Quantifying excess mortality by cause of death against a pre-pandemic and socio-economic factor-dependent baseline

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RCLR Research Centre for Longevity Risk

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Research objectives and approach

Overall objective: to quantify and to analyze excess mortality against a pre-pandemic baseline for expected cause-specific mortality in 2020 and 2021, taking socio-economic factors into account.

A phased approach, with intermediate research objectives:

1. to establish a cause-specific, pre-pandemic baseline mortality level, taking socio-economic factors into account

2.a. to quantify cause-specific excess mortality during the COVID waves in 2020 and 2021

2.b. to analyze to what extent excess mortality can be attributed to socio-economic risk factors and information on COVID-19 testing and vaccination.

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Related literature

We contribute to the literature developed by:

- national statistics and public health institutes (e.g., CBS and RIVM) on excess mortality in 2020 and 2021, see CBS, 2022a and Office for National Statistics (ONS), 2024
- actuarial researchers on cause-specific mortality models and subpopulation-specific mortality levels, see van Berkum et al., 2020
- demographers and epidemiologists on the importance of the baseline mortality level to quantify excess mortality, see Schöley, 2021; Schöley et al., 2023 and Ferenci, 2023.

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CBS microdata

Overview of datasets used

Dutch registry data

Made available via CBS microdata service

125 jaar
Centraal Bureau voor de Statistiek

We combine data sources on:

- (per spell) start and end date of residence spells in the Netherlands
- (per event) cause, date and location of death + (during pandemic) vaccination uptake and COVID-19 tests
- (static) date of birth, gender, migration background, education
- (annual) property value, medical expenses, income and socio-economic status.

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CBS microdata

Construction of annual, pre-pandemic data

Merge the microdata to individual spells:

- time $t \in \mathcal{T} = \{2016, ..., 2019\}$
- CoDs $c \in \mathcal{C} = \{1, ..., C = 20\}$
- individuals $j \in \mathcal{J}_t = \{1, ..., J_t\}$
- individual-specific spells $i \in \mathcal{I}_{t,j} = \{1, ..., I_{t,j}\}$ with constant socio-economic factors

For each (t, j, i) combination we have:

- exposure-to-risk $\tau_{t,j,i}$
- death indicator $\delta_{t,j,i}$ and cause-specific death indicator $\delta^{c}_{t,j,i}$
- combination of constant risk factors.

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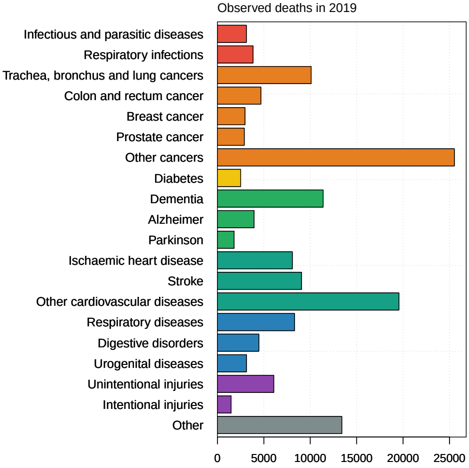
CBS microdata

Construction of annual, pre-pandemic data, CoDs under investigation

Mapping based on WHO, 2020:

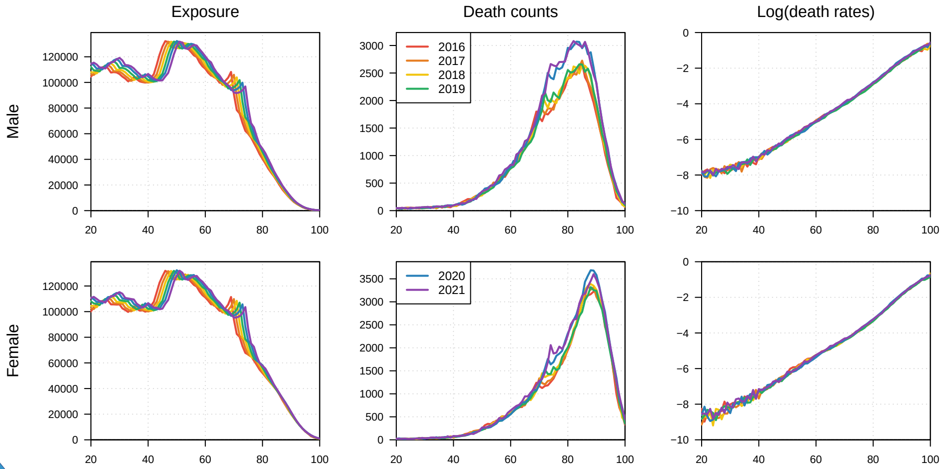
1. Communicable diseases
2. Non-communicable diseases
3. Injuries

Final selection of 20 pre-COVID causes based on materiality.



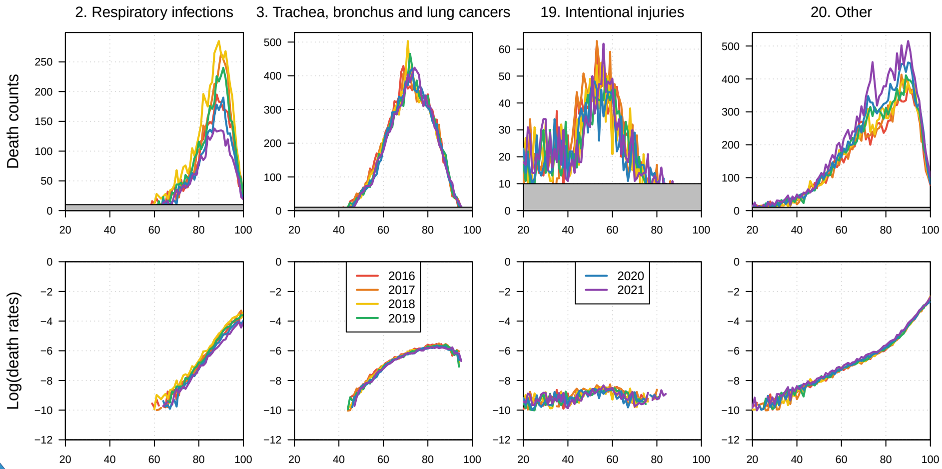
CBS microdata

All-cause mortality



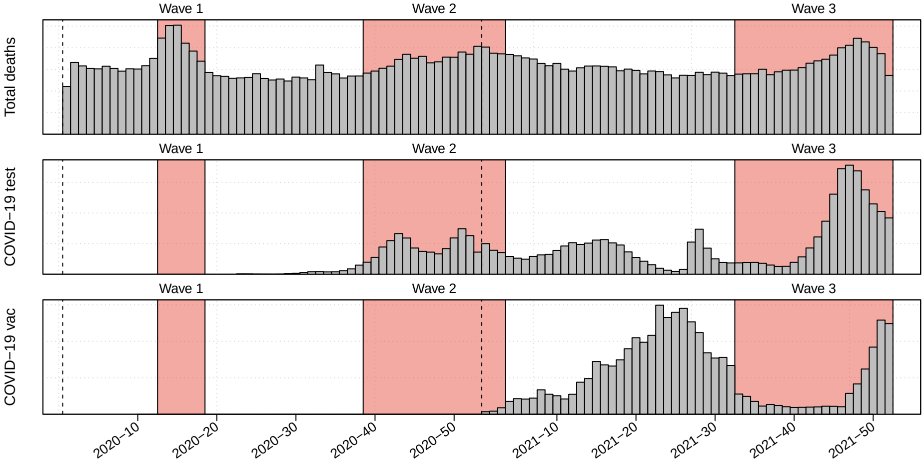
CBS microdata

Cause-specific mortality



CBS microdata

Observed deaths and COVID-19 information



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Pre-pandemic mortality levels

Rationale: importance of the baseline mortality level when studying excess mortality during the pandemic.

Use statistical learning to calibrate

on the data from $\{2016, \ldots, 2019\}$

- $\mu_{t,j,i}$: the all cause force of mortality
- $\mu^{c}_{t,j,i}$: the cause c specific force of mortality,

applicable to individual j, in year t, with socio-economic factors specific to spell i,

including a time trend, an age and gender effect and the effect of selected socio-economic factors.

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Pre-pandemic mortality levels

Quasi-Poisson regression with GAMs, all-cause and cause-specific mortality

From the (t, j, i) records of individual-specific spells we construct

$$\mathcal{L}(\boldsymbol{\theta}|\boldsymbol{\delta}, \boldsymbol{\tau}) = \prod_{t \in \mathcal{T}} \prod_{j \in \mathcal{J}_t} \prod_{i \in \mathcal{I}_{t,j}} \exp\left[-\tau_{t,j,i} \cdot \mu_{t,j,i}(\boldsymbol{\theta})\right] \cdot \left(\mu_{t,j,i}(\boldsymbol{\theta})\right)^{\delta_{t,j,i}},$$

the survival likelihood, where the force of mortality depends on parameter vector $\boldsymbol{\theta}$.

This likelihood function is proportional a Poisson likelihood, see Brouhns et al., 2002. We switch to quasi-Poisson to allow for overdispersion.

We use Generalized Additive Models (GAMs) to calibrate an additive predictor (with smooth functions of covariates) for log $\mu_{t,j,i}$, see van Berkum et al., 2020.

Pre-pandemic mortality levels

Lee-Carter structure

Recall the Lee-Carter structure:

$$\log \mu_{t,x} \quad = \quad \alpha_x + \beta_x \cdot \kappa_t.$$

We calibrate a smooth variant of the Lee-Carter model:

$$\log \mu_j \quad = \quad f_{g_j}(x_j) + h_{g_j}(x_j) \cdot (\bar{t} - t_j),$$

where only the gender g, the time t and age x of an individual j is used as covariate information. Hereby,

- $f_g(x)$ and $h_g(x)$ are gender specific smoothers of age x
- $\bar{t}$ is the average of t for $t \in \mathcal{T}$.

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Pre-pandemic mortality levels

Lee-Carter baseline plus socio-economic factors

To assess pandemic excess mortality we want to account for pre-pandemic existing differences in mortality among socio-economic groups.

Hereto, we examine model specifications built-up as follows:

$$\begin{aligned}
\log \mu_i &= f_{g_i}(x_i) + h_{g_i}(x_i) \cdot (\bar{t} - t_i) \\
&+ s_{\text{ME}}(\log \text{ME}_i) \cdot \mathbb{I}(\text{ME}_i > 0) + \beta_{\text{ME_0}} \cdot \mathbb{I}(\text{ME}_i = 0) \\
&+ s_{\text{Wealth}}(\text{Wealth}_i) \cdot \mathbb{I}(\text{Wealth}_i \text{ not missing}) \\
&+ \sum \beta_\ell \cdot \mathbb{I}(\text{PersIncSrc}_i = \ell) + \sum \beta_\ell \cdot \mathbb{I}(\text{HomeOwn}_i = \ell) \\
&+ \sum \beta_\ell \cdot \mathbb{I}(\text{Geo}_i = \ell),
\end{aligned}$$

where i denotes a spell for individual j in year t during which the covariates do not change.

Pre-pandemic mortality levels

Lee-Carter baseline plus socio-economic factors

A closer look at the building blocks in the specification of μ_i:

$$\begin{aligned}
\log \mu_i &= f_{g_i}(x_i) + h_{g_i}(x_i) \cdot (\bar{t} - t_i) \\
&+ s_{\text{ME}}(\log \text{ME}_i) \cdot \mathbb{I}(\text{ME}_i > 0) + \beta_{\text{ME_0}} \cdot \mathbb{I}(\text{ME}_i = 0) \\
&+ s_{\text{Wealth}}(\text{Wealth}_{,i}) \cdot \mathbb{I}(\text{Wealth}_i \text{ not missing}) \\
&+ \sum \beta_\ell \cdot \mathbb{I}(\text{PersIncSrc}_i = \ell) + \sum \beta_\ell \cdot \mathbb{I}(\text{HomeOwn}_i = \ell) \\
&+ \sum \beta_\ell \cdot \mathbb{I}(\text{Geo}_i = \ell).
\end{aligned}$$

Based on pre-screening with single factor specifications (BIC + data availability): focus on: medical expenses + wealth (property value or income quantiles), source of personal income and home ownership + migration background.

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Pre-pandemic mortality levels

Lee-Carter baseline plus socio-economic factors: variable selection strategy

From this generic specification for μ_i we select:

- the best combination of socio-economic factors to explain mortality on top of the baseline Lee-Carter structure (with age x, gender g and time t)
- for all cause mortality (μ_{tji}) and per cause of death (μ^c_{tji}).

Hereto we examine and compare model fits using:

- information criteria (e.g., BIC) that balance goodness-of-fit and model complexity
- in sample fit via Pearson residuals and Standardized Mortality Ratios (SMR) $d_\ell/\hat{d}_\ell$ across covariate levels ℓ.

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Example of model selection results

Alternatives considered: seven for Model 2 and nine for Model 3

Model for Diabetes	logL	EDF	BIC	ΔlogL	ΔEDF	ΔBIC
Model 1 (base)	-88.411	14,3	177.086			
Model 2 (pharmacy)	-83.840	19,5	168.041	4.571	5,2	-9.046
Model 2 (hospital)	-87.046	19,1	174.446	1.365	4,8	-2.641
...	...	...	...	...	...	...
Model 2 (chronic)	-85.682	18,9	171.715	2.729	4,7	-5.371
Model 2 (total expenses)	-84.954	20,3	170.283	3.457	6,0	-6.804
Model 2 (pharmacy)	-83.840	19,5	168.041			
Model 3 (property value)	-82.468	23,8	165.376	1.372	4,3	-2.665
Model 3 (property value + income source)	-82.088	27,4	164.684	1.752	7,9	-3.357
Model 3 (household income)	-82.403	23,5	165.241	1.437	4,0	-2.800
...	...	...	...	...	...	...
Model 3 (personal income by percentile and source)	-82.432	43,1	165.661	1.408	23,6	-2.380
Model 3 (property value + income source)	-82.088	27,4	164.684			
Model 4 (home ownership)	-81.720	32,5	164.040	368	5,1	-643
Model 4 (home ownership)	-81.720	32,5	164.040			
Model 5 (migration background)	-81.645	41,5	164.058	74	9,0	18

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Overview of selected risk factors

Medical expenses and wealth information

- Medical expenses considered: chronic, geriatric, hospital, mental, nursing, pharmacy and total
- Only four were chosen:
  1. Pharmacy expenses (10x)
  2. Total expenses (7x)
  3. Hospital expenses (3x)
  4. Mental care expenses (1x)
- Wealth considered and selected:
  1. Property value (17x)
  2. Household income (4x)
  3. Personal income (0x)
- Source of personal income contributes substantially to overall fit
- Home ownership and migration background are often selected, but are of less importance

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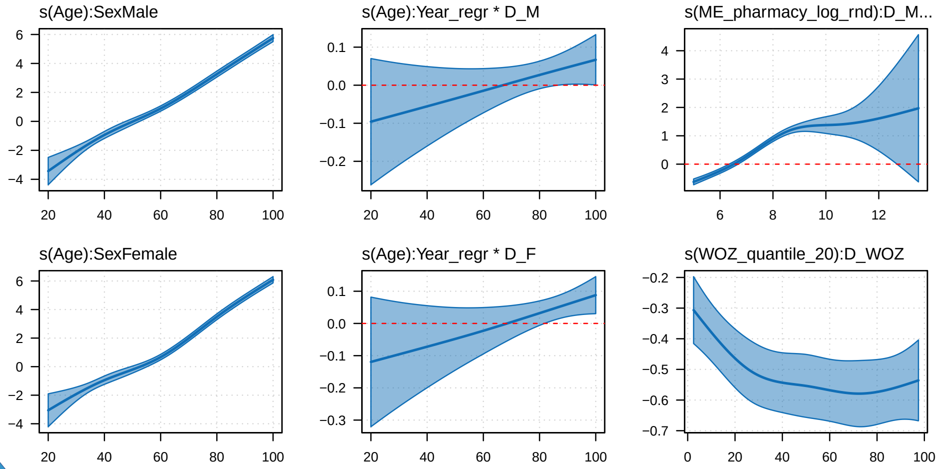
Example of calibrated risk factors

Other cardiovascular diseases



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From expected annual to weekly mortality

What we have at this point:

- the expected number of deaths (total or per cause) over an exposure period $\tau \in [0, 1]$ for individual j with characteristics i

$$\tau \cdot \hat{\mu}_{tji} \text{ or } \tau \cdot \hat{\mu}^{c}_{tji} \text{ with } t \in \{2020, 2021\},$$

  where only the baseline Lee-Carter structure (t, x and g) or the LC structure + selected socio-economic factors can be included

However, this approach ignores the seasonality observed in weekly, empirical data on death counts (cfr. supra)!

From expected annual to weekly mortality

Strategy to incorporate seasonal effect

Inspired by van Berkum et al., 2022 and Koninklijk Actuarieel Genootschap, 2022 we calibrate:

- week effects $\phi_{w,x,g}$ (all-cause) and $\phi^{c}_{w,x,g}$ (cause-specific) using cyclical cubic splines
- for males and females separately
- for all ages, but also for specific age groups $20-54$, $55-64$, $65-74$, $75-84$ and $85+$ separately
- on the pre-pandemic period 2016-2019, thus: no calibrated seasonal effect for COVID-19 CoD!

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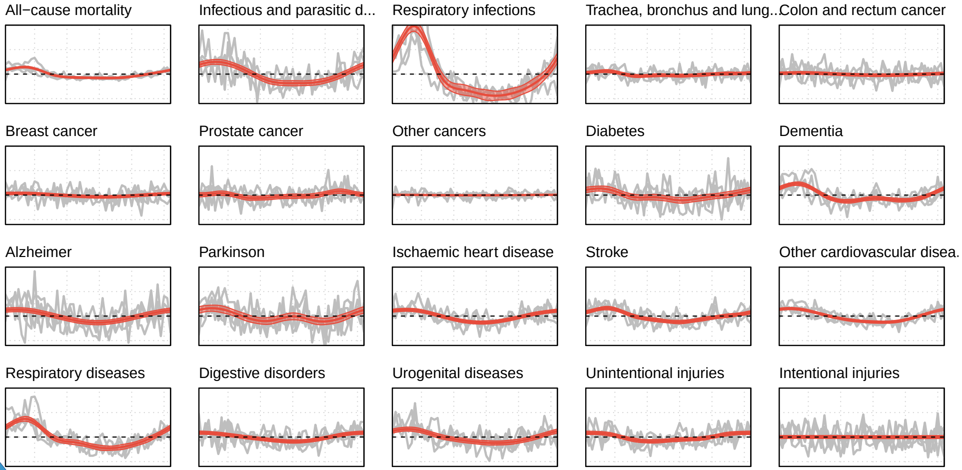
Quantifying excess mortality

Empirical and calibrated seasonal patterns



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Quantifying excess mortality in 2020 and 2021

As such, we obtain the expected number of deaths for every week w in $t = \{2020, 2021\}$, assuming pre-pandemic conditions:

$$\begin{array}{ll} \text{all-cause} & \hat{d}_{t,w,j,i} = \tau_{t,w} \cdot \hat{\mu}_{tji} \cdot \hat{\phi}_{w,x,g} \\ \text{cause-specific} & \hat{d}^{c}_{t,w,j,i} := \tau_{t,w} \cdot \hat{\mu}^{c}_{tji} \cdot \hat{\phi}^{c}_{w,x,g} \end{array}$$

We compare expected and observed weekly death counts in order to quantify excess mortality.

We quantify excess all-cause mortality on an annual basis (and similarly for individual causes) as:

- absolute excess mortality : $\sum_{w \in t,j,i} \{d^{\text{obs}}_{t,w,j,i} - \hat{d}_{t,w,j,i}\}$
- relative excess mortality : $\sum_{w \in t,j,i} d^{\text{obs}}_{t,w,j,i} / \sum_{w \in t,j,i} \hat{d}_{t,w,j,i} - 1.$

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Analyzing excess mortality in 2020 and 2021

Strategy

To dig deeper in the differences between expected and observed deaths during the pandemic, we explore

$$D_{t,w,j,i} \sim \text{POI}(\quad . \quad)$$

with a specification for the mean that is built up from

$$\underbrace{\tau_{t,w} \cdot \hat{\mu}_{tji} \cdot \hat{\phi}_{w,x}}_{\text{pre-pandemic}} \quad \cdot \quad \underbrace{\exp(\quad . \quad)}_{\text{socio-econ info}} \quad \cdot \quad \underbrace{\exp(\quad . \quad)}_{\text{infection + vacc info}} \quad ,$$

where

- further adjustments based on socio-economic factors and information on COVID-19 infections and vaccinations.

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Quantifying excess mortality

Disclaimer on results

- The results for this phase are based on calibrations using 50% of the Dutch population because of computational challenges (even when using OSSC, the ODISSEI Secure Super Computer).
- The results on the following slides are preliminary; we have not yet been able to complete the analyses for all causes and for the separate COVID-waves.

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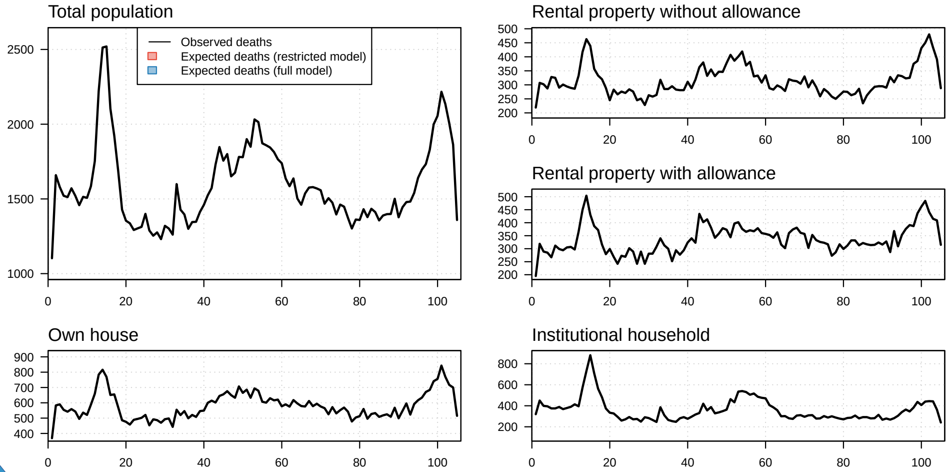
Quantifying excess mortality

Illustrating the importance of a good baseline



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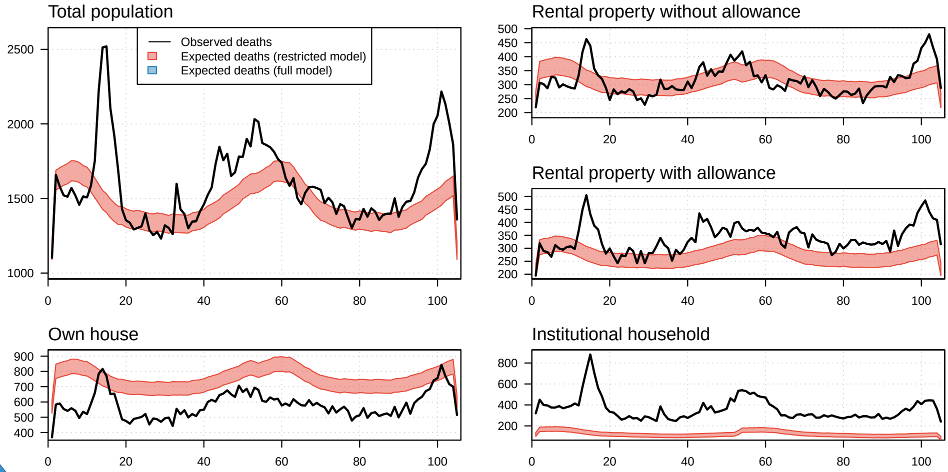
Quantifying excess mortality

Illustrating the importance of a good baseline



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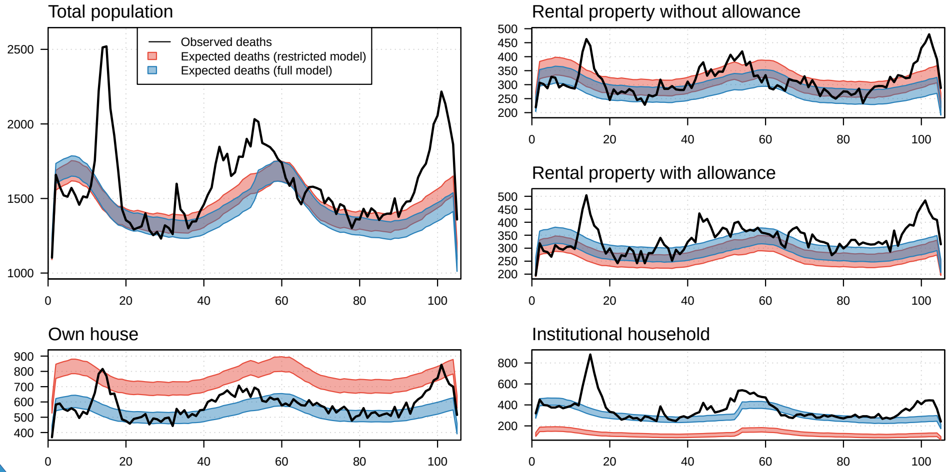
Quantifying excess mortality

Illustrating the importance of a good baseline



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Analyzing excess mortality

Diabetes regression results (baseline mortality based on restricted model)

Model	logL	EDF	BIC	Delta_logL	Delta_EDF	Delta_BIC
Baseline mortality (restricted model)	-36.726	1,0	73.473,1			
Baseline + home ownership	-36.150	7,0	72.443,0	576,3	6,0	-1.030,1
Baseline + property value + income source	-36.057	12,4	72.367,6	669,3	11,4	-1.105,5
Baseline + household income + income source	-36.104	12,2	72.457,7	622,1	11,2	-1.015,4
Baseline + personal income + income source	-36.147	16,6	72.632,4	579,2	15,6	-840,7
Baseline + medical expenses (pharmacy)	-35.197	7,0	70.537,1	1.529,0	6,0	-2.936,0
Baseline + migration background	-36.626	11,0	73.476,7	100,3	10,0	3,6
Baseline + COVID-19 infection	-36.710	4,1	73.503,7	16,5	3,1	30,6
Baseline + COVID-19 vaccination	-36.642	6,9	73.424,9	84,3	5,9	-48,2
Baseline + COVID-19 infection + vaccination	-36.652	5,9	73.424,8	74,5	4,9	-48,3

Table: logL = log-likelihood, EDF = number of parameters, BIC: lower is better

- Medical expenses seem to be the key predictor in explaining excess mortality
- COVID information on infections and testing seems to be of little importance

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Analyzing excess mortality

Diabetes regression results (baseline mortality based on full model)

Model	logL	EDF	BIC	Delta_logL	Delta_EDF	Delta_BIC
Baseline mortality (full)	-34.567	1,0	69.153,8			
Baseline + home ownership	-34.556	7,0	69.255,7	10,3	6,0	101,9
Baseline + property value + income source	-34.553	8,0	69.268,8	13,9	7,0	115,1
Baseline + household income + income source	-34.530	10,5	69.275,3	36,4	9,5	121,5
Baseline + personal income + income source	-34.529	13,5	69.333,8	37,2	12,5	180,0
Baseline + medical expenses (pharmacy)	-34.549	5,0	69.200,6	17,8	4,0	46,9
Baseline + migration background	-34.525	11,0	69.274,8	41,5	10,0	121,0
Baseline + COVID-19 infection	-34.559	3,0	69.178,4	8,1	2,0	24,6
Baseline + COVID-19 vaccination	-34.501	5,6	69.118,0	65,2	4,6	-35,7
Baseline + COVID-19 infection + vaccination	-34.506	5,4	69.122,0	61,0	4,4	-31,8

Table: logL = log-likelihood, EDF = number of parameters, BIC: lower is better

- When using a more refined baseline model, all socio-economic risk factors are no longer relevant in explaining excess mortality

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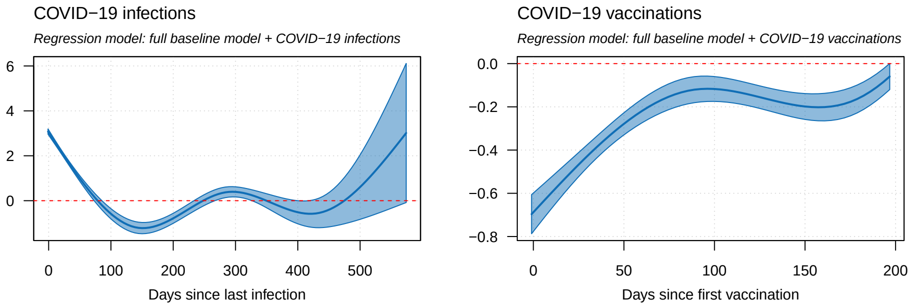
Analyzing excess mortality

All-cause mortality, estimated COVID-effects



- COVID-19 infections: increased risk of mortality immediately after infection, protection after some time but this protection wears off
- COVID-19 vaccinations: decreased risk of mortality immediately after vaccination, protection wears off over time

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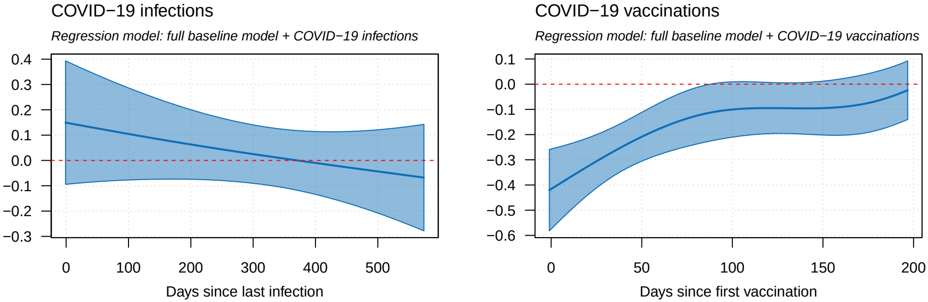
Analyzing excess mortality

Ischaemic heart disease, estimated COVID-effects



- COVID-19 infections: less influential on ischaemic heart diseases than on all-cause mortality
- COVID-19 vaccinations: similar pattern but slightly less important than for all-cause mortality

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Key findings and limitations

After completion of phase 1 of the project

We learned that:

- information on wealth / income and medical expenses are key in predicting the level of individuals' mortality
- one should be careful when using risk factors that might be affected by the dependent variable (income for deceased people can be low).

However, the main limitation of our work is that:

- mortality occurs most often at higher ages and risk factors that are available for older people are therefore likely to be more relevant
- since we used registry data only, i.e., variables that are available for practically all individuals in NL we have limited risk factors available.

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Key findings and limitations

After completion of phase 2 of the project

We learned that:

- though on all-cause mortality there is substantial excess mortality in the period 2020-2021, for many individual causes observed mortality was lower than predicted (in line with previous CBS publications)
- when an appropriate baseline is used to define expected mortality, there seem to be limited differences in excess mortality between individuals with different socio-economic risk factors; COVID information is more relevant in explaining differences in excess mortality
- medical expenses should be treated with the utmost care when analyzing mortality first on annual basis and then predicting mortality on a weekly basis.

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Key findings and limitations

After completion of phase 2 of the project (cont.)

There are some limitations in our current work:

- for some subgroups, we observe unexpected discontinuities when moving from week 52 year t to week 1 year $t+1$, probably caused by changes in risk factors that change on annual basis
- we have taken the cause of death information as given, while the number of 'unclear' or 'undefined' causes of death has increased from ca. 3500 pre-COVID to 4400 in 2020 and 5800 in 2021. These non-allocated deaths complicate the task of assessing excess mortality in other causes since it is unclear whether death counts in other causes are complete.

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Wrap up and outlook

Our research on excess mortality is not yet finished:

- we intend to zoom in on separate COVID-waves to investigate different dynamics in the beginning and later in the pandemic
- the results are now available in terms of regression output which is difficult for policymakers to interpret; we will look into other ways of presenting our results (e.g. quantifying the years lost)
- we wish to include neighbourhood information in the set of explanatory variables
- including mortality observations from the years 2022-2023 may provide useful insights as to where current excess mortality occurs

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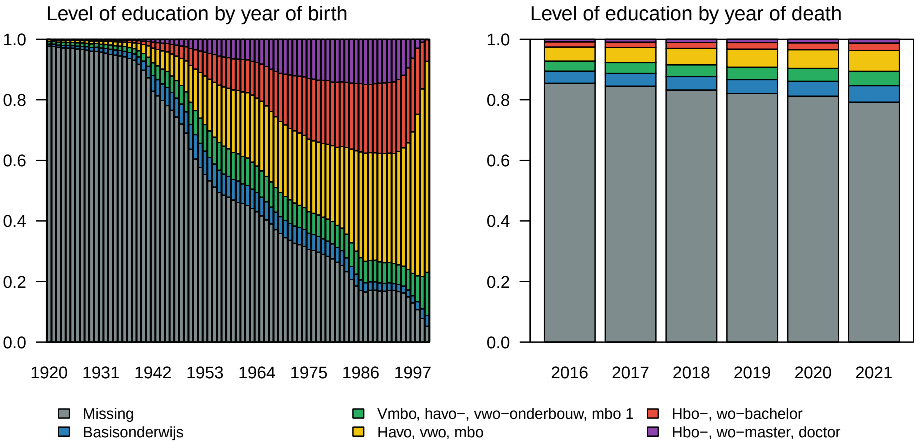
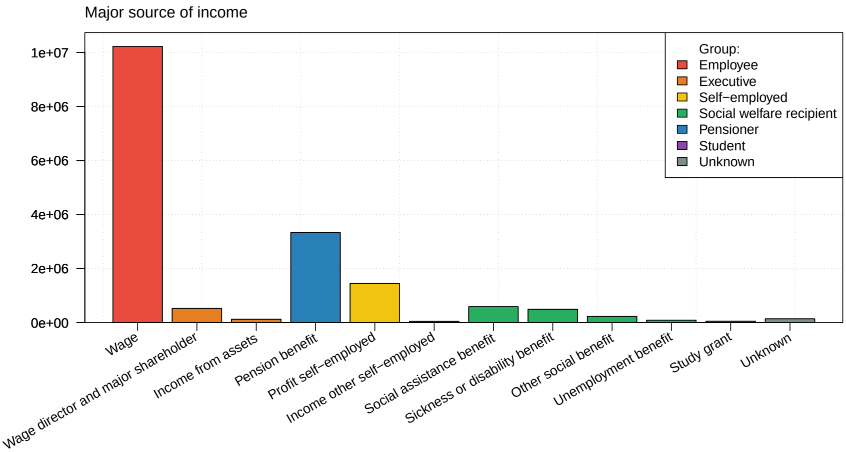
CBS microdata

Education



CBS microdata

Source of income



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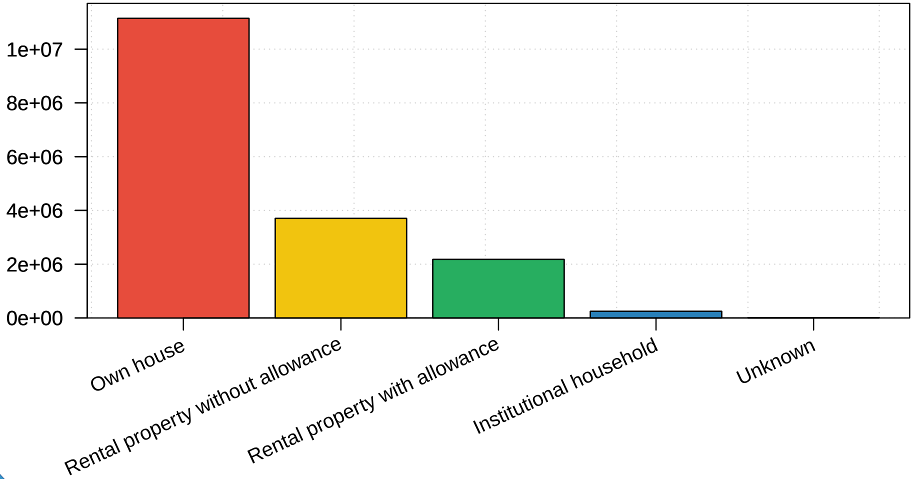
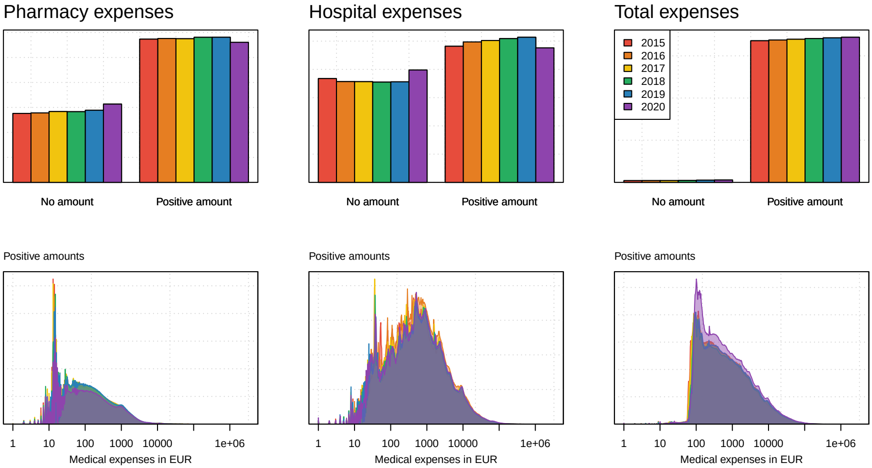
CBS microdata

Home ownership



CBS microdata

Medical expenses



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