# Supplementary Materials to: Compression or Expansion? Health Surveillance Trends in Cardiovascular and Diabetes Morbidity in the United States

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| Model | # Parameters | Log Loss | AUC |
|---|---|---|---|
| expert large | 80 | 0.3239 | 0.7699 |
| expert mini | 38 | 0.3243 | 0.7692 |
| lasso $\lambda_{1se}$ | 46 | 0.3243 | 0.7696 |
| lasso $\lambda_{min}$ | 69 | 0.3239 | 0.7700 |
| full linear | 97 | 0.3238 | 0.7700 |
| stepwise n=10 | 72 | 0.3240 | 0.7698 |
| stepwise n=2 | 83 | 0.3238 | 0.7700 |
| random forest | 87 | 0.3380 | 0.7454 |

Table 1: Summary of comparison of models by number of parameters, log loss, and AUC for diabetes.

| Model | # Parameters | Log Loss | AUC |
|---|---|---|---|
| expert large | 71 | 0.1831 | 0.7175 |
| expert mini | 57 | 0.1833 | 0.7165 |
| lasso $\lambda_{1se}$ | 29 | 0.1843 | 0.7117 |
| lasso $\lambda_{min}$ | 76 | 0.1831 | 0.7177 |
| full linear | 87 | 0.1831 | 0.7179 |
| stepwise n=1 | 85 | 0.1831 | 0.7179 |
| stepwise n=10 | 61 | 0.1831 | 0.7174 |
| random forest | 87 | 0.1882 | 0.6929 |

Table 2: Summary of comparison of models by number of parameters, log loss, and AUC for CVs.

| Term | Estimate | Std. Error | Pr(> $\|z\|$) | Sig. |
|---|---|---|---|---|
| (Intercept) | -1.0662 | 0.0215 | 0.0000 | *** |
| age_scl | 0.3851 | 0.0111 | 0.0000 | *** |
| bmi_scl | 0.8121 | 0.0066 | 0.0000 | *** |
| cohort_scl | 0.0047 | 0.0027 | 0.0897 | . |
| edu: high school or less | 0.1650 | 0.0195 | 0.0000 | *** |
| edu: some college | 0.1111 | 0.0215 | 0.0000 | *** |
| female | -0.0926 | 0.0125 | 0.0000 | *** |
| income: no info | -0.6998 | 0.0264 | 0.0000 | *** |
| income: other | -0.6110 | 0.0642 | 0.0000 | *** |
| income: rich | -0.6347 | 0.0206 | 0.0000 | *** |
| race: hispanic | 0.1119 | 0.0117 | 0.0000 | *** |
| race: other | 0.0536 | 0.0117 | 0.0000 | *** |
| race: white | -0.5452 | 0.0075 | 0.0000 | *** |
| region: Northeast | 0.0032 | 0.0082 | 0.6989 | |
| region: South | 0.2148 | 0.0070 | 0.0000 | *** |
| region: West | -0.0949 | 0.0079 | 0.0000 | *** |
| smoker | 0.1260 | 0.0048 | 0.0000 | *** |
| $I$(age_scl$^2$) | -0.1088 | 0.0055 | 0.0000 | *** |
| $I$(bmi_scl$^2$) | -0.0956 | 0.0007 | 0.0000 | *** |
| age_scl:bmi_scl | -0.0578 | 0.0034 | 0.0000 | *** |
| age_scl:income no info | 0.0996 | 0.0153 | 0.0000 | *** |
| age_scl:income other | 0.1269 | 0.0114 | 0.0000 | *** |
| age_scl:income rich | 0.1107 | 0.0119 | 0.0000 | *** |
| bmi_scl:income no info | 0.1219 | 0.0081 | 0.0000 | *** |
| bmi_scl:income other | 0.0959 | 0.0061 | 0.0000 | *** |
| bmi_scl:income rich | 0.2025 | 0.0064 | 0.0000 | *** |
| bmi_scl:region Northeast | 0.0169 | 0.0066 | 0.0110 | * |
| bmi_scl:region South | -0.0481 | 0.0056 | 0.0000 | *** |
| bmi_scl:region West | 0.0205 | 0.0064 | 0.0014 | ** |
| edu: high school or less × income no info | 0.3598 | 0.0272 | 0.0000 | *** |
| edu: some college × income no info | 0.2123 | 0.0304 | 0.0000 | *** |
| edu: high school or less × income other | 0.1465 | 0.0644 | 0.0229 | * |
| edu: some college × income other | 0.1224 | 0.0650 | 0.0594 | . |
| edu: high school or less × income rich | 0.0291 | 0.0939 | 0.7564 | |
| edu: some college × income rich | 0.1249 | 0.0245 | 0.0000 | *** |
| female × income no info | -0.0599 | 0.0197 | 0.0023 | ** |
| female × income other | -0.1065 | 0.0144 | 0.0000 | *** |
| female × income rich | -0.2011 | 0.0152 | 0.0000 | *** |

Table 3: Logistic regression coefficients for the selected expert mini model for diabetes with standard errors, z values, p-values, and significance codes (p-value < 0.001 '***', < 0.01 '**', < 0.05 '*', < 0.1 '.')

The significance tests reported are unadjusted for multiple comparisons.

The coefficients of the selected model for diabetes are presented in Table 3. In the table, "scl" indicates the scaled version of the continuous variable, with mean 0 and standard deviation equal 1. Individuals with higher BMI show the strongest positive association with diabetes risk (0.8121, $p < 0.0001$), followed by older age (0.3851, $p < 0.0001$). Having only a high school degree or less (0.1650, $p < 0.0001$) or some college education (0.1111, $p < 0.0001$) is also linked with higher odds compared to higher educational attainment. Belonging to a Hispanic racial group (0.1119, $p < 0.0001$) or the "other" racial groups (0.0536, $p < 0.0001$) is associated with increased diabetes risk compared to the reference category. Living in Southern states (0.2148, $p < 0.0001$) also increases risk, as does being a smoker (0.1260, $p < 0.0001$). Some income-related interaction effects are strong positive predictors. For example, age interacting with no info on income (0.0996, $p < 0.0001$), age × other income (0.1269, $p < 0.0001$), and age × rich income (0.1107, $p < 0.0001$) all increase diabetes risk with age. Similarly, BMI × income no info (0.1219, $p < 0.0001$), BMI × income other (0.0959, $p < 0.0001$), and BMI × income rich (0.2025, $p < 0.0001$) indicate that higher BMI amplifies risk across income groups. There are also education-income interactions, including high school or less × no income info (0.3598, $p < 0.0001$), some college ×

no income info (0.2123, $p < 0.0001$), high school or less × other income (0.1465, $p = 0.0229$), and some college × rich income (0.1249, $p < 0.0001$), which all increase diabetes risk. A smaller but significant positive effect is seen for BMI × Northeast states (0.0169, $p = 0.0110$) and BMI × West states (0.0205, $p = 0.0014$). On the other hand, several variables show negative or protective associations. Being female is associated with a lower risk (–0.0926, $p < 0.0001$). Individuals reporting no income information (–0.6998, $p < 0.0001$), other income categories (–0.6110, $p < 0.0001$), or rich income (–0.6347, $p < 0.0001$) also have significantly lower baseline risk compared to the reference income group (income < 25.000\$). Belonging to the white racial group reduces risk (–0.5452, $p < 0.0001$), and living in the Western states similarly shows a protective effect (–0.0949, $p < 0.0001$). There are also significant negative quadratic terms, indicating non-linear relationships: age$^2$ (–0.1088, $p < 0.0001$) and BMI$^2$ (–0.0956, $p < 0.0001$), suggesting that risk increases at lower to moderate levels but plateaus or declines at extreme values. The age × BMI interaction is negative (–0.0578, $p < 0.0001$), meaning the combined effect of older age and higher BMI is somewhat attenuated compared to their individual effects. Additionally, BMI × living in Southern states shows a negative interaction (–0.0481, $p < 0.0001$). Finally, several interactions involving sex and income categories are protective: female × no income info (–0.0599, $p = 0.0023$), female × other income (–0.1065, $p < 0.0001$), and female × rich income (–0.2011, $p < 0.0001$), indicating that women in these income groups have lower diabetes risk relative to men. A few variables show weak or non-significant effects. Cohort (scaled) is marginally positive (0.0047, $p = 0.0897$), while region Northeast has no significant effect (0.0032, $p = 0.699$). Education × rich income for those with high school or less is also non-significant (0.0291, $p = 0.756$).

| Term | Estimate | Std. Error | Pr(> $\|z\|$) | Sig. |
|---|---|---|---|---|
| (Intercept) | -2.9352 | 0.0733 | 0.0000 | *** |
| age_scl | 0.0298 | 0.0333 | 0.3713 | |
| bmi_scl | 0.2273 | 0.0121 | 0.0000 | *** |
| cohort_scl | -0.1197 | 0.0244 | 0.0000 | *** |
| edu: high school or less | 0.1781 | 0.0395 | 0.0000 | *** |
| edu: some college | 0.1378 | 0.0429 | 0.0013 | ** |
| female | -0.0584 | 0.0436 | 0.1798 | |
| income: no info | -0.7246 | 0.0918 | 0.0000 | *** |
| income: other | -0.8060 | 0.1367 | 0.0000 | *** |
| income: rich | -0.7797 | 0.0812 | 0.0000 | *** |
| race: hispanic | 0.0209 | 0.1208 | 0.8626 | |
| race: other | 0.5398 | 0.0850 | 0.0000 | *** |
| race: white | 0.3240 | 0.0613 | 0.0000 | *** |
| region: Northeast | -0.1103 | 0.0727 | 0.1293 | |
| region: South | -0.1092 | 0.0503 | 0.0299 | * |
| region: West | 0.0363 | 0.0995 | 0.7154 | |
| smoker | 0.6990 | 0.0122 | 0.0000 | *** |
| $I$(bmi_scl$^2$) | -0.0317 | 0.0028 | 0.0000 | *** |
| age_scl:income no info | 0.2789 | 0.0557 | 0.0000 | *** |
| age_scl:income other | 0.2077 | 0.0398 | 0.0000 | *** |
| age_scl:income rich | 0.4191 | 0.0463 | 0.0000 | *** |
| bmi_scl:income no info | 0.1038 | 0.0197 | 0.0000 | *** |
| bmi_scl:income other | 0.0621 | 0.0138 | 0.0000 | *** |
| bmi_scl:income rich | 0.1663 | 0.0170 | 0.0000 | *** |
| cohort_scl:income no info | 0.1172 | 0.0400 | 0.0034 | ** |
| cohort_scl:income other | -0.0347 | 0.0291 | 0.2329 | |
| cohort_scl:income rich | 0.0036 | 0.0340 | 0.9145 | |
| edu: high school or less × income no info | 0.4405 | 0.0581 | 0.0000 | *** |
| edu: some college × income no info | 0.2796 | 0.0633 | 0.0000 | *** |
| edu: high school or less × income other | 0.3819 | 0.1264 | 0.0025 | ** |
| edu: some college × income other | 0.3116 | 0.1274 | 0.0145 | * |
| edu: some college × income rich | 0.2633 | 0.1215 | 0.0302 | * |
| female × income no info | -0.2742 | 0.0419 | 0.0000 | *** |
| female × income other | -0.3851 | 0.0307 | 0.0000 | *** |
| female × income rich | -0.6127 | 0.0375 | 0.0000 | *** |
| income no info × race hispanic | -0.0933 | 0.1126 | 0.4070 | |

| Term | Estimate | Std. Error | Pr(> $\|z\|$) | Sig. |
|---|---|---|---|---|
| income other × race hispanic | -0.1525 | 0.0815 | 0.0613 | . |
| income rich × race hispanic | -0.1075 | 0.1194 | 0.3679 | |
| income no info × race other | -0.1832 | 0.0968 | 0.0584 | . |
| income other × race other | -0.1258 | 0.0691 | 0.0688 | . |
| income rich × race other | -0.0691 | 0.0890 | 0.4372 | |
| income no info × race white | -0.4089 | 0.0665 | 0.0000 | *** |
| income other × race white | -0.2913 | 0.0483 | 0.0000 | *** |
| income rich × race white | -0.3940 | 0.0657 | 0.0000 | *** |
| female × race hispanic | -0.2316 | 0.0713 | 0.0012 | ** |
| female × race other | -0.1559 | 0.0583 | 0.0075 | ** |
| female × race white | -0.4952 | 0.0408 | 0.0000 | *** |
| race hispanic × region Northeast | 0.2042 | 0.1350 | 0.1304 | |
| race other × region Northeast | -0.0233 | 0.1065 | 0.8269 | |
| race white × region Northeast | 0.0863 | 0.0750 | 0.2501 | |
| race hispanic × region South | 0.1053 | 0.1184 | 0.3739 | |
| race other × region South | 0.3200 | 0.0780 | 0.0000 | *** |
| race white × region South | 0.3694 | 0.0527 | 0.0000 | *** |
| race hispanic × region West | -0.1175 | 0.1422 | 0.4088 | |
| race other × region West | -0.3950 | 0.1157 | 0.0006 | *** |
| race white × region West | -0.1519 | 0.1012 | 0.1334 | |

Table 4: Logistic regression coefficients for the selected expert mini model for CVDs with standard errors, z values, p-values, and significance codes (p-value < 0.001 '***', < 0.01 '**', < 0.05 '*', < 0.1 '.').

The significance tests reported are unadjusted for multiple comparisons.

The coefficients of the selected model for cardiovascular diseases (CVDs) are reported in Table 4. Similar to the diabetes model, all continuous predictors (with suffix "_scl") are standardized to mean 0 and standard deviation 1. BMI shows a strong positive association with CVD risk (0.2273, $p < 0.0001$), confirming its relevance as a key metabolic determinant. Smoking is also one of the strongest predictors (0.6990, $p < 0.0001$). Education and income remain significant, with lower educational attainment, high school or less (0.1781, $p < 0.0001$) and some college (0.1378, $p = 0.0013$), associated with higher risk compared to college graduates. Individuals with incomplete or missing income information (–0.7246, $p < 0.0001$), other income categories (–0.8060, $p < 0.0001$), and rich income (–0.7797, $p < 0.0001$) exhibit lower baseline risk relative to the lowest income group. Cohort effects are negative and significant (–0.1197, $p < 0.0001$), suggesting a modest morbidity compression for younger generations once other covariates are controlled.

Interaction terms reveal several important patterns. Age interacts positively with income, with stronger effects for higher-income respondents, indicating that socioeconomic advantage amplifies age-related CVD risk. BMI interacts positively with income categories as well, reinforcing that the impact of adiposity on CVD risk is more pronounced in wealthier groups. Educational level and income combinations, such as high school or less × no income info (0.4405, $p < 0.0001$) and some college × no income info (0.2796, $p < 0.0001$), also increase risk. Sex and income interactions show consistently negative signs, implying that women in all income groups have lower CVD risk than men (female × income rich = –0.6127, $p < 0.0001$). Ethnic and regional interactions reveal additional heterogeneity: being of "other" race in Southern states (0.3200, $p < 0.0001$) or being White in the South (0.3694, $p < 0.0001$) significantly increases risk, while residing in Western regions mitigates it (race other × West = –0.3950, $p = 0.0006$). The quadratic term for BMI (–0.0317, $p < 0.0001$) indicates a nonlinear pattern where risk rises with BMI but plateaus at higher levels. Overall, the CVD model confirms that both behavioral (smoking, BMI) and socioeconomic factors (education, income, region) remain central to explaining cardiovascular morbidity across U.S. cohorts.

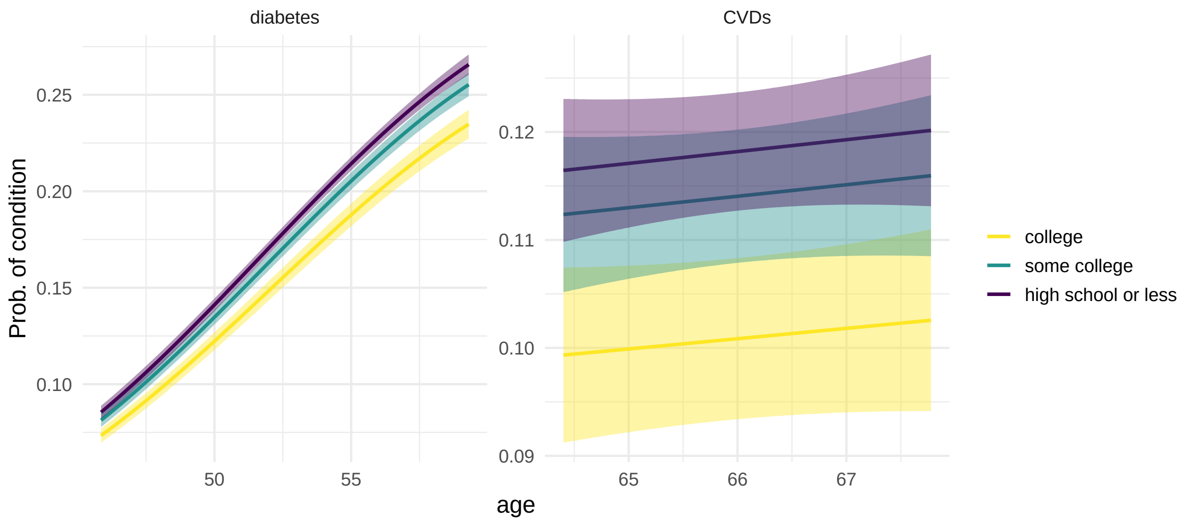



Figure 1: Estimated probability of diabetes and cardiovascular disease by age and education. Shaded areas show 95% confidence intervals based on the logistic model. Reference individual: living in south, in poverty, female, born in 1952, white, education: some college, BMI of 28.

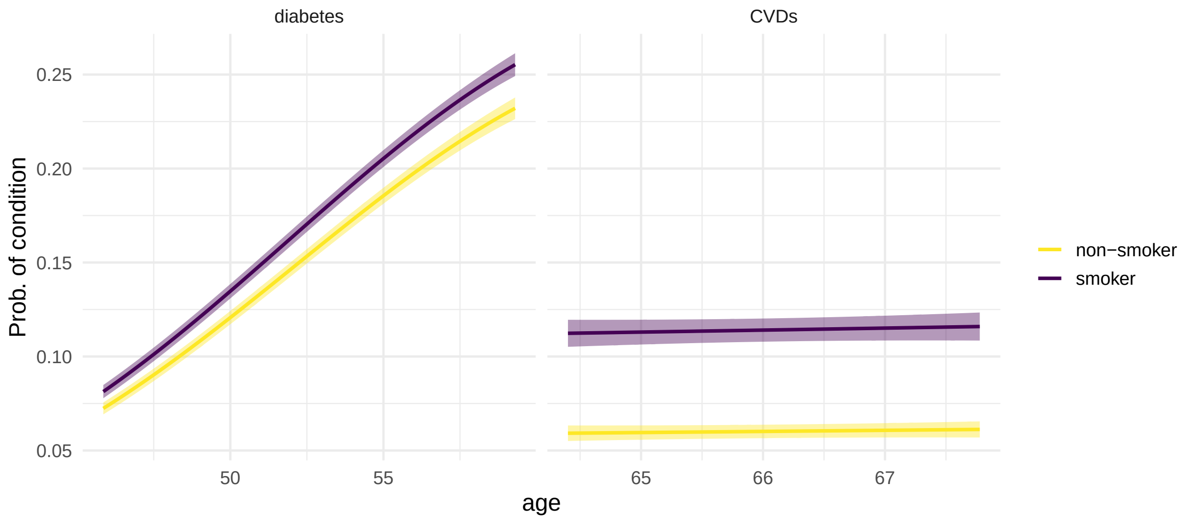
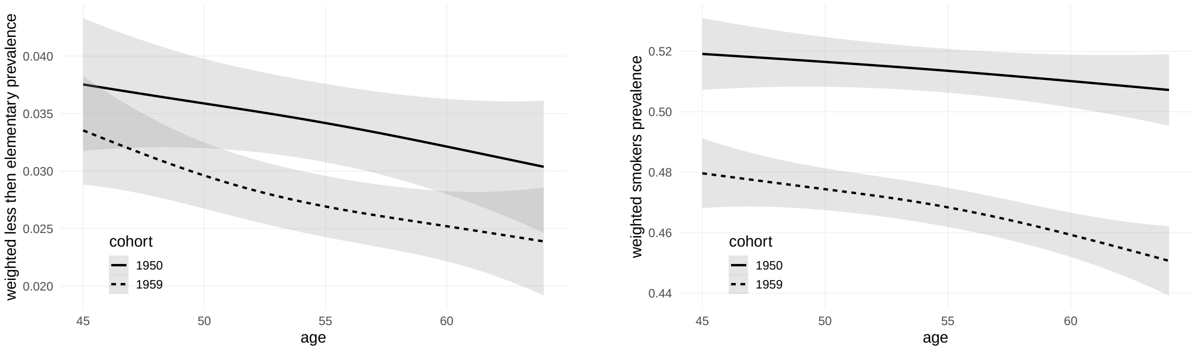



Figure 2: Estimated probability of diabetes and cardiovascular disease by age and smoking. Shaded areas show 95% confidence intervals based on the logistic model. Reference individual: living in south, smoker, female, born in 1952, white, in poverty, BMI of 28.




(a) Low Education

(b) Smokers

Figure 3: Smoothed weighted prevalence curves for low education (attained less than elementary) and smokers (smoking or ever smoked 100 cigarettes). Shaded areas represent smoothing standard deviation.

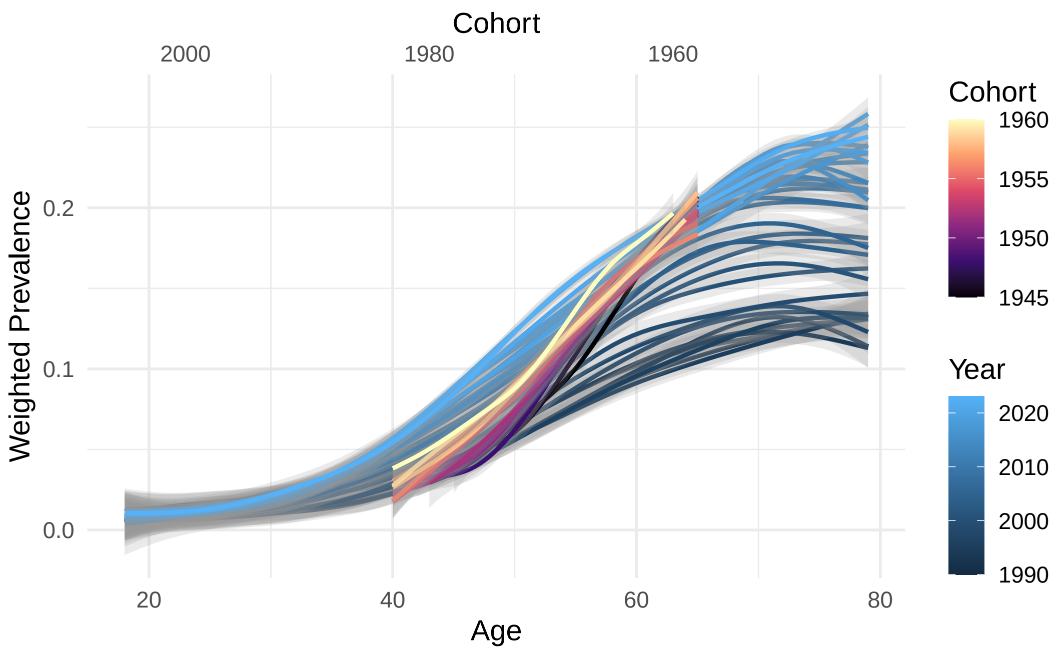



Figure 4: Diabetes prevalence curves by age under cohort (red) and survey year (blue) perspective.

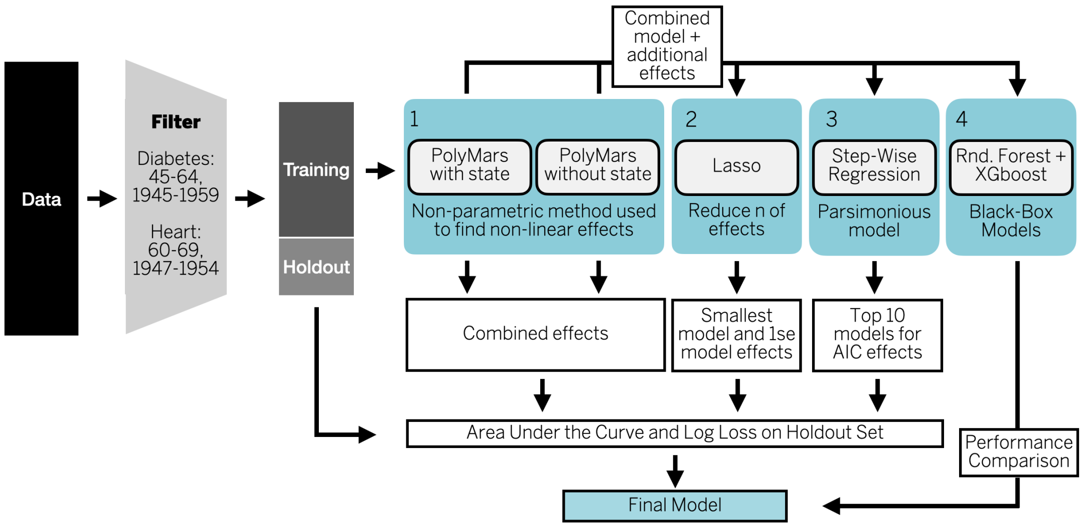



Figure 5: Schematic representation of the model selection pipeline