1 Results

The section is divided in two parts. First, I present the results of the uncertainty analysis for an overview of the general variation in QoI Y. Thereafter, I present the results of the qualitative GSA. The aim is to draw inferences about the contribution of an individual input X_i and its uncertainty on the uncertainty in QoI Y to a degree that allows the identification of non-influential parameters.

1.1 Uncertainty Analysis

The following results are obtained by evaluating the occupational choice model at each parameter vector from a random sample. This sample is drawn from the estimated joint distribution. The number of draws is $10,000$. A reasonable level of convergence has already been achieved after about 800 evaluation.[1]

Figure 1 incorporates the input uncertainty in the shares of life-time occupation decisions that we have previously seen in Figure **??**. It depicts the mean and the intervals for 99% of the shares' probability distribution. We can see that the input uncertainty has an effect on the decisions for white- and blue-collar occupation but almost none on the decision for occupation in the education and home sector. This suggests that individuals mainly tend to change between occupation in blue- and white-collar occupation given the distribution of input parameters. Yet, the uncertainty in the shares for both labour sectors is not strikingly large. There is also no visible difference in the uncertainties between both scenarios.

[1]See the respective notebook in the *Master's Thesis Replication Repository*.

Figure 1. Comparison of shares of occupation decision over time between scenarios including 99% confidence intervals

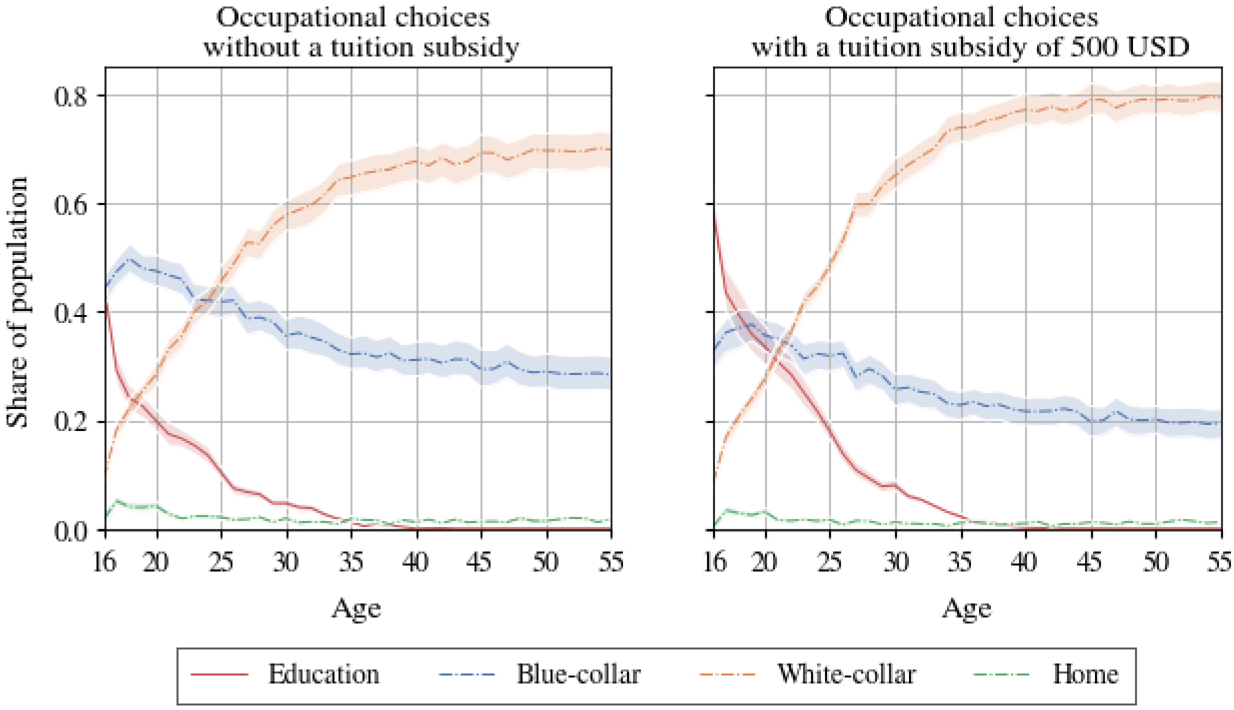


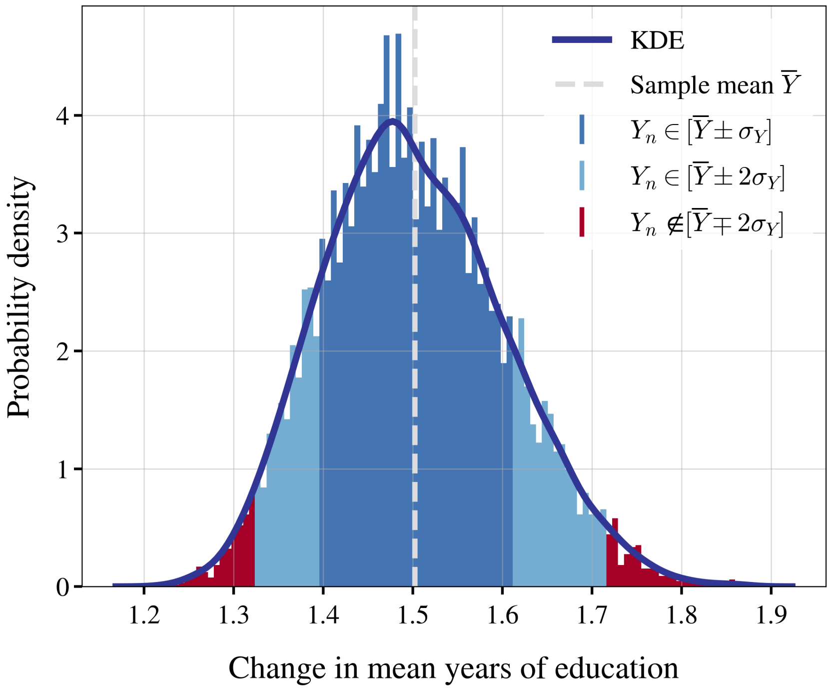
Figure 2 shows the probability distribution for QoI Y. The colorised bars depict the realisations within one and two and outside of two standard deviations, σ_Y, from sample mean $\overline{Y}$. The distribution is minimally skewed to the left but can be considered as almost normal. This leads to the first conclusion for a potential quantitative GSA. That is, variance-based measures like Sobol' indices can be used because the variance is a good summary measure for normally distributed random variables.

Standard deviation σ_Y equals 0.1 and variance σ_Y^2 equals 0.01. The final goal of a quantitative GSA is to compute the share that input parameter X_i and its variation contribute to σ_Y or σ_Y^2. We can expect that reasonable measures for the contribution of X_i are not completely detached from the measures for the total variation in Y if they are on the same scale. As we have seen earlier, for a linear function without interactions and correlations, we would even expect that the contribution of X_i are smaller than the measure for the variation in Y.

The next section computes measures for these contributions.[2]

[2]For QoI Y, it is not necessary to compute the probabilities for specific regions in the probability space of Y. The reasons is that, for example in contrary to models for nuclear power plants, there are no regions that are particularly critical.

Figure 2. Probability distribution of quantity of interest q



1.2 Experiment Ge and Menendez (2017)

Table 1. EE-based measures by Ge and Menendez (2017) for 100 trajectories

Parameter	$\mu_T^{*,full}$	$\mu_T^{*,ind}$	$\sigma_T^{*,full}$	$\sigma_T^{*,ind}$
General				
δ	53.40	0.00	69.23	0.09
Blue-collar				
β^b	3.55	0.05	4.38	0.07
β^b_e	39.84	0.05	49.69	0.07
β^b_b	77.21	0.05	90.23	0.07
β^b_{bb}	2616.50	0.05	3357.92	0.06
β^b_w	94.74	0.05	113.49	0.06
β^b_{ww}	1136.58	0.03	1405.94	0.04
White-collar				
β^w	5.07	0.05	6.42	0.06
β^w_e	90.25	0.07	111.50	0.08
β^w_w	82.88	0.05	103.66	0.07
β^w_{ww}	2444.13	0.06	3044.69	0.07
β^w_b	452.91	0.07	490.31	0.09
β^w_{bb}	4317.58	0.05	4851.54	0.06
Education				
β^e	0.00	0.09	0.00	0.10
β^e_{he}	0.00	0.11	0.00	0.13
β^e_{re}	0.00	0.04	0.000	0.09
Home				
β^h	0.00	0.04	0.00	0.05
Lower Triangular Cholesky Matrix				
c_1	27.94	0.07	33.72	0.08
c_2	31.89	0.05	38.58	0.06
c_3	0.00	0.06	0.00	0.07
c_4	0.00	0.04	0.00	0.09
$c_{1,2}$	12.41	0.06	14.33	0.08
$c_{1,3}$	0.00	0.09	0.00	0.10
$c_{2,3}$	0.00	0.05	0.00	0.06
$c_{1,4}$	0.00	0.04	0.00	0.05
$c_{2,4}$	0.00	0.03	0.00	0.03
$c_{3,4}$	0.00	0.04	0.00	0.05

1.3 Qualitative Sensitivity Analysis

Table 2. Mean absolute correlated and uncorrelated elementary effects (based on 100 subsamples in trajectory and radial design)

Parameter	$\mu_T^{*,c}$	$\mu_R^{*,c}$	$\mu_T^{*,u}$	$\mu_R^{*,u}$
General				
δ	17	23	476	415
Blue-collar				
β^b	1	3	43	88
β^b_e	11	14	406	443
β^b_b	25	51	688	1169
β^b_{bb}	871	934	15 540	17 860
β^b_w	29	48	73	143
β^b_{ww}	389	460	869	1183
White-collar				
β^w	1	3	50	117
β^w_e	26	28	943	852
β^w_w	24	47	718	1521
β^w_{ww}	933	997	12 257	18 069
β^w_b	131	127	309	356
β^w_{bb}	120	1352	2088	2477
Education				
β^e	0.0008	0.0002	0.001	0.003
β^e_{he}	0.0001	0.0002	0.001	0.001
β^e_{re}	0.0003	0.0002	0.0003	0.0006
Home				
β^h	0.0003	0.0003	0.000 02	0.000 02
Lower Triangular Cholesky Matrix				
c_1	8	16	18	37
c_2	8	11	22	24
c_3	0.0004	0.0004	0.0004	0.0007
c_4	0.0004	0.000 08	0.0002	0.0003
$c_{1,2}$	4	4	10	10
$c_{1,3}$	0.0005	0.0006	0.0006	0.0005
$c_{2,3}$	0.0003	0.0005	0.0006	0.001
$c_{1,4}$	0.000 04	0.000 05	0.0004	0.0005
$c_{2,4}$	0.0001	0.0002	0.0001	0.0002
$c_{3,4}$	0.0001	0.0001	0.000 08	0.0001

Figure 3. Sigma-normalized mean absolute Elementary Effects for trajectory design

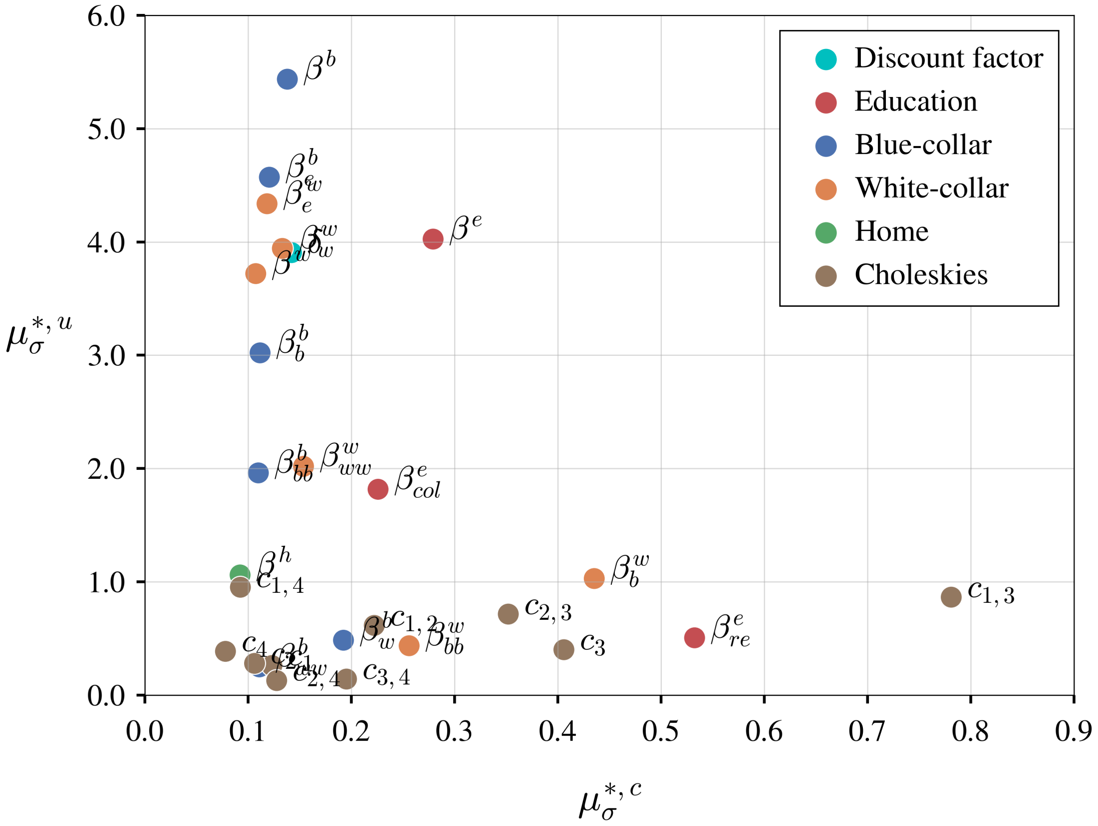
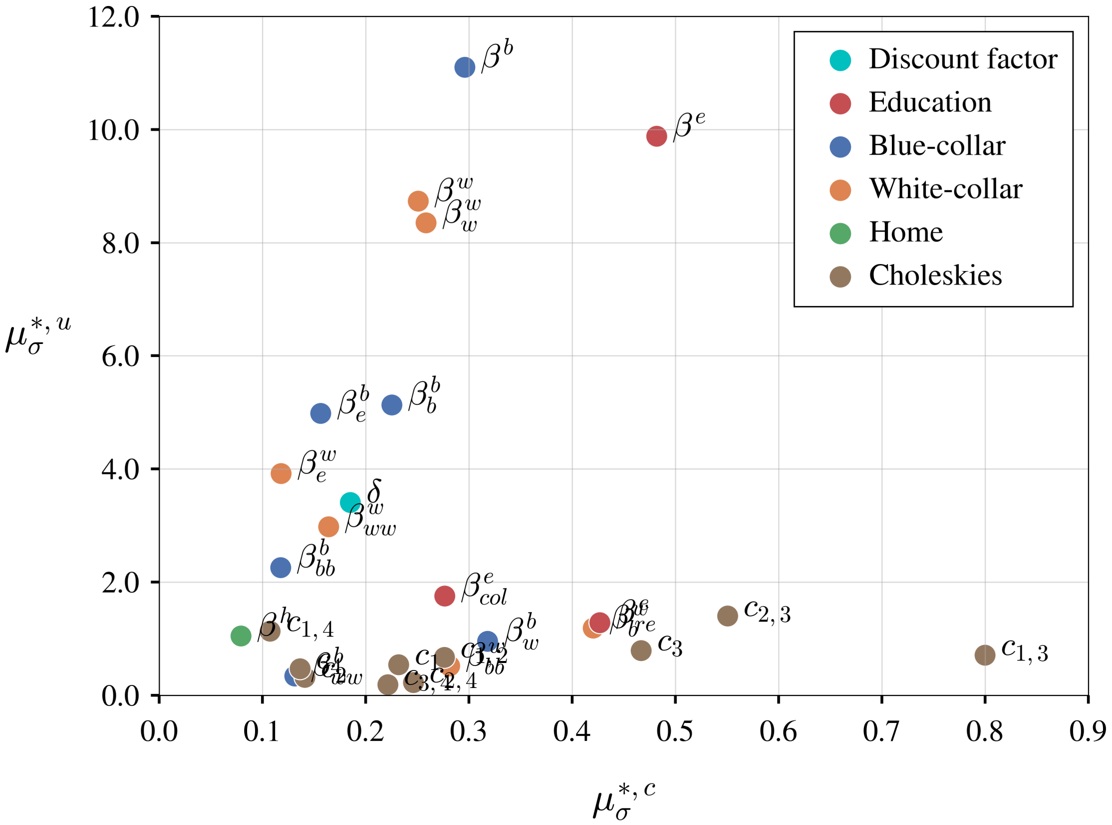


Figure 4. Sigma-normalized mean absolute Elementary Effects for radial design



References

Ge, Q. and M. Menendez (2017). Extending morris method for qualitative global sensitivity analysis of models with dependent inputs. *Reliability Engineering & System Safety 100*(162), 28–39.

Stenzel, T. (2020). *Master's Thesis Replication Repository.*
URL: https://github.com/HumanCapitalAnalysis/thesis-projects-tostenzel.