Revisiting the Causal Impact of Response Time on Health Outcomes: a Semi-Parametric Estimation Using Air Temperature as an IV

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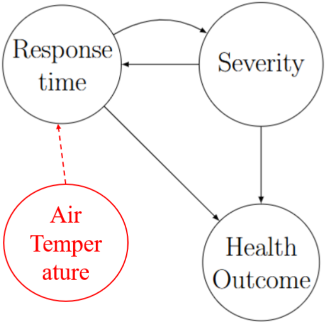
Motivations for this paper

- **Time to get appropriate treatment** is likely to be one of the **leading determinants of healthcare services** effectiveness and equity
- Yet **inferring causality** from response time to health outcomes remains challenging: data availability, non random assignment
- Focus on **Acute Ischaemic Stroke (AIS)**:
    - 69.9 million cases globally in 2021
    - Leading cause of acquired disability among adults and early death among women in France
    - Time-sensitive condition and data available about the precise timing of events along the episode of care

Objectives

- The primary objective of this paper is to estimate the **causal impact of response time (RT) on health outcomes for AIS**.
- Secondary objective: to recover the full data-generating process to **identify the nature of the existing selection** and measure its impact on health outcomes

Key econometric challenges



- **Sources of endogeneity:**
  - More severe cases arrive earlier at the hospital, and severity also affects health outcomes
  - Severity is measured at admission and may already reflect prior RT delays
- **Identification strategy:** exploit exogenous variation in RT
  $\Rightarrow$ *Instrumental variable -IV-: ambient air temperature*
- **Additional concern:** absence of knowledge about the shape of the response curve
  $\Rightarrow$ *Semi-parametric estimation*

Data

Two sources of data:

- **Endovascular Treatment in Ischaemic Stroke Registry (ETIS):** 15,467 hospital stays (March 2017 – November 2023), 34 hospitals
- **Weather observational data (Météo-France):** hourly air temperature measurements from the nearest station, matched to hospital admissions by date and hour

Identification Strategy

- Semi-parametric control function approach [Newey et al., 1999]:

$$\begin{cases} f(Y) &= s_1(RT) + s_2(v) + s_3(RT, v) + X\beta_1 + \epsilon, \\ RT &= s_4(Z) + X\beta_2 + v \end{cases} \tag{1}$$

$s_1(\cdot)$, $s_2(\cdot)$, and $s_4(\cdot)$ $\rightarrow$ splines of degree 4
$s_3(\cdot,\cdot)\rightarrow$ tensor product

- **Y:** change in disability score (modified Rankin Scale, mRS) before and after treatment, converted into a utility index
- **RT**: time from symptom onset to treatment initiation
- **X:** hospital and year fixed effects, direct vs. transferred admission, age, stroke severity (NIH Stroke Scale)
- **Z:** ambient air temperature hospital entry

Identification Strategy

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$s_1(\cdot)$, $s_2(\cdot)$, and $s_4(\cdot)$ → splines of degree 4
$s_3(\cdot,\cdot)$→ tensor product

- **Average Structural Function (ASF)**: $E[h(t,\epsilon)] = \hat{s}_1(t)$
- **Group-specific ASF** [Florens et al., 2008, Altonji and Matzkin, 2005]: $E[h(t,\epsilon) \mid v = g] = \hat{s}_1(t) + \hat{s}_2(g) + \hat{s}_3(t,g)$

- **Inference:** non-parametric bootstrap (with replacement), 1,000 replications of the two steps
- **Robustness checks**: alternative estimation strategy (instrument by identity of the physician performing the procedure)

Descriptive statistics

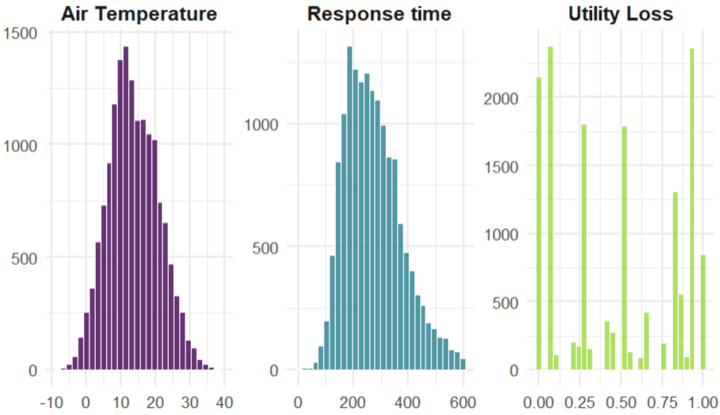
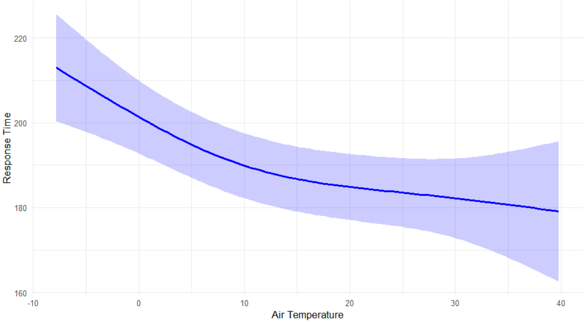


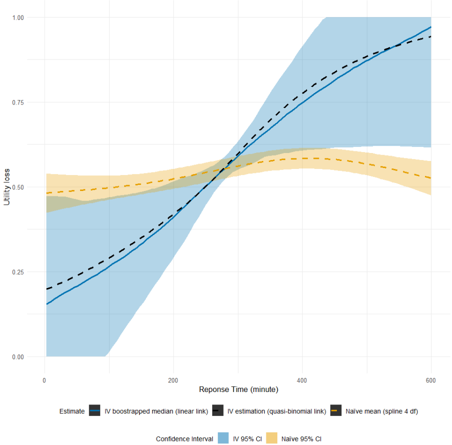
Figure: Distribution of the key variables

First equation



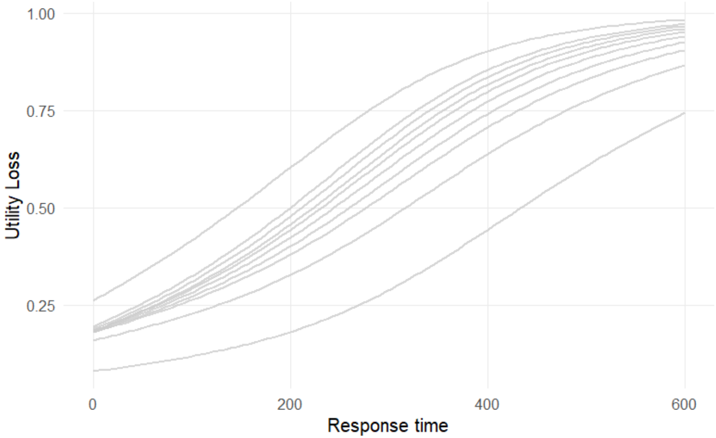
Model	Res.Df	RSS	Df	Sum of Sq	F	p-value
Model 1	15431	125033543	-	-	-	-
Model 2	15428	124670971	3	339398	22.936	5.701×10^{-9}
Model 3	15427	124672478	4	350907	19.283	6.039×10^{-10}

Average Structural Function



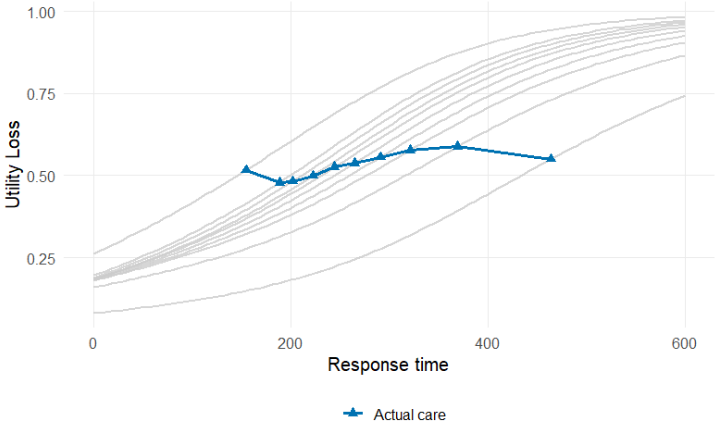
Note: Average structural function (blue) and naive spline regression (yellow). The solid blue line represents the median of the bootstrapped distribution, while the black dashed line shows the point estimate using a quasi-binomial link in the second equation ($f(Y) = \log(Y/(1-Y))$).

Group Specific ASF



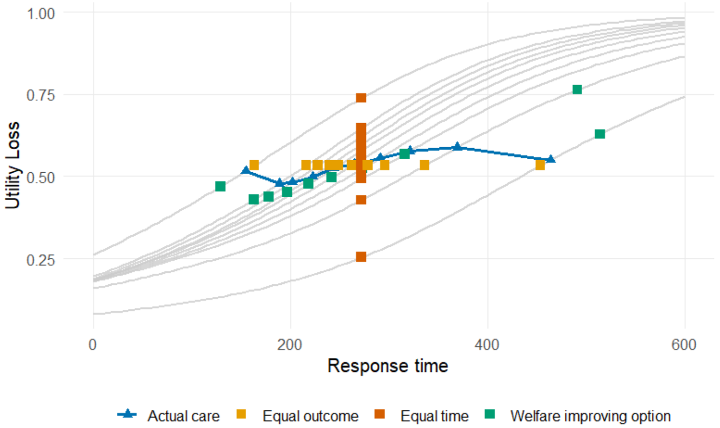
Note: this figure shows group specific average structural functions. Lines are defined with respect to each decile of the first stage residual (g): $E[h(t, \epsilon) \mid v = g] = \hat{s}_1(t) + \hat{s}_2(g) + \hat{s}_3(t, g)$

Group-specific ASF and actual patient management



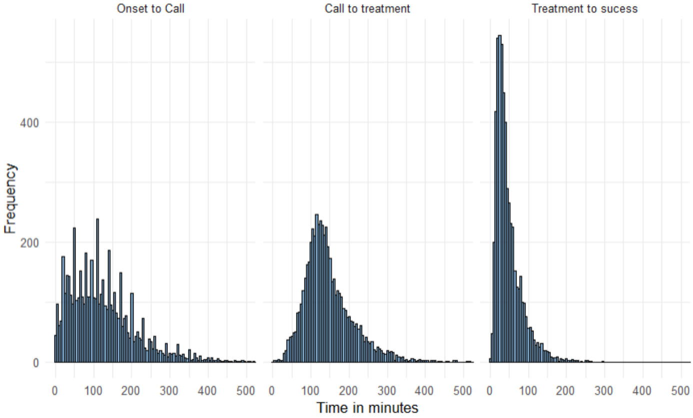
Note: This figure illustrates the data-generating process. Each subgroup of patients is represented by its own average structural function, highlighting the selection mechanism at play. Based on these results, selection appears to occur both in trends and in levels.

Simulation of alternative selection strategies



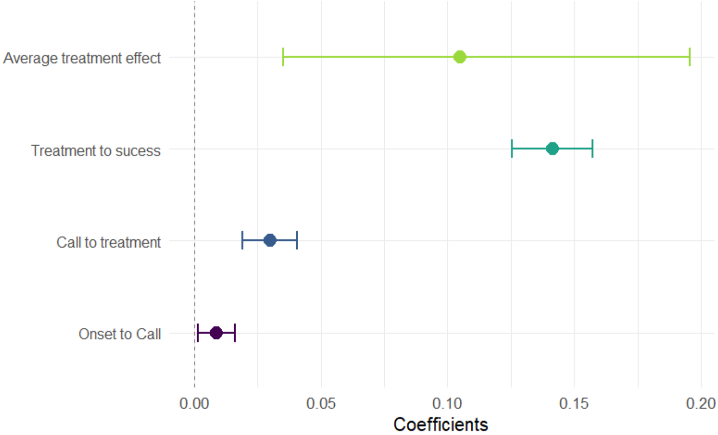
Note: This figure illustrates alternative possible selection strategies that maintain the same overall time constraint.
Interpretation: The observed selection mechanism lies between equalizing patient outcomes and a welfare-improving option that requires more selection, potentially at the expense of the least severe patients.

What factors drive the selection?



Note: This figure shows the time distribution of the three main stages of patient management. The first stage is the time from the onset of the disease to the first contact with the healthcare system (**Onset to Call** in our study). The second stage is the time from the first contact to the initiation of appropriate treatment (**Call to Treatment**). The final stage is the treatment duration until success (**Treatment to Success**).

What factors drive the selection?



Note: each Treatment to success, Call to treatment, and Onset to call coefficient is derived from the regression of Utility Loss on the corresponding variable and controls. These estimates are potentially biased, and any differences from the Average Treatment Effect (which is a linear approximation of the previously presented estimation) arise from various forms of selection.

Conclusion

- Reducing RT by one hour for AIS patients lowers utility loss by at least 10% (measured in this study as functional capacity)
- Patient selection arises from both demand- and supply-side factors. This mechanism appears effective in reducing utility loss under a fixed time constraint
- However, the central role of symptom detection in the selection process suggests scope for improvement at this stage of care, where the opportunity cost of reducing time is likely to be very low

Thank you!
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Appendix

Univariate Descriptive Statistics

N Patient pathway = 15,467
N Hospital = 34
N Year = 8
N Operator = 206

First observation 2017-01-02
Last observation 2024-12-31

Variable	**Mean**	**SD**	**Median**	**Trimmed**	**MAD**	**Min**	**Max**
Utility loss	0.48	0.38	0.53	0.47	0.61	0.00	1
Resp. Time	272.25	103.07	260	264.65	103.78	3.00	600
Temperature	13.61	7.26	13.10	13.48	7.56	-7.80	39.80
Diabetes	0.17	0.38	0.00	0.09	0.00	0.00	1.00
HBP	0.60	0.49	1.00	0.63	0.00	0.00	1.00
Age	70.93	14.59	73.00	72.15	14.83	0.00	102
Mode admission	1.56	0.50	2.00	1.57	0.00	1.00	2.00
Severity	15.51	6.76	16.00	15.57	7.41	0.00	42.00

Note
MAD: median adjusted deviation
Trimmed: outlier adjusted mean
HBP: High Blood Pressure

Bivariate Descriptive Statistics

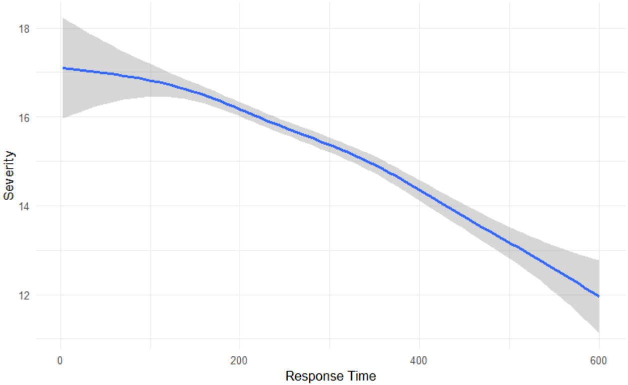


Figure: Descriptive relationship Severity - Health Loss. (Kernel regression)

Motivation for the instrument

Relevance

- **Cold weather influences individual behaviour**, such as spending less time outdoors and interacting less with others, which reduces the probability of early stroke detection
- **Hospital congestion is known to be greater during cold weather events**, slowing access to treatment
- Cold weather can also **disrupt transportation networks**

Independence

- Differences in geographical location → time and hospital FE

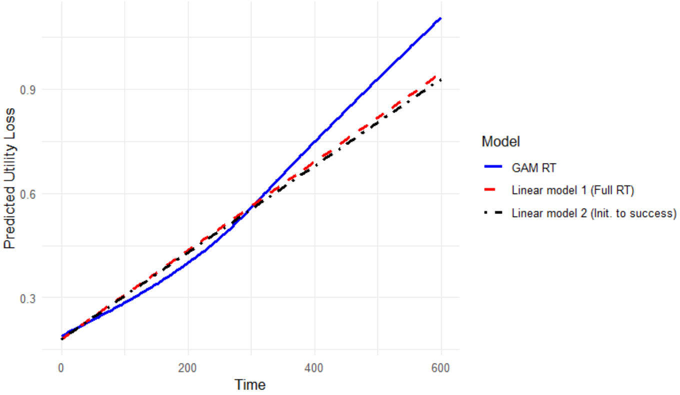
Exclusion restriction

- Mellon [2023] reviews 195 papers using meteorological instrumental variables, highlighting numerous cases of violations, D'Haultfœuille et al. [2024] provides a test for this hypothesis

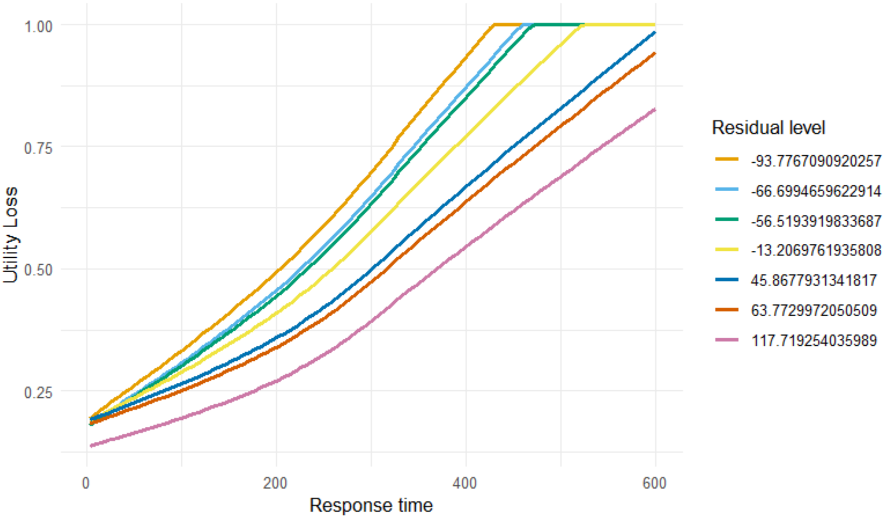
A robustness check

To avoid selection effects in the alternative segments → instrument by the physician performing the procedure

- Lasso + stepwise regression to select 18 physicians among 200
- F statistic: 12.99
- “Exact” same average linear effect



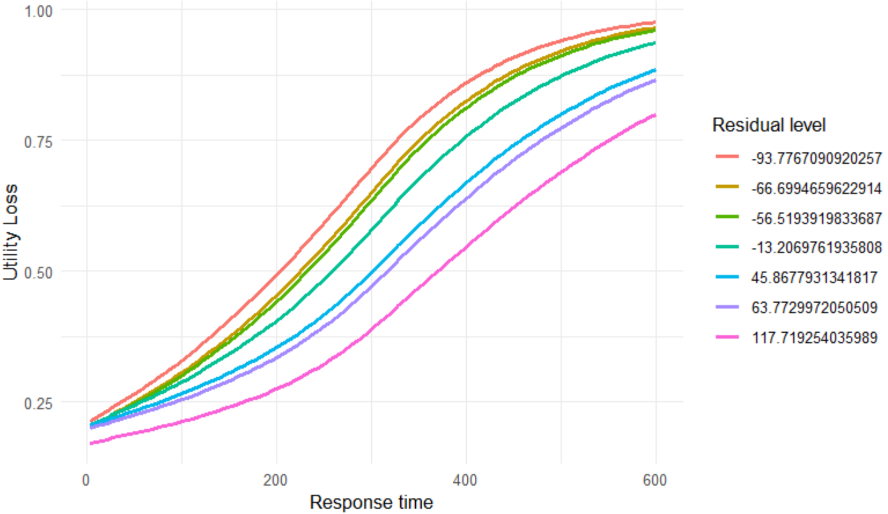
Results: Group Specific ASF



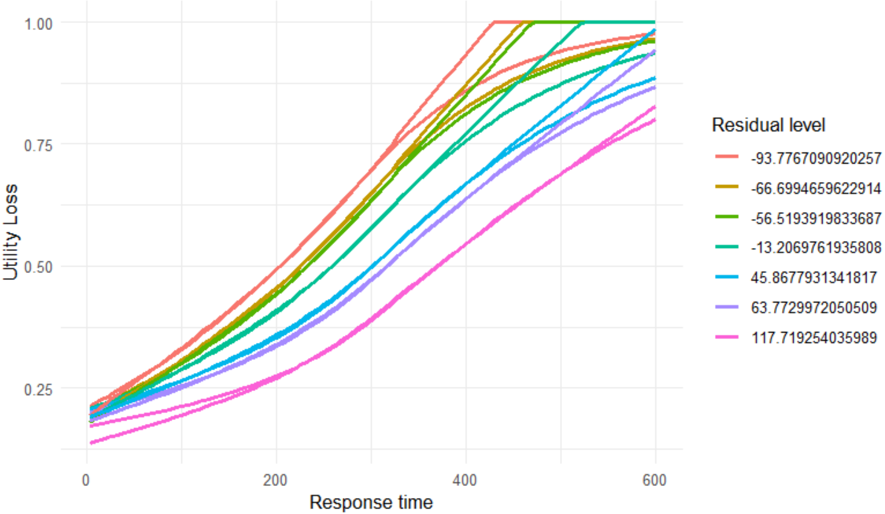
Alternative Identification strategy

$$\begin{cases} \log\left(\dfrac{Y}{1-Y}\right) = f_1(RT) + f_2(v) + f_3(v, RT) + X\beta_1 + u \\ RT = s(Z) + X\beta_2 + v \end{cases} \tag{3}$$

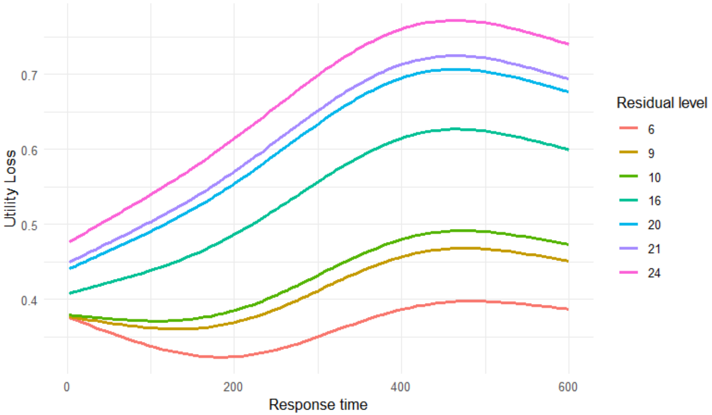
Alternative Identification strategy



Alternative Identification strategy



Robustness checks: controlling by the severity



Exclusion restriction hypothesis testing

Subset boundaries $Z \in$	]-2, 18 [	]2, 22[	]6, 26[	]10, 30[	]14, 34[	]18, 38[
Mean Z	10.12	12.27	14.56	17.14	19.98	22.69
x^*	2.75	2.62	2.55	2.57	2.5	2.5
KS statistic	3.34	3.93	3.01	1.86	2.27	2.76
p-value	0.35	0.3	0.5	0.87	0.72	0.55
N	7432	8414	8130	6622	4549	2774

Note: D'Haultfœuille et al. [2024]. H0: the instrument is valid (e.g. has no direct impact on the dependant variable).

Severity Reponse to RT

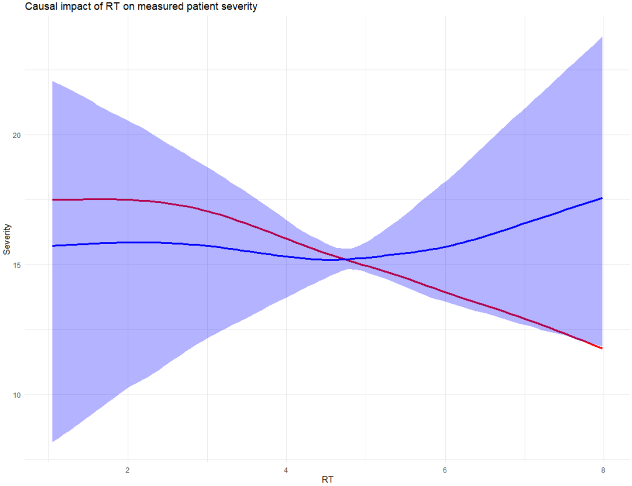
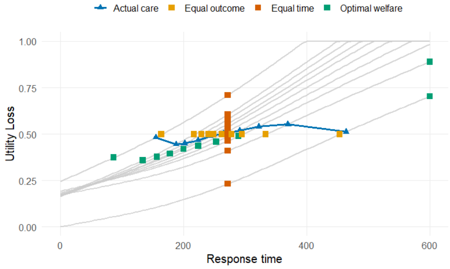


Figure: Enter Caption

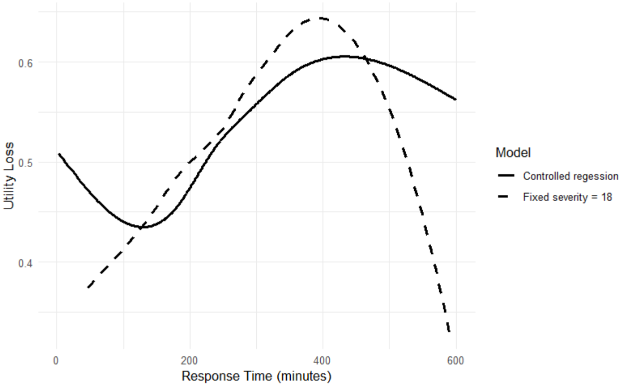
Results: Counterfactual Scenarios



Scenario	Objective function	Constraint	Utility Loss
Optimal Welfare	min(Utility loss)	Total time	4897.865
Actual Care	-	-	4957.511
Equal Outcome	$ULoss_{g_1} = ... = Uloss_{g10}$	Total time	4976.073
Equal Time	$RT_{g_1} = ... = RT_{g_1 0}$	Total time	5097.611

Table: Scenarios performance: 10,000 individuals

Descriptive statistics



Note: Descriptive relationship between Utility Loss and RT using different methods to control for severity. The solid black line represents a spline regression in which every 40 values of severity are dichotomized and used as controls, whereas the dashed black line corresponds to patients with a severity of 18 being selected.

References

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