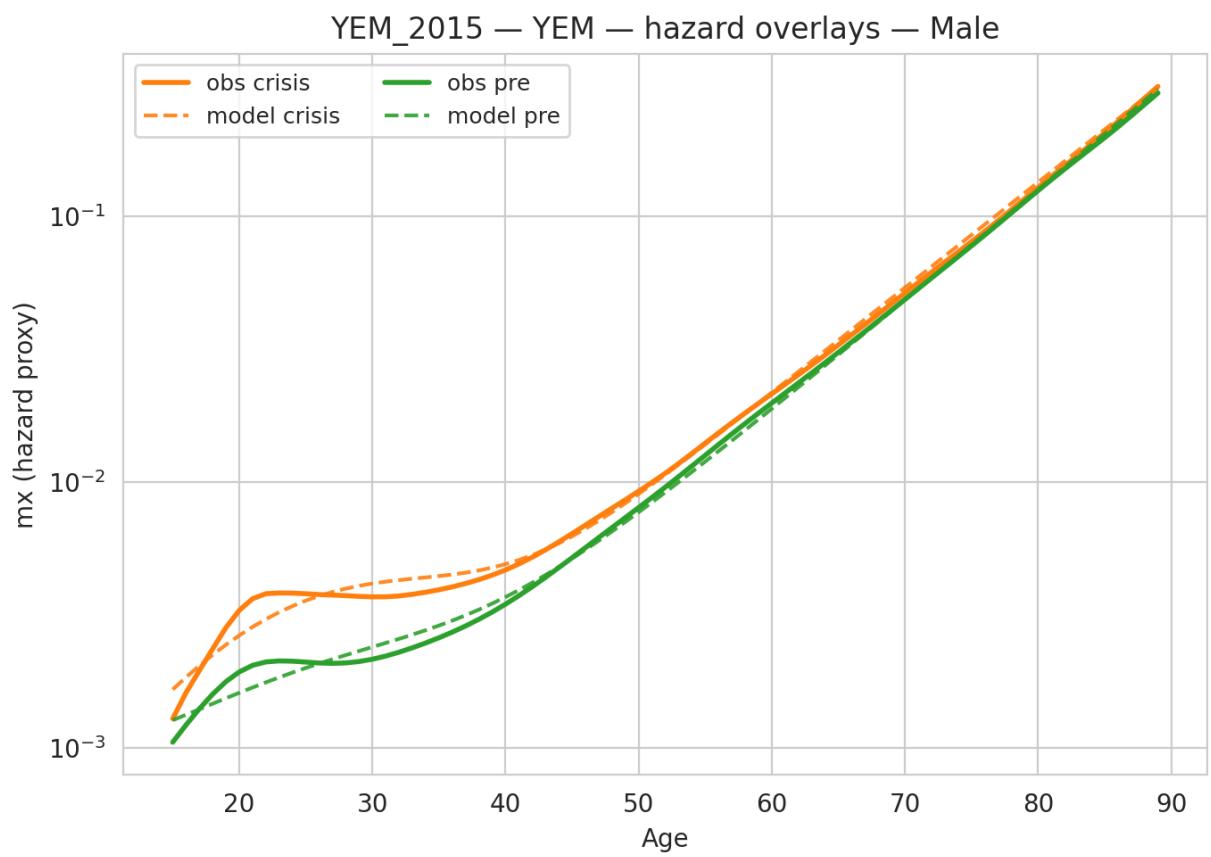


Figure 27: YEM_2015_YEM_Male_hazard_overlays

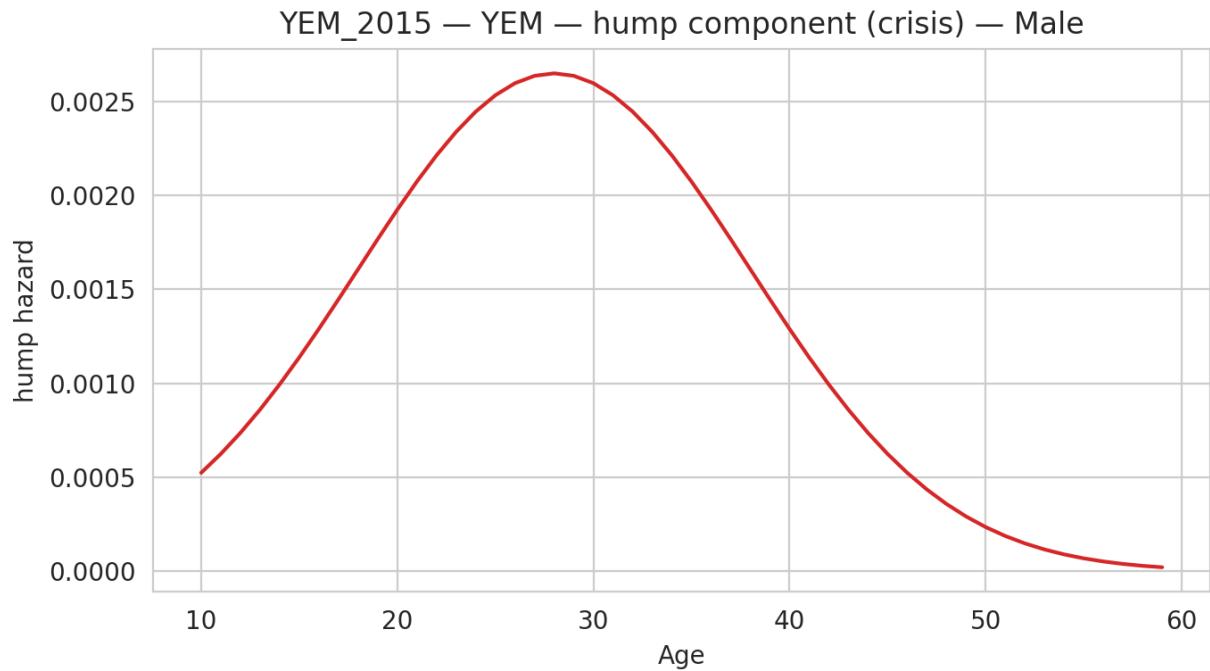


Figure 28: YEM_2015_YEM_Male_hump_component

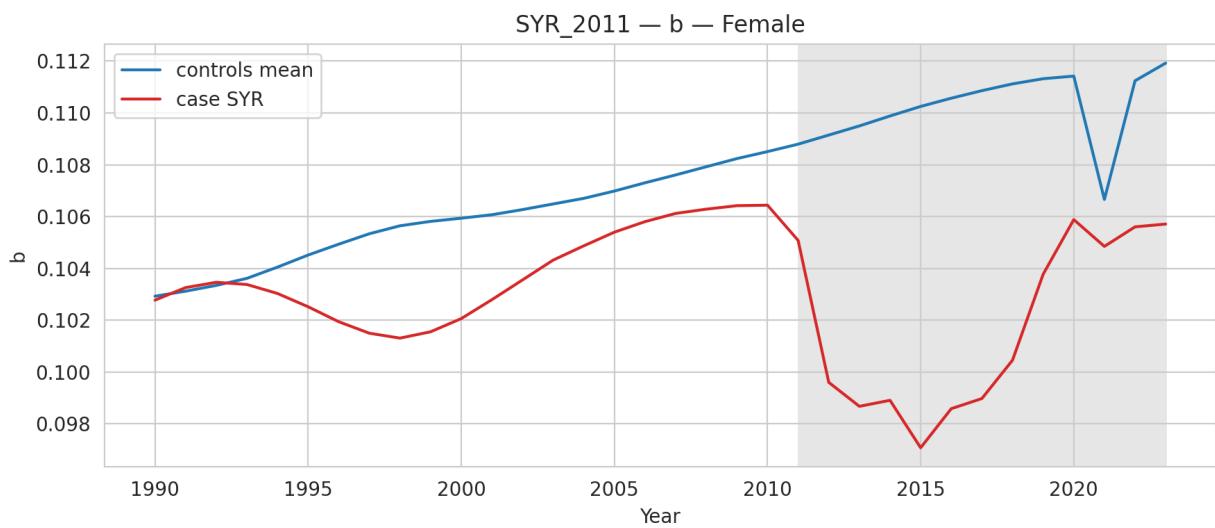


Figure 29: SYR_2011_SYR_Female_timeseries_b

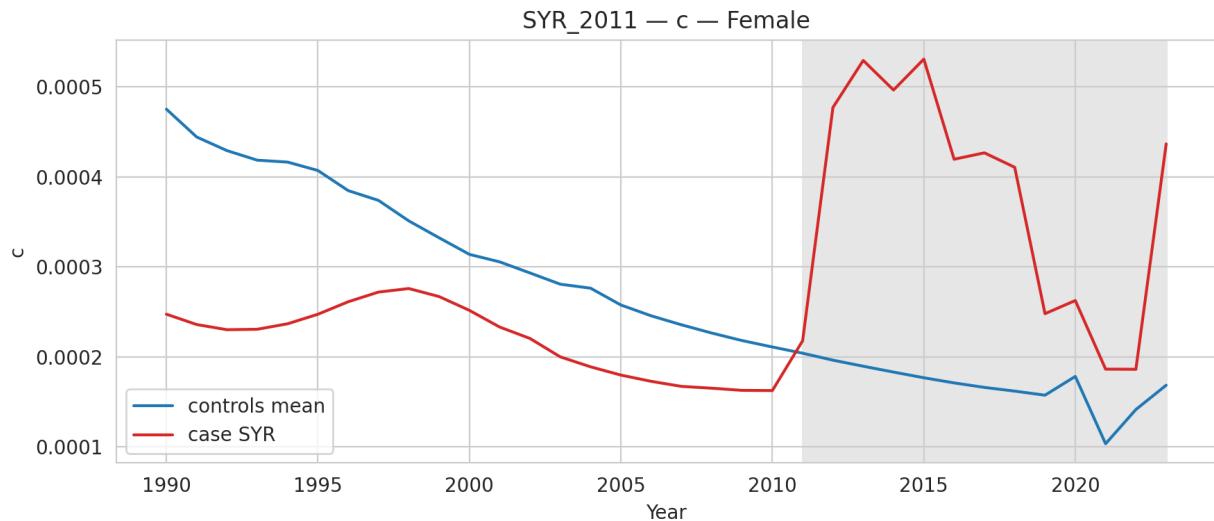


Figure 30: SYR_2011_SYR_Female_timeseries_c

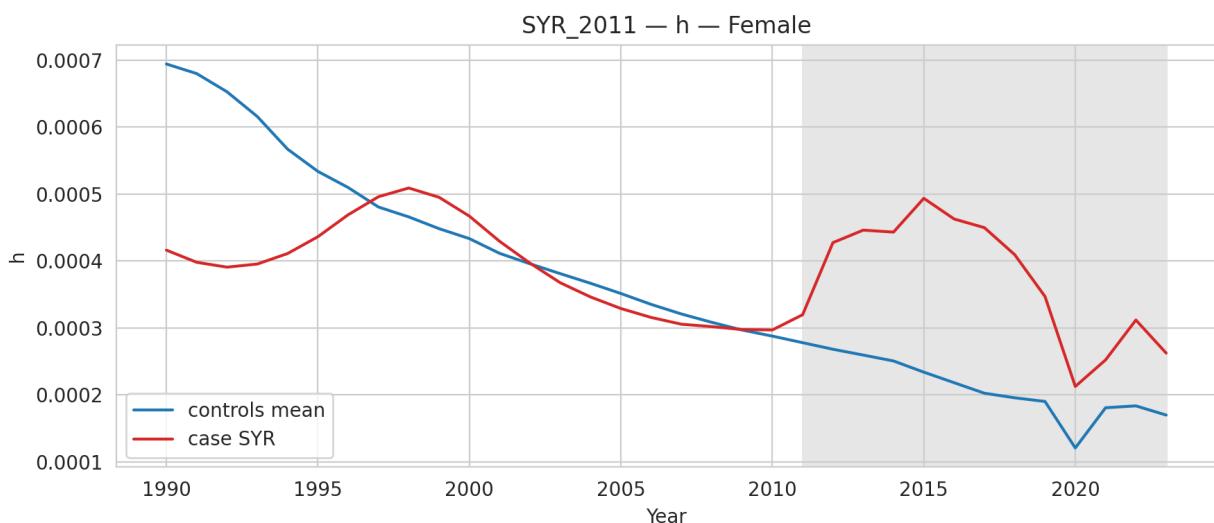


Figure 31: SYR_2011_SYR_Female_timeseries_h

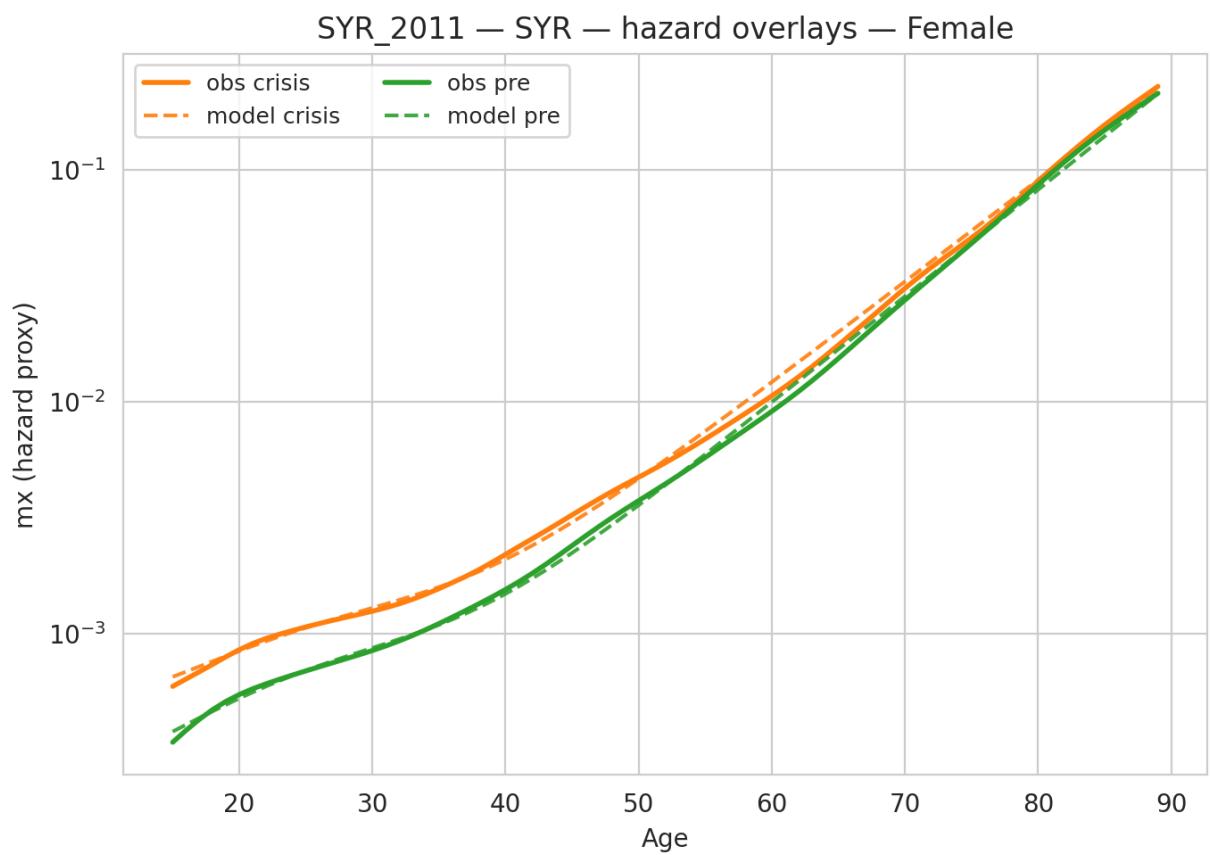


Figure 32: SYR_2011_SYR_Female_hazard_overlays

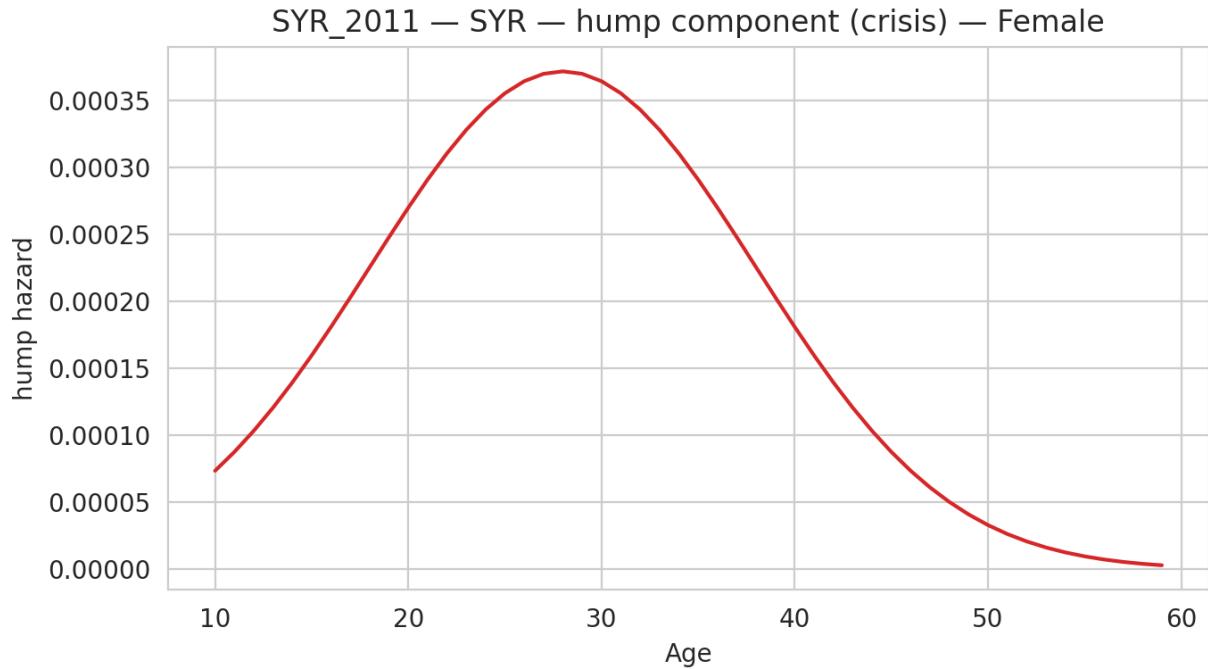


Figure 33: SYR_2011_SYR_Female_hump_component

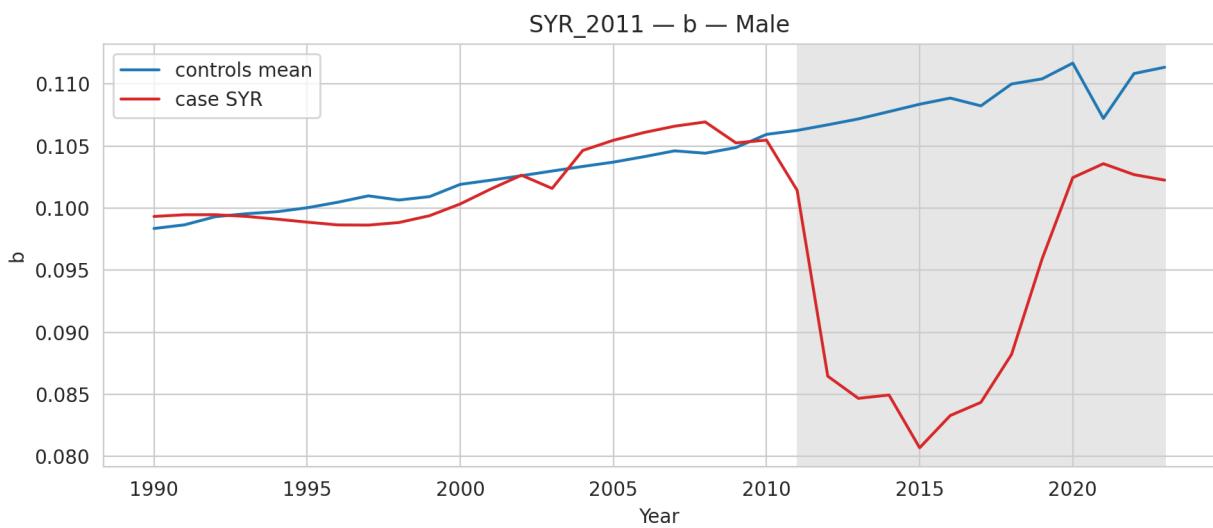


Figure 34: SYR_2011_SYR_Male_timeseries_b

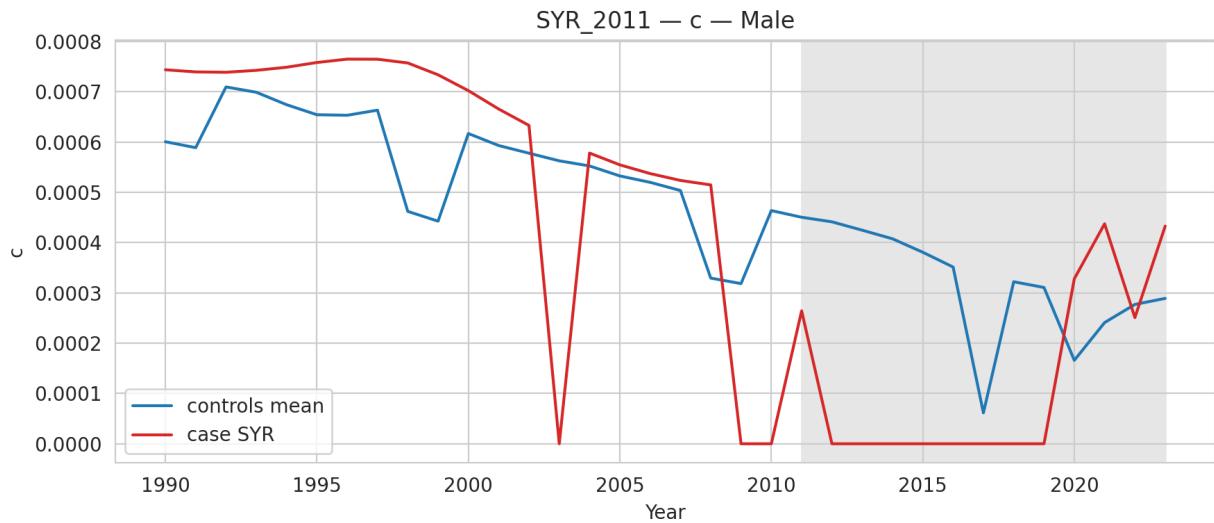


Figure 35: SYR_2011_SYR_Male_timeseries_c

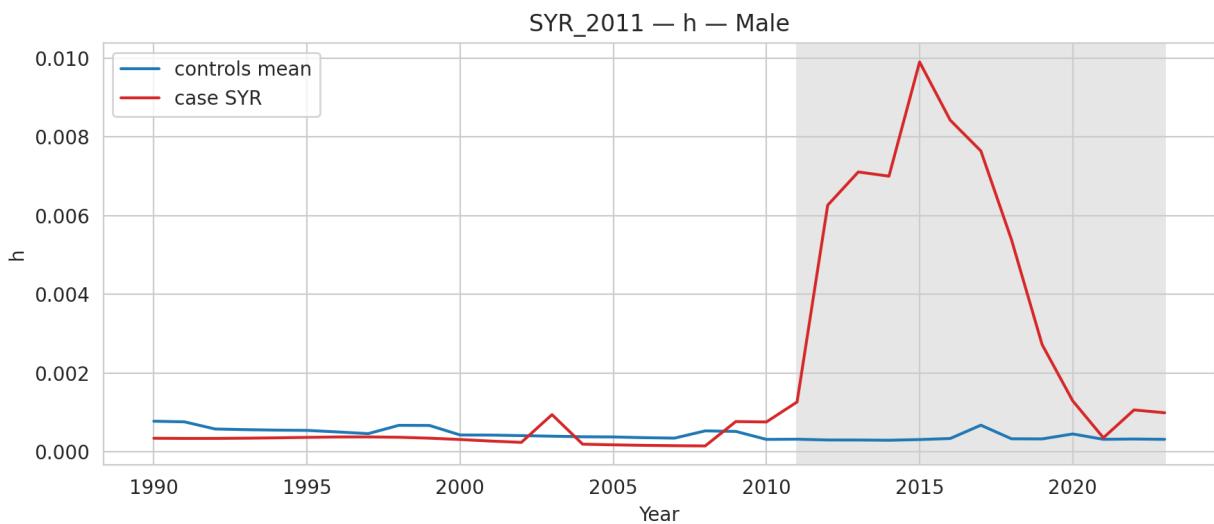


Figure 36: SYR_2011_SYR_Male_timeseries_h

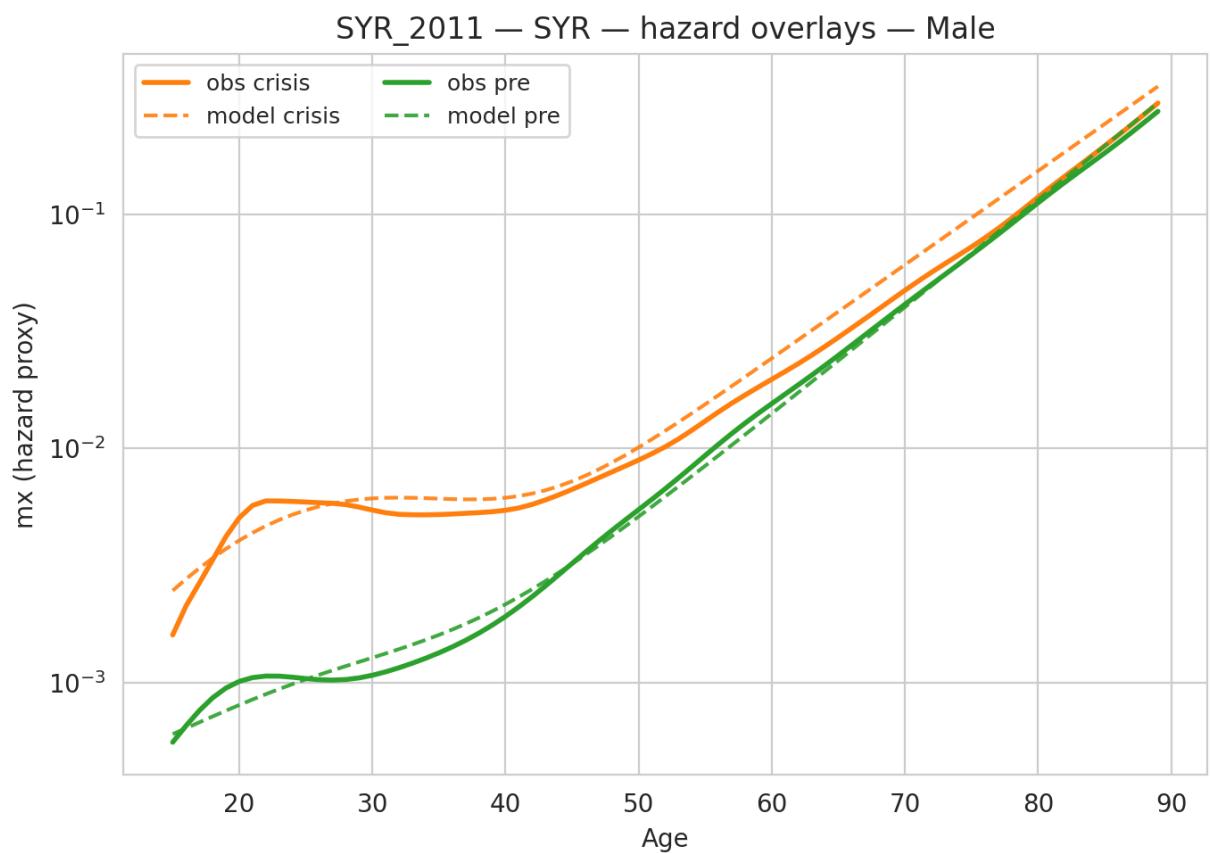


Figure 37: SYR_2011_SYR_Male_hazard_overlays

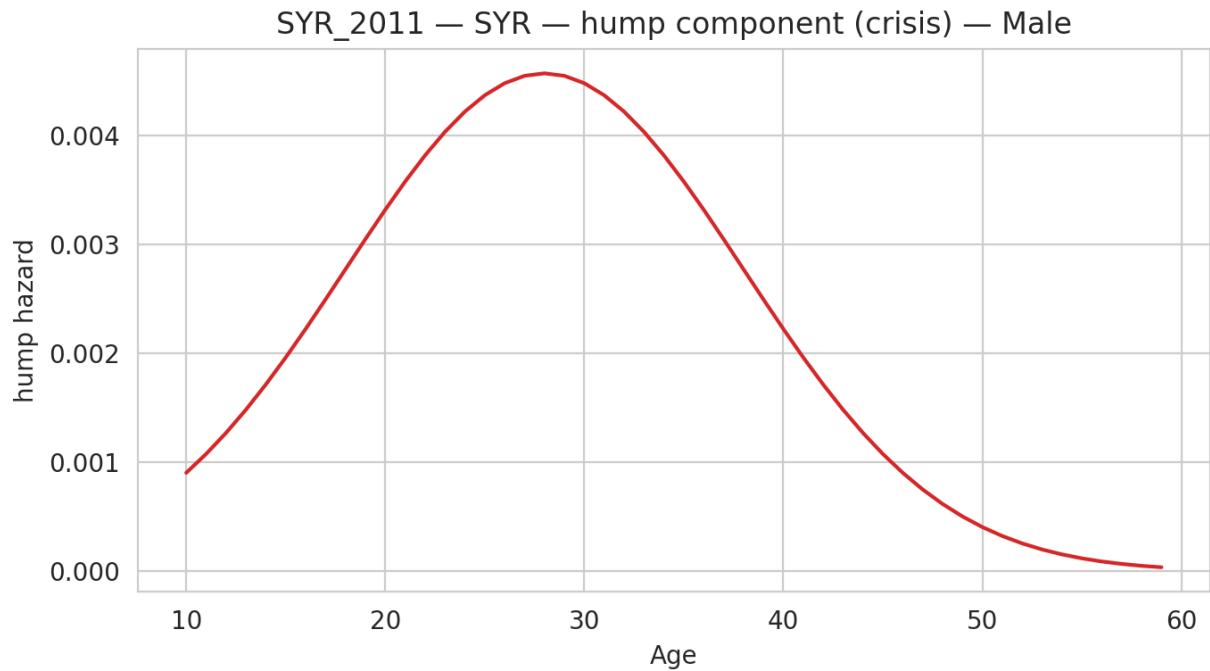


Figure 38: SYR_2011_SYR_Male_hump_component

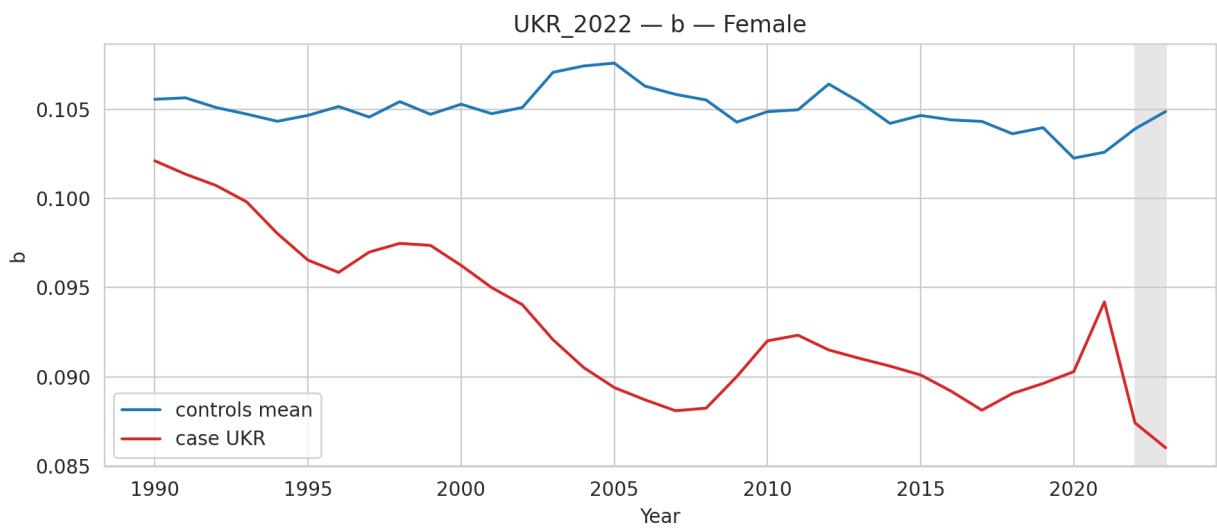


Figure 39: UKR_2022_UKR_Female_timeseries_b

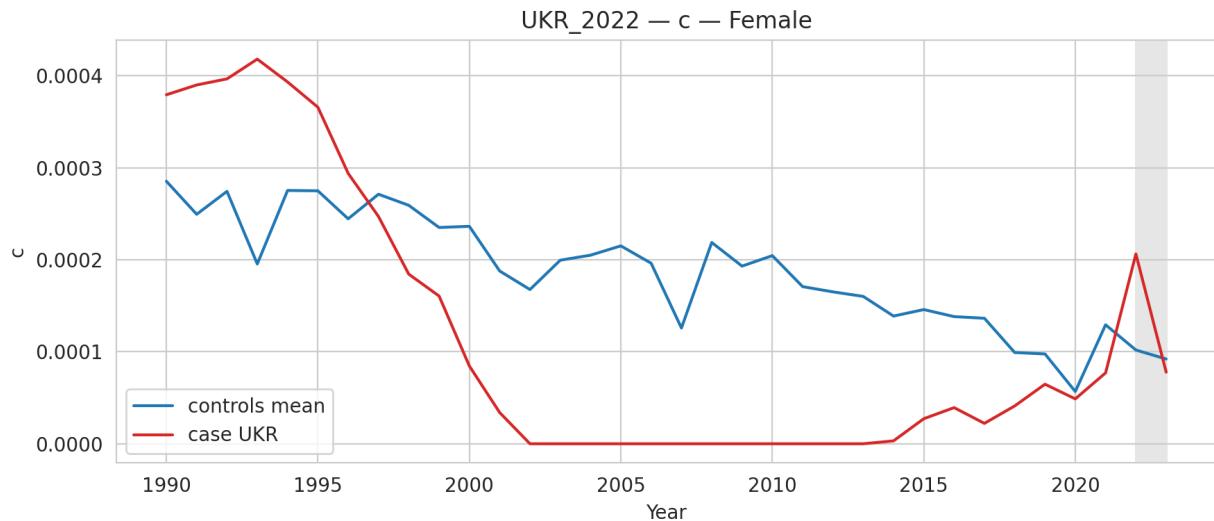


Figure 40: UKR_2022_UKR_Female_timeseries_c

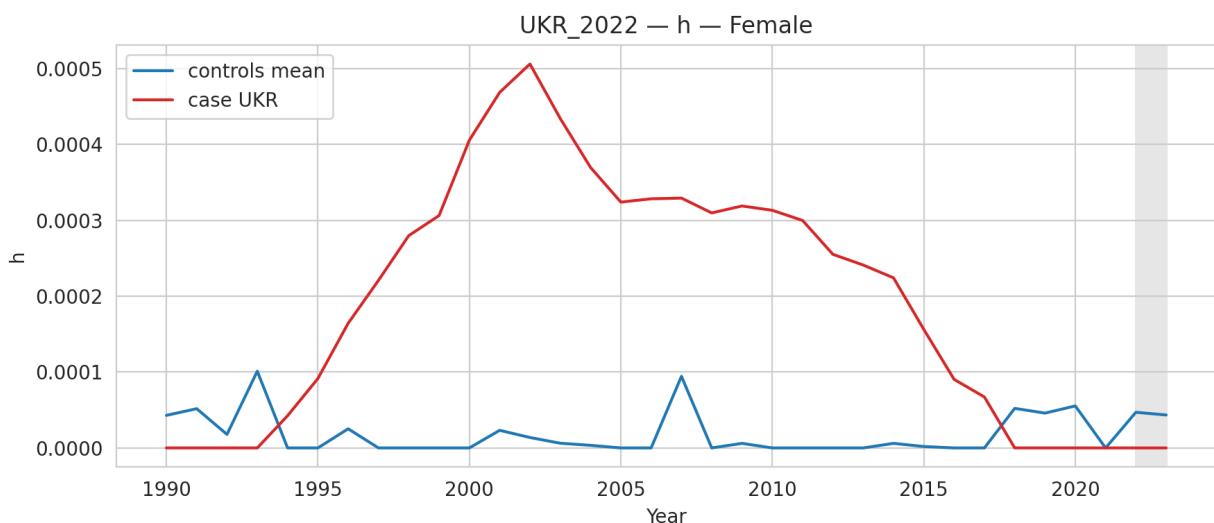


Figure 41: UKR_2022_UKR_Female_timeseries_h

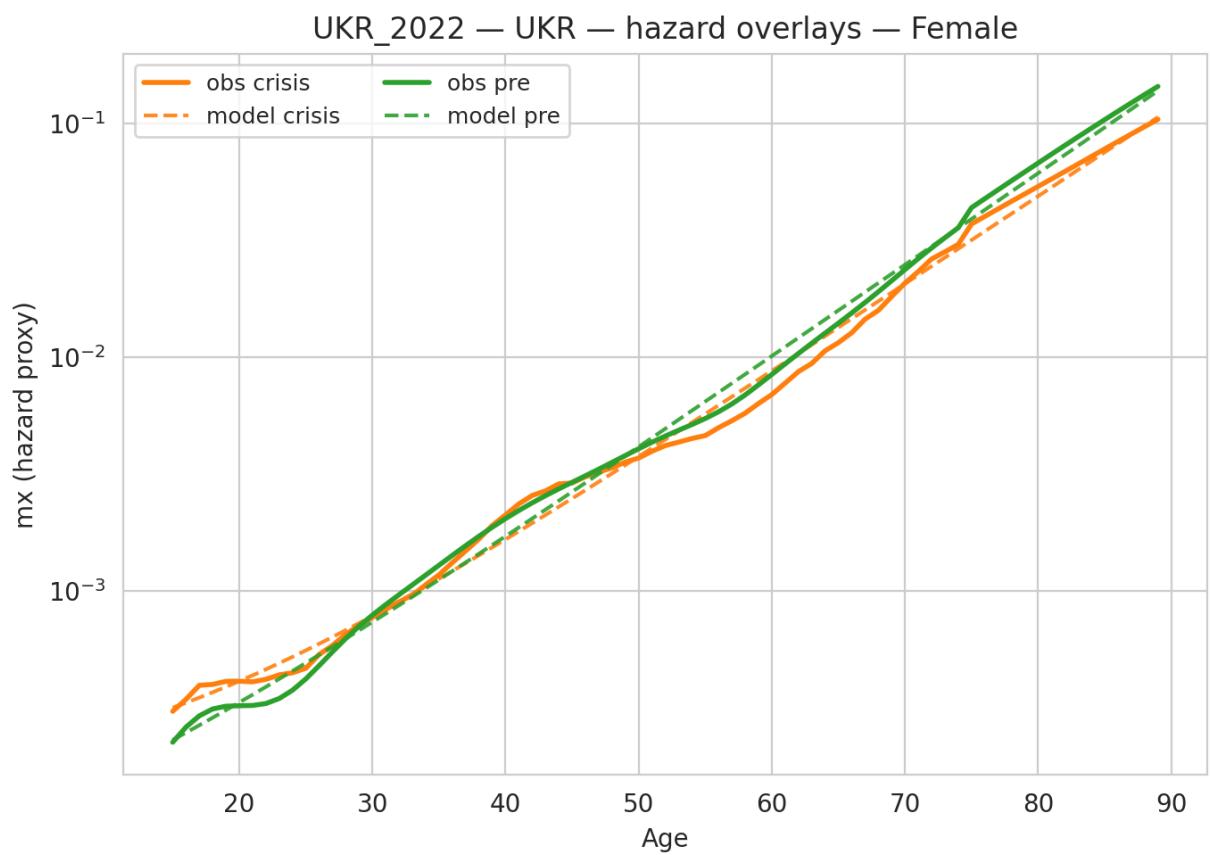


Figure 42: UKR_2022_UKR_Female_hazard_overlays

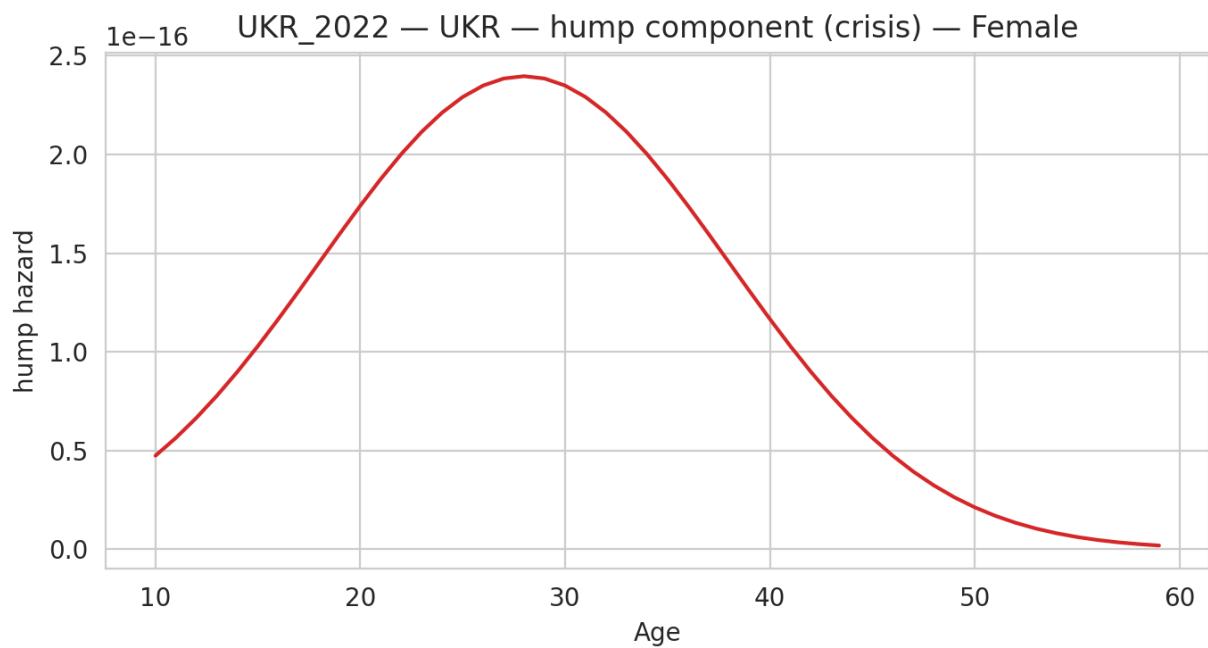


Figure 43: UKR_2022_UKR_Female_hump_component

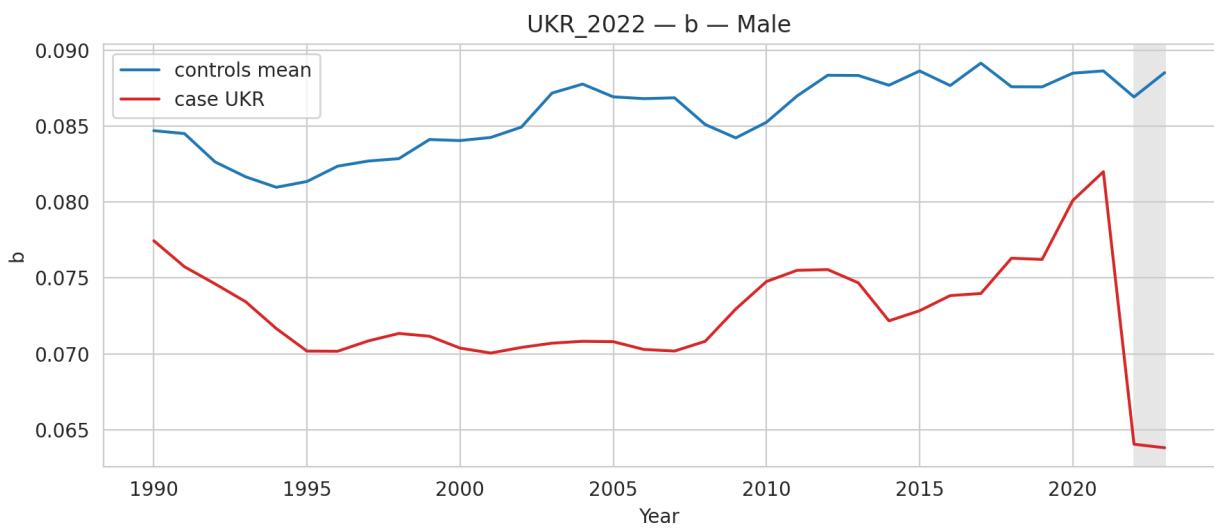


Figure 44: UKR_2022_UKR_Male_timeseries_b

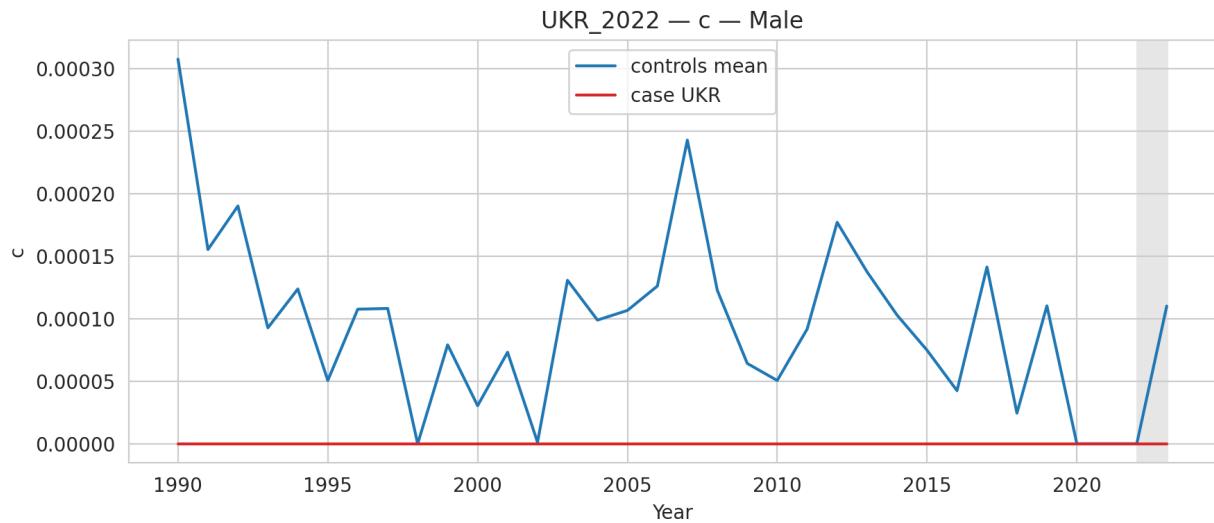


Figure 45: UKR_2022_UKR_Male_timeseries_c

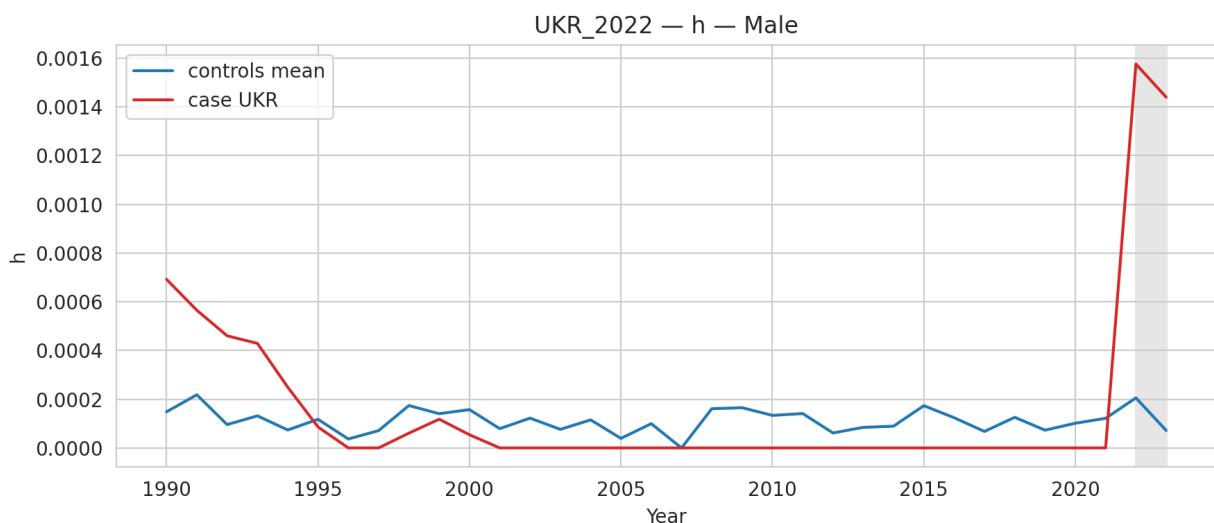


Figure 46: UKR_2022_UKR_Male_timeseries_h

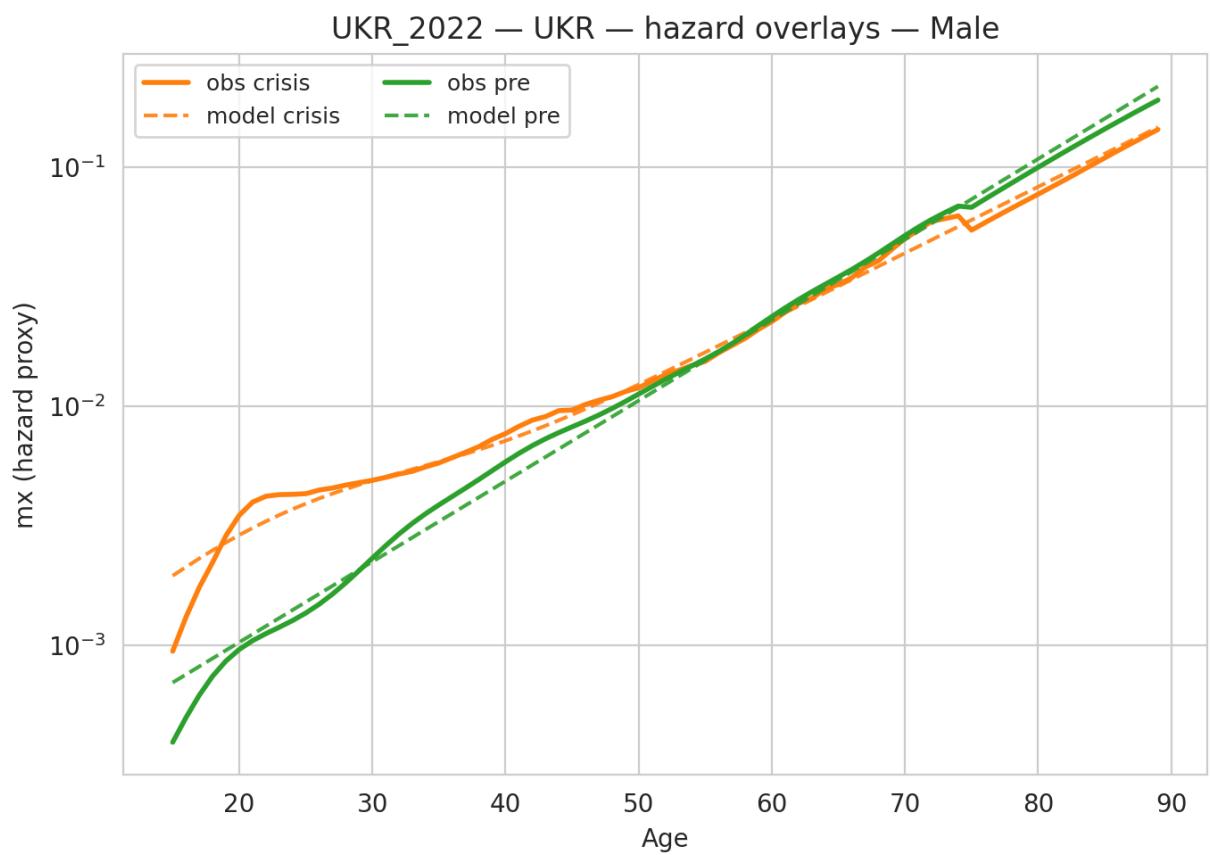


Figure 47: UKR_2022_UKR_Male_hazard_overlays

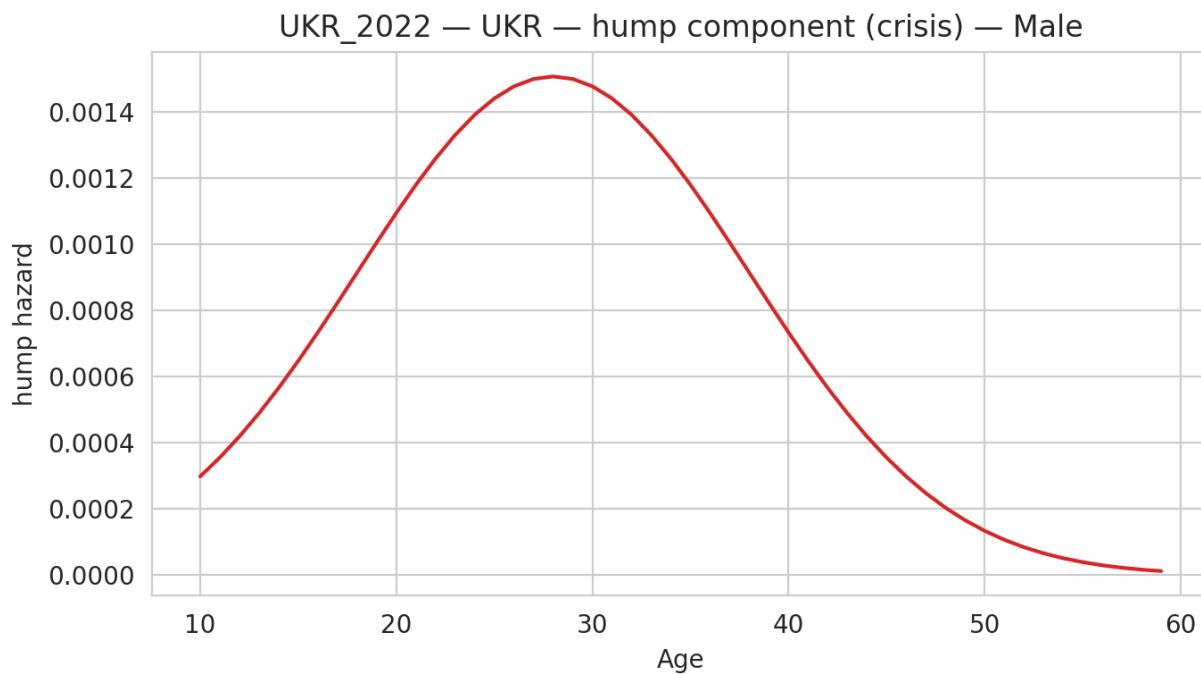


Figure 48: UKR_2022_UKR_Male_hump_component

2.13.3.2 Male

2.14 Regressions

2.14.1 Female

2.14.1.1 Outcome: c

OLS Regression Results						
Dep. Variable:	c	R-squared:	0.772			
Model:	OLS	Adj. R-squared:	0.654			
Method:	Least Squares	F-statistic:	1.634			
Date:	Thu, 05 Feb 2026	Prob (F-statistic):	0.323			
Time:	22:21:29	Log-Likelihood:	400.40			
No. Observations:	45	AIC:	-768.8			
Df Residuals:	29	BIC:	-739.9			
Df Model:	15					
Covariance Type:	cluster					
	coef	std err	z	P> z	[0.025	0.975]
Intercept	9.418e-05	2.3e-05	4.103	0.000	4.92e-05	0.000
C(iso3)[T.POL]	-5.718e-05	1.35e-05	-4.226	0.000	-8.37e-05	-3.07e-05
C(iso3)[T.ROU]	7.685e-06	1.24e-05	0.619	0.536	-1.66e-05	3.2e-05
C(iso3)[T.TUN]	4.844e-05	2.6e-05	1.862	0.063	-2.55e-06	9.94e-05
C(iso3)[T.UKR]	-9.24e-05	1.51e-05	-6.112	0.000	-0.000	-6.28e-05
C(year)[T.2016]	-9.241e-06	7.51e-06	-1.231	0.218	-2.4e-05	5.47e-06
C(year)[T.2017]	-1.299e-05	1.35e-05	-0.960	0.337	-3.95e-05	1.35e-05

C(year) [T.2018]	-3.231e-05	2.55e-05	-1.266	0.205	-8.23e-05	1.77e-05
C(year) [T.2019]	-3.339e-05	2.87e-05	-1.162	0.245	-8.97e-05	2.3e-05
C(year) [T.2020]	-6.86e-05	2.04e-05	-3.362	0.001	-0.000	-2.86e-05
C(year) [T.2021]	-4.554e-05	3.11e-05	-1.464	0.143	-0.000	1.54e-05
C(year) [T.2022]	-2.297e-05	4.05e-05	-0.567	0.571	-0.000	5.65e-05
C(year) [T.2023]	-5.257e-05	3e-05	-1.752	0.080	-0.000	6.23e-06
battle_deaths_per_100k	-1.563e-05	8.32e-06	-1.879	0.060	-3.19e-05	6.78e-07
pou	1.237e-05	1.15e-05	1.080	0.280	-1.01e-05	3.48e-05
fies	2.538e-06	2.4e-06	1.058	0.290	-2.16e-06	7.24e-06
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Omnibus:	3.085	Durbin-Watson:	2.165			
Prob(Omnibus):	0.214	Jarque-Bera (JB):	2.312			
Skew:	0.182	Prob(JB):	0.315			
Kurtosis:	4.049	Cond. No.	252.			
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Notes:

[1] Standard Errors are robust to cluster correlation (cluster)

Coefficients CSV: reports/tables/regression_c_Female_coef.csv

2.14.1.2 Outcome: b

OLS Regression Results

Dep. Variable:	b	R-squared:	0.969			
Model:	OLS	Adj. R-squared:	0.952			
Method:	Least Squares	F-statistic:	56.23			
Date:	Thu, 05 Feb 2026	Prob (F-statistic):	0.000905			
Time:	22:21:29	Log-Likelihood:	228.45			
No. Observations:	45	AIC:	-424.9			
Df Residuals:	29	BIC:	-396.0			
Df Model:	15					
Covariance Type:	cluster					
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	coef	std err	z	P> z	[0.025	0.975]
Intercept	0.1042	0.001	96.866	0.000	0.102	0.106
C(iso3) [T.POL]	0.0011	0.001	1.014	0.311	-0.001	0.003
C(iso3) [T.ROU]	0.0034	0.001	4.535	0.000	0.002	0.005
C(iso3) [T.TUN]	0.0147	0.002	7.786	0.000	0.011	0.018
C(iso3) [T.UKR]	-0.0117	0.001	-8.381	0.000	-0.014	-0.009
C(year) [T.2016]	-0.0004	0.000	-1.360	0.174	-0.001	0.000
C(year) [T.2017]	-0.0008	0.001	-1.268	0.205	-0.002	0.000
C(year) [T.2018]	-0.0011	0.001	-2.167	0.030	-0.002	-0.000
C(year) [T.2019]	-0.0007	0.001	-1.205	0.228	-0.002	0.000
C(year) [T.2020]	-0.0013	0.001	-1.228	0.220	-0.003	0.001
C(year) [T.2021]	-0.0015	0.002	-0.665	0.506	-0.006	0.003
C(year) [T.2022]	-0.0010	0.001	-1.947	0.052	-0.002	6.76e-06
C(year) [T.2023]	-0.0008	0.001	-0.702	0.483	-0.003	0.001
battle_deaths_per_100k	-3.563e-05	0.000	-0.273	0.785	-0.000	0.000
pou	0.0002	0.001	0.436	0.662	-0.001	0.001
fies	-0.0001	0.000	-0.753	0.452	-0.000	0.000
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Omnibus:	15.104	Durbin-Watson:	1.855			

Prob(Omnibus):	0.001	Jarque-Bera (JB):	42.831
Skew:	0.603	Prob(JB):	5.00e-10
Kurtosis:	7.625	Cond. No.	252.

Notes:

[1] Standard Errors are robust to cluster correlation (cluster)

Coefficients CSV: reports/tables/regression_b_Female_coef.csv

2.14.1.3 Outcome: h

OLS Regression Results

Dep. Variable:	h	R-squared:	0.684			
Model:	OLS	Adj. R-squared:	0.520			
Method:	Least Squares	F-statistic:	5.096			
Date:	Thu, 05 Feb 2026	Prob (F-statistic):	0.0719			
Time:	22:21:29	Log-Likelihood:	401.28			
No. Observations:	45	AIC:	-770.6			
Df Residuals:	29	BIC:	-741.7			
Df Model:	15					
Covariance Type:	cluster					
	coef	std err	z	P> z	[0.025	0.975]
Intercept	-1.336e-05	2.34e-05	-0.570	0.569	-5.93e-05	3.26e-05
C(iso3)[T.POL]	7.005e-05	2.19e-05	3.199	0.001	2.71e-05	0.000
C(iso3)[T.ROU]	8.867e-07	2.07e-05	0.043	0.966	-3.97e-05	4.15e-05
C(iso3)[T.TUN]	0.0001	4.45e-05	2.259	0.024	1.33e-05	0.000
C(iso3)[T.UKR]	-1.142e-05	1.55e-05	-0.735	0.462	-4.19e-05	1.9e-05
C(year)[T.2016]	6.619e-06	2.05e-05	0.322	0.747	-3.36e-05	4.69e-05
C(year)[T.2017]	9.166e-06	1.99e-05	0.460	0.646	-2.99e-05	4.82e-05
C(year)[T.2018]	3.157e-05	4.57e-05	0.690	0.490	-5.81e-05	0.000
C(year)[T.2019]	2.733e-05	4.3e-05	0.636	0.525	-5.69e-05	0.000
C(year)[T.2020]	3.478e-05	4.92e-05	0.707	0.480	-6.16e-05	0.000
C(year)[T.2021]	1.904e-05	2.24e-05	0.851	0.395	-2.48e-05	6.29e-05
C(year)[T.2022]	3.901e-05	4.91e-05	0.795	0.427	-5.72e-05	0.000
C(year)[T.2023]	3.531e-05	4.32e-05	0.818	0.414	-4.93e-05	0.000
battle_deaths_per_100k	5.173e-05	1.52e-05	3.400	0.001	2.19e-05	8.15e-05
pou	2.243e-06	1.71e-05	0.131	0.896	-3.12e-05	3.57e-05
fies	-9.637e-07	4.14e-06	-0.233	0.816	-9.07e-06	7.14e-06

Omnibus:	0.386	Durbin-Watson:	1.730
Prob(Omnibus):	0.824	Jarque-Bera (JB):	0.074
Skew:	0.092	Prob(JB):	0.964
Kurtosis:	3.074	Cond. No.	252.

Notes:

[1] Standard Errors are robust to cluster correlation (cluster)

Coefficients CSV: reports/tables/regression_h_Female_coef.csv

2.14.2 Male

2.14.2.1 Outcome: c

OLS Regression Results

Dep. Variable:	c	R-squared:	0.660			
Model:	OLS	Adj. R-squared:	0.484			
Method:	Least Squares	F-statistic:	14.30			
Date:	Thu, 05 Feb 2026	Prob (F-statistic):	0.0123			
Time:	22:21:29	Log-Likelihood:	379.74			
No. Observations:	45	AIC:	-727.5			
Df Residuals:	29	BIC:	-698.6			
Df Model:	15					
Covariance Type:	cluster					
	coef	std err	z	P> z	[0.025	0.975]
Intercept	0.0001	3.94e-05	3.613	0.000	6.51e-05	0.000
C(iso3)[T.POL]	-8.88e-05	3.38e-05	-2.629	0.009	-0.000	-2.26e-05
C(iso3)[T.ROU]	1.051e-05	2.32e-05	0.453	0.651	-3.5e-05	5.61e-05
C(iso3)[T.TUN]	0.0001	5.41e-05	1.891	0.059	-3.75e-06	0.000
C(iso3)[T.UKR]	-4.75e-05	3.14e-05	-1.513	0.130	-0.000	1.4e-05
C(year)[T.2016]	-3.421e-05	2.91e-05	-1.178	0.239	-9.11e-05	2.27e-05
C(year)[T.2017]	1.606e-05	6.04e-05	0.266	0.790	-0.000	0.000
C(year)[T.2018]	-5.683e-05	3.92e-05	-1.448	0.148	-0.000	2.01e-05
C(year)[T.2019]	-4.194e-06	8.66e-05	-0.048	0.961	-0.000	0.000
C(year)[T.2020]	-6.852e-05	7.01e-05	-0.978	0.328	-0.000	6.88e-05
C(year)[T.2021]	-8.411e-05	7.8e-05	-1.078	0.281	-0.000	6.88e-05
C(year)[T.2022]	-6.963e-05	7.6e-05	-0.916	0.359	-0.000	7.93e-05
C(year)[T.2023]	-4.415e-06	9.04e-05	-0.049	0.961	-0.000	0.000
battle_deaths_per_100k	-1.571e-05	1.69e-05	-0.928	0.353	-4.89e-05	1.75e-05
pou	-5.572e-06	2.05e-05	-0.272	0.786	-4.58e-05	3.46e-05
fies	-9.396e-07	5.22e-06	-0.180	0.857	-1.12e-05	9.3e-06
Omnibus:	3.559	Durbin-Watson:	2.246			
Prob(Omnibus):	0.169	Jarque-Bera (JB):	2.953			
Skew:	0.627	Prob(JB):	0.228			
Kurtosis:	3.018	Cond. No.	252.			

Notes:

[1] Standard Errors are robust to cluster correlation (cluster)

Coefficients CSV: reports/tables/regression_c_Male_coef.csv

2.14.2.2 Outcome: b

OLS Regression Results

Dep. Variable:	b	R-squared:	0.966
Model:	OLS	Adj. R-squared:	0.949
Method:	Least Squares	F-statistic:	14.93
Date:	Thu, 05 Feb 2026	Prob (F-statistic):	0.0113
Time:	22:21:29	Log-Likelihood:	215.52
No. Observations:	45	AIC:	-399.0

Df Residuals:	29	BIC:	-370.1			
Df Model:	15					
Covariance Type:	cluster					
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	coef	std err	z	P> z	[0.025	0.975]
Intercept	0.1003	0.004	28.613	0.000	0.093	0.107
C(iso3)[T.POL]	-0.0079	0.002	-3.335	0.001	-0.013	-0.003
C(iso3)[T.ROU]	-0.0013	0.001	-1.028	0.304	-0.004	0.001
C(iso3)[T.TUN]	0.0206	0.004	5.449	0.000	0.013	0.028
C(iso3)[T.UKR]	-0.0094	0.003	-2.827	0.005	-0.016	-0.003
C(year)[T.2016]	-0.0015	0.001	-1.435	0.151	-0.003	0.001
C(year)[T.2017]	-0.0015	0.001	-1.184	0.237	-0.004	0.001
C(year)[T.2018]	-0.0023	0.001	-1.564	0.118	-0.005	0.001
C(year)[T.2019]	-0.0016	0.001	-1.140	0.254	-0.004	0.001
C(year)[T.2020]	0.0007	0.002	0.339	0.735	-0.003	0.005
C(year)[T.2021]	0.0015	0.003	0.472	0.637	-0.005	0.008
C(year)[T.2022]	-0.0026	0.002	-1.491	0.136	-0.006	0.001
C(year)[T.2023]	-0.0020	0.002	-1.252	0.211	-0.005	0.001
battle_deaths_per_100k	-0.0018	0.000	-4.709	0.000	-0.002	-0.001
pou	-0.0012	0.001	-1.668	0.095	-0.003	0.000
fies	-0.0004	0.000	-1.101	0.271	-0.001	0.000
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Omnibus:	18.038	Durbin-Watson:	1.727			
Prob(Omnibus):	0.000	Jarque-Bera (JB):	37.550			
Skew:	0.997	Prob(JB):	7.02e-09			
Kurtosis:	7.006	Cond. No.	252.			
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Notes:

[1] Standard Errors are robust to cluster correlation (cluster)

Coefficients CSV: reports/tables/regression_b_Male_coef.csv

2.14.2.3 Outcome: h

OLS Regression Results						
Dep. Variable:	h	R-squared:	0.832			
Model:	OLS	Adj. R-squared:	0.746			
Method:	Least Squares	F-statistic:	2.164			
Date:	Thu, 05 Feb 2026	Prob (F-statistic):	0.237			
Time:	22:21:29	Log-Likelihood:	329.69			
No. Observations:	45	AIC:	-627.4			
Df Residuals:	29	BIC:	-598.5			
Df Model:	15					
Covariance Type:	cluster					
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	coef	std err	z	P> z	[0.025	0.975]
Intercept	-0.0010	0.000	-2.784	0.005	-0.002	-0.000
C(iso3)[T.POL]	0.0005	0.000	2.412	0.016	8.69e-05	0.001
C(iso3)[T.ROU]	-3.766e-05	9.79e-05	-0.385	0.700	-0.000	0.000
C(iso3)[T.TUN]	0.0004	0.000	1.463	0.144	-0.000	0.001
C(iso3)[T.UKR]	-0.0004	0.000	-1.216	0.224	-0.001	0.000

C(year) [T.2016]	2.311e-05	6.55e-05	0.353	0.724	-0.000	0.000
C(year) [T.2017]	7.49e-05	8.66e-05	0.865	0.387	-9.47e-05	0.000
C(year) [T.2018]	0.0001	8.46e-05	1.494	0.135	-3.95e-05	0.000
C(year) [T.2019]	2.59e-05	5.54e-05	0.467	0.640	-8.27e-05	0.000
C(year) [T.2020]	-4.405e-05	0.000	-0.356	0.722	-0.000	0.000
C(year) [T.2021]	-0.0001	0.000	-0.546	0.585	-0.001	0.000
C(year) [T.2022]	0.0002	0.000	1.318	0.187	-9.89e-05	0.001
C(year) [T.2023]	0.0001	8.65e-05	1.178	0.239	-6.77e-05	0.000
battle_deaths_per_100k	4.846e-05	5.68e-05	0.853	0.394	-6.29e-05	0.000
pou	0.0002	7.89e-05	2.714	0.007	5.95e-05	0.000
fies	3.117e-05	2.69e-05	1.159	0.246	-2.15e-05	8.39e-05
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Omnibus:	8.358	Durbin-Watson:	1.684			
Prob(Omnibus):	0.015	Jarque-Bera (JB):	16.281			
Skew:	-0.183	Prob(JB):	0.000291			
Kurtosis:	5.924	Cond. No.	252.			
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Notes:

[1] Standard Errors are robust to cluster correlation (cluster)

Coefficients CSV: reports/tables/regression_h_Male_coef.csv

2.15 Notes

3 Results

This file is intentionally lightweight. Run the pipeline to populate: - reports/figures/ for event-study figures - reports/tables/ for regression outputs and summaries

3.1 India SRS (optional add-on)

If you have SRS-Abridged_Life_Tables_2018-2022.pdf in the repo root, you can extract and fit models for India + states/UTs:

```
python3 scripts/05_extract_srs_life_tables.py
python3 scripts/55_fit_srs_models.py
```

Key outputs: - data/intermediate/srs_abridged_life_tables_2018_22.csv - data/processed/srs_params.parquet - data/processed/srs_urban_rural_deltas.parquet - reports/figures/srs/ (Urban – Rural delta plots; optional hazard overlays)

3.2 Extra APIs (optional)

If your environment has internet access, you can fetch additional series:

```
python3 scripts/11_fetch_wdi_extra.py
python3 scripts/12_fetch_who_gho.py
```