

1 **Dynamic Importance of Genomic and Clinical Risk for Coronary Artery Disease Over the**
2 **Life Course**

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34
35 Tweet: Genomic and clinical risk factors of coronary artery disease have time-varying effects
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39

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64

65 **Key Points**

66

67 **Question**

68

69 How do genomic and clinical risk factors contribute to coronary artery disease (CAD) risk across
70 a broad age range?

71

72 **Findings**

73

74 This longitudinal observational study across two cohorts found that both genomic and clinical
75 risk factors exhibit age-dependent significance for CAD risk. Polygenic risk scores (PRS) are
76 most informative for individuals younger than 55 years, improving the predictive accuracy of
77 current risk equations for these individuals.

78

79 **Meaning**

80

81 The study emphasizes the need to incorporate the dynamic effects of cardiovascular risk factors,
82 particularly genomic risk, for more accurate early-life risk prediction and efficient CAD
83 prevention strategies.

84

85

86 **Structured Abstract**

87

88 **Importance**

89 Earlier identification of high coronary artery disease (CAD) risk individuals may enable more
90 effective prevention strategies. However, existing 10-year risk frameworks are ineffective at
91 earlier identification. Understanding the variable importance of genomic and clinical factors
92 across life stages may significantly improve lifelong CAD event prediction.

93

94 **Objective**

95 To assess the time-varying significance of genomic and clinical risk factors in CAD risk
96 estimation across various age groups.

97

98 **Design, Setting, and Participants**

99 A longitudinal study was performed using data from two cohort studies: the Framingham
100 Offspring Study (FOS) with 3,588 participants aged 19-57 years and the UK Biobank (UKB)
101 with 327,837 participants aged 40-70 years. A total of 134,765 and 3,831,734 person-time years
102 were observed in FOS and UKB, respectively.

103

104 **Main Outcomes and Measures**

105 Hazard ratios (HR) for CAD were calculated for polygenic risk scores (PRS) and clinical risk
106 factors at each age of enrollment. The relative importance of PRS and Pooled Cohort Equations
107 (PCE) in predicting CAD events was also evaluated by age groups.

108

109 **Results**

110 The importance of CAD PRS diminished over the life course, with an HR of 3.58 (95% CI 1.39-
111 9.19) at age 19 in FOS and an HR of 1.51 (95% CI 1.48-1.54) by age 70 in UKB. Clinical risk
112 factors exhibited similar age-dependent trends. PRS significantly outperformed PCE in
113 identifying subsequent CAD events in the 40-45-year age group, with 3.2-fold more
114 appropriately identified events. The mean age of CAD events occurred 1.8 years earlier for those
115 at high genomic risk but 9.6 years later for those at high clinical risk ($p < 0.001$). Overall, adding
116 PRS improved the area under the receiving operating curve of the PCE by an average of +5.1%
117 (95% CI 4.9-5.2%) across all age groups; among individuals < 55 years, PRS augmented the
118 AUC-ROC of the PCE by 6.5% (95% CI 5.5-7.5%, $p < 0.001$).

119

120 **Conclusions and Relevance**

121 Genomic and clinical risk factors for CAD display time-varying importance across the lifespan.
122 The study underscores the added value of CAD PRS, particularly among individuals younger
123 than 55 years, for enhancing early risk prediction and prevention strategies.

124	Non-standard Abbreviations and Acronyms	
125	CAD	Coronary artery disease
126	FOS	Framingham Offspring Study
127	UKB	UK Biobank
128	PRS	Polygenic risk score
129	PCE	Pooled Cohort Equations
130	LDL-C	Low-density lipoprotein cholesterol
131	ASCVD	Atherosclerotic cardiovascular disease

132 **Introduction**

133 Accurate risk estimation for coronary artery disease (CAD) early in the life course is a
134 major goal in medicine, as CAD remains the leading cause of mortality and morbidity.¹ Since
135 coronary atherosclerosis often begins early in life and progresses over the life course, early
136 identification of high-risk individuals offers the possibility for substantial risk mitigation.²

137 There are several reasons why contemporary risk estimators in clinical practice do not
138 adequately identify high-risk individuals early in life. First, guideline-based risk calculators are
139 valid only for ages 40 years or older and are often limited to short-term (e.g. 10-year) fixed-time
140 horizons.^{3,4} Therefore, chronologic age remains the primary determinant of estimated 10-year
141 risk, and high risk cannot be identified earlier in life, thereby delaying effective prevention
142 opportunities.⁵ Second, even when prediction is extended to estimate lifetime risk, it fails to
143 capture the dynamic trajectory of an individual's changing risk profile, such as changing
144 biomarker, biometric measurements, or lifestyle. Finally, models are developed assuming
145 proportional hazards, which impose that the effect of each risk factor is either constant over the
146 baseline hazard ratio through life or that interaction is a linear function of time. Both
147 assumptions are empirically inaccurate for CAD clinical risk factors.⁶

148 CAD polygenic risk score (PRS) has emerged as a tool to estimate risk complementary to
149 clinical risk factors and is uniquely available very early in life. Traditional models considering
150 these scores often employ a fixed-time horizon and rely on assumptions that do not hold true for
151 the dynamic and complex landscape of CAD risk factors. We aim to break down existing barriers
152 in CAD risk prediction by integrating both genomic and clinical risk factors in a single,
153 dynamically-adjusting model. Using two cohorts ranging from 19 to 70 years of age, followed
154 for up to 44 years, we illuminate how the relevance of these risk factors shifts over an

155 individual's life course, thereby offering a more nuanced and applicable framework for CAD risk
156 estimation. While recent work by Marston et al. in the UK Biobank has shown that CAD PRS
157 carries greater effects for younger people,⁷ its comparative and complementary performance with
158 clinical risk calculators is less clear for both premature and cumulative events across a broad age
159 range. The integration of genomic and clinical risk in a single model continues to be a barrier to
160 clinical implementation of CAD PRS at scale. Such integration will ideally incorporate the
161 dynamic importance of genomic and clinical risk for CAD over the life course for optimal utility.

162 Here, we leverage two cohorts of individuals enrolled across the ages of 19 to 70 years
163 and followed for up to 44 years to show that genomic and clinical risk factors vary in their
164 importance over the life course and to explain a changing proportion of variation for CAD risk.
165 We show that CAD PRS adds the most information for young and early middle-aged individuals
166 when compared with older individuals and predicts a greater number of both premature and
167 overall events for younger individuals. This framework mitigates current age-dependent
168 limitations of CAD clinical risk scores.

169 **Methods**

170 **Study participants**

171 Two cohorts were included in this study. First, the Framingham Offspring Study (FOS) is
172 a longitudinal US-based cohort study consisting of the children of the original participants of the
173 Framingham Heart Study, recruited between 1971 and 1975 and followed through 2018.⁹
174 Clinical data on cardiovascular risk factors and incident disease were available for 3,821
175 participants, and genetic data for a subset (N=2,754), through the database of Genotypes and
176 Phenotypes (dbGaP; accession phs000007.v33.p14). We conducted an analysis of clinical risk
177 factors on the complete dataset (N=3,588) and the genetic analysis on the subset (N=2,629), after
178 excluding 233 individuals for missing risk factor data, current lipid-lowering medication, or pre-
179 existing CAD (Supplementary Figure 1).

180 Second, the UK Biobank (UKB) is a prospective nationwide population-based study that
181 enrolled middle-aged adults between 2006 and 2010 and followed through present. Examiners
182 collected baseline phenotypic, genetic, self-reported, and electronic health records on 502,485
183 participants.¹⁰ In the present study, we included 327,837 participants from the UKB after
184 excluding 174,378 who lacked quality-controlled genotyping, risk factor, lipid, or medication
185 information or carried a diagnosis of CAD at baseline (Supplementary Figure 2).

186 Informed consent was obtained from all participants, and secondary data analyses of
187 dbGAP based FOS and UKB were approved by the Mass General Brigham Institutional Review
188 Board applications 2016P002395 and 2021P002228.

189

190 **Study outcomes**

191 In the FOS, CAD was defined as coronary death or myocardial infarction and recorded
192 by independent reviewers over a follow-up period of a median 43.0 [Interquartile Range (IQR)
193 38.6-47.4] years encompassing 134,765.2 person-years, using medical histories, physical
194 examinations at the study clinic, hospitalization records, and communication with participants'
195 physicians, as previously described.^{11,12}

196 In the UKB, participants were followed for a median of 12.2 [IQR 11.4-15.1] years
197 encompassing 3,831,734 person-years. CAD was defined as a composite of myocardial
198 infarction, coronary revascularization, or death related to either as previously described.¹³
199 Myocardial infarction was based on self-report or hospital admission diagnosis as performed
200 centrally and recorded in I21-I21.4, I21.9, I22-I22.1, I22.8, I22.9, I23-I23.6, I23.8, I24-I24.1,
201 I24.8, I24.9, I25.2.¹³ Coronary revascularization was assessed based on an OPCS-4 coded
202 procedure for coronary artery bypass grafting (K40.1–40.4, K41.1–41.4, K45.1–45.5) or
203 coronary angioplasty with or without stenting (K49.1–49.2, K49.8–49.9, K50.2, K75.175.4,
204 K75.8–75.9).

205

206 **Genomic risk**

207 CAD PRS, a measure of the cumulative risk from many genetic variations across the
208 genome, was used to quantify genomic risk.¹⁴ Genetic data for the FOS were made available
209 from the NHLBI SNP Health Association Resource (SHARe) project, in which genotyping was
210 conducted using approximately 550,000 SNPs (Affymetrix 500K mapping array plus Affymetrix
211 50K supplemental array) and imputed using the 1000 Genomes reference panel as reported
212 previously.⁹ The genetic data for UKB was phased and imputed centrally to ~96 million variants
213 with the Haplotype Reference Consortium (HRC) and the UK10K + 1000 Genomes reference

214 panel.¹⁰ In both cohorts, we computed a CAD PRS using publicly available weights for GPS_{CAD},
215 a genome-wide polygenic score for CAD consisting of 6.6 million variants.¹⁴ In clarifying
216 analyses, participants were classified as having low genomic risk if they fell in the bottom
217 quintile, intermediate genomic risk if they fell in the middle three quintiles, and high genomic
218 risk if they fell in the top quintile, of the population distribution of PRS.

219

220 **Clinical risk factors**

221 Individual clinical risk factors of CAD as well as a guideline-supported clinical risk
222 score (i.e., the Pooled Cohort Equations [PCE]) were used to estimate CAD risk. Clinical risk
223 factors such as current smoking, diagnosis of diabetes, antihypertensives prescription, blood
224 pressure, and lipids were collected at cohort enrollment based on a combination of self-report,
225 blood test, and medical chart review.¹¹ Systolic blood pressure measurement was adjusted for
226 anti-hypertensive medication use by adding 15mmHg. Lipids were adjusted for the use of
227 lipid-lowering medication by dividing the LDL-C and total cholesterol value by 0.7 and 0.8,
228 respectively, as previously described.¹⁵

229 The PCE was computed in the UKB, which provided a ten-year risk estimate of
230 atherosclerotic cardiovascular disease (ASCVD).¹⁶ Guideline-based risk strata were indicated
231 as follows: low or borderline (<7.5%), intermediate (≥ 7.5 to <20%), and high ($\geq 20\%$).¹⁶

232

233 **Statistical Analysis**

234 At enrollment, we computed the age-specific hazard ratios (HRs) and proportions of
235 variation explained by each risk factor for cumulative risk of CAD. We divided each dataset into
236 individuals whose age at enrollment and baseline ascertainment of risk factor levels were within

237 one calendar year of each age under consideration. We report the results from a locally estimated
238 smoothed scatter (loess)¹⁷ weighted according to the tricube distance function to borrow
239 information from nearby windows. After confirming that the Cox proportional hazard
240 assumption was now satisfied by this approach (Supplementary Figure 3, Supplementary
241 Methods), we reported the average HR and proportion of variation explained (PVE) of CAD
242 over the study period with respect to one unit increase in standardized risk factor for individuals
243 within one calendar year of assessment (Supplementary Methods).

244 For age-dependent relative incidence analyses, we computed the incidence rates for each
245 CAD PRS percentile and divided by the incidence rate for those individuals of the lowest risk
246 percentile per age group, so that the lowest age-relative incidence rate equals one. For
247 cumulative hazard analyses, we computed cumulative hazard in strata of PRS and PCE within
248 each age category (younger than 55 years, 55-65 years, and older than 65 years). Within each age
249 category, we then stratified by PRS category (bottom quintile, middle three quintiles, top
250 quintile) and then by age-specific PCE risk categories (bottom quintile, middle three quintiles,
251 top quintile).

252 For prediction of cumulative events, we identified individuals with a diagnosis of CAD
253 over the observed time-period and computed the number of events that were predicted for
254 individuals categorized as intermediate or high risk by PCE (10-year ASCVD risk $\geq 7.5\%$), high
255 polygenic score (top quintile) at age of enrollment, or both. Traditional area-under-the-curve
256 (AUC) was evaluated for development of CAD on PRS or PCE categories based on logistic
257 regression and fitted for each age group separately.

258

259 **Results**

260 **Study Participants**

261 We studied two cohorts free of cardiovascular disease at baseline and spanning the life
262 course: (i) FOS comprising 3,588 individuals (50.9% female) ages 19-50 years at enrollment and
263 followed for a median of 43.7 (interquartile range [IQR] 38.7-47.4) years and (ii) UKB,
264 comprising 327,837 participants (57% female) ages 40-70 years at enrollment followed for a
265 median of 12.1 (IQR 11.4-12.7) years (Table 1). Apart from smoking, clinical risk factors were
266 more prevalent in the UKB as expected given the age differences. For example, 1581 (44%) of
267 FOS participants (enrolled 1971-1975) were current smokers, compared to 33,869 (10%) of
268 UKB participants (enrolled 2006-2010). During follow-up, 695 (19.4%) of FOS participants and
269 11,190 (3.4%) of UKB participants developed CAD. Of those incident events, the proportion of
270 premature CAD events – defined as occurring before age 55 years – were 179 of 695 (25.8%) in
271 the FOS and 1085 of 11,190 (9.7%) in the UKB, respectively.

272

273 **Age-dependent effects of genomic and clinical risk factors**

274 We calculated the hazard ratio of CAD per standard deviation of PRS at each age of
275 enrollment. The HR per standard deviation of CAD PRS decreased over the life course – from
276 3.58 (95% CI 1.39-9.19) at age 19 years to 1.99 (95% CI 1.06-3.70) at age 56 years in FOS, and
277 from 2.25 (95% CI 1.77-2.87) at age 41 years to 1.39 (95% CI 1.30-1.48) by age 70 years in
278 UKB (Figure 1, Supplementary Tables 1 and 2).

279 We next calculated the HR of clinical risk factors at each age of enrollment and similarly
280 observed decreasing hazard ratios over the life course. For example, the HR (95% CI) of CAD
281 for smoking decreased from 1.98 (0.44-8.84) at age 19 years to 0.98 (0.41-2.33) at age 56 years

282 in the FOS and from 3.51 (2.13-5.80) at age 41 years to 1.62 (1.28-2.04) at age 70 years in the
283 UKB. The trends were similar for systolic blood pressure and diabetes (Figure 1, Supplementary
284 Tables 1 and 2). Excess risk associated with male sex similarly declined with age – from 3.29
285 (95% CI 0.64-16.95) at age 19 to 2.59 (95% CI 0.92-7.25) at age 57 in the FOS and from 3.20
286 (95% CI 1.82-5.64) at age 41 to 1.99 (95% CI 1.74-2.26) at age 70 in the UKB (Figure 1,
287 Supplementary Tables 1 and 2).

288 When clinical risk factors were considered in composite as part of the PCE, the HR for
289 CAD for a 1% increase in estimated 10-year risk remained relatively stable over the life course –
290 1.24 (95% CI 1.18-1.30) at age 41 years and 1.04 (95% CI 1.03-1.04) at age 70 years
291 (Supplementary Figure 4). However, when scaling the PCE by its SD of 7.2%, HR (95% CI) per
292 SD ranges from 4.4 (3.31-5.95) at age 41 years to 1.3 (1.29-1.31) at age 70 years (Supplementary
293 Figure 4). A high PCE was exceedingly rare among young participants (0.14%, 95% CI 0.13-
294 0.16) (Supplementary Figure 5).

295 We next computed the PVE of CAD on each risk factor for individuals up to and
296 including the age in question. We observed a decreasing PVE with increasing age for PRS, from
297 19% (95% CI 18.9-19.1) at age 19 years to 3.2% (95% CI 3.19-3.21) at age 57 years in the FOS and
298 from 5.9% (95% CI 5.89-5.91) at age 40 years to 1.7% (95% CI 1.69-1.71) at age 70 years.
299 (Supplementary Figure 4, Supplementary Tables 3 and 4).

300

301 **Relative importance of genomic and clinical risk of CAD by age**

302 To compare the relative importance of genomic versus clinical risk, we limited our
303 analysis to the UKB where both could be calculated. The distributions of PRS of participants
304 across all age groups were similar and the absolute risk of CAD increased with increasing PRS

305 (Figures 2A and 2B, Supplementary Figure 6). Over the study period, the absolute CAD risk
306 difference between those < 55 years in the 1st and 99th percentiles was 3.1%, while at >65 years
307 rose to 7.1% (Figure 2A). However, the corresponding relative risks were 5.2-fold (95% CI 5.1-
308 5.4) and 3.2-fold (95% CI 3.1-3.3), respectively (Figure 2C).

309 When classifying PCE and PRS strata within each age group as high (top quintile),
310 intermediate (middle three quintiles), and low (bottom quintile) (Supplementary Table 5), there
311 was a marked gradient of cumulative hazard of CAD events over the 12-year follow-up period
312 (Figure 3). This stratification was highest in the <55 years age group, ranging from 0.045% (95%
313 CI 0.023-0.067) for individuals with low PRS and low PCE to 14.6% (95% CI 12.8-15.5) for
314 individuals with high PRS and high PCE. The corresponding stratification in the >65 years age
315 group was 4.6% (95% CI 0.01-0.09) to 37.6% (95% CI 0.11-0.64) (Figure 3).

316 We then compared the ability of a high PRS vs. high PCE in predicting CAD events
317 across different age groups (Figure 4A). At younger ages of enrollment (40-45 years), high PRS
318 predicted over 3.5-fold more events compared to high PCE – 32.3% (95% CI 32.0-32.5) of CAD
319 events occurring in this age group were predicted by high PRS alone compared to only 9.1%
320 (95% CI 9.0-9.2) by high PCE alone.

321

322 **Prediction of premature CAD events**

323 Individuals with high PRS developed CAD earlier in life (mean 65.3 [95% CI 65.0-65.5]
324 years), whereas the average age of first CAD among high PCE group was 70.8 [95% CI 70.6-
325 71.0] years (Supplementary Tables 7 and 8). Mean age of CAD event decreased with increasing
326 PRS, from 67.2 (95% CI 66.6-67.8) years in the lowest decile to 64.5 (95% CI 64.1-65.0) years
327 in the highest decile. Conversely, individuals in the highest PCE decile had events 13.7 years

328 later in life than those of the lowest PCE (Figure 4B, Supplementary Table 9, Supplementary
329 Figure 8). Among individuals with CAD events occurring at less than 55 years, 427 (39.3%) had
330 high PRS but only 32 (2.9%) had high PCE.

331

332 **Augmenting clinical risk models with genomic risk**

333 Adding PRS to PCE augmented AUC across all ages but with the greatest impact in younger
334 individuals (Figure 4C, Supplementary Table 10). For individuals <55 years, the improvement
335 was 6.3% (95% CI 4.8-7.8) compared to only 2.9% (95% CI 2.2-3.8) for those over 55.
336 Furthermore, the AUC increased by 8.8% (95% CI 8.4-9.2%) in the 40-45 age group, 7.8% (95%
337 CI 7.6-8.0%) in the 45–50-year group, and 4.9% (95% CI 4.7-5.1%) in the 50-55 age group,
338 respectively (Figure 4C). The net proportion of CAD cases correctly reclassified by genomic
339 risk (high PRS) was the highest in younger participants (16.1% for age <50 years and 3.4% for
340 age <55 years) but receded for those over 55. The net proportion of controls correctly reclassified
341 by genomic risk (low PRS) was the highest at older ages (15.1% at age <75 years) but
342 diminishes in utility for those younger than 60 (Supplementary Figure 9, Supplementary Table
343 11).

344 Discussion

345 Our findings enhance our understanding of CAD risk factors by illustrating their dynamic
346 importance throughout life. Unlike traditional models that operate under the constraints of fixed
347 windows of time and proportional hazards, our work goes beyond these limitations to embrace
348 the time-varying nature of these risk factors. The ability to track this dynamic trajectory provides
349 new granularity in risk assessment, particularly for younger individuals. Our approach not only
350 reconciles the time-varying impact of genomic and clinical risk factors but also highlights that
351 CAD PRS offers value for risk assessment in individuals under 55 years over clinical risk factors
352 alone.

353 While current risk stratification emphasizes a focus on short-term risk, even an emphasis
354 on a longer duration of risk fails to capture the dynamic trajectory of an individual's changing
355 risk profile over time. Our dynamic model of both genomic and clinical risk factors offers
356 several practical implications. First, it is more accurate than existing risk calculators based on
357 clinical risk factors alone. Second, it allows for more precise clinical risk stratification among
358 younger individuals, for whom clinical risk factors perform least well. Lastly, our work supports
359 the integration of genomics into clinical practice toward improved prevention of premature CAD
360 events, which are generally missed by current clinical risk calculators.

361 Hazard ratios for conventional CAD risk factors and PRS are both age-dependent and
362 challenges traditional modeling assumptions. This is important for consideration of risk across
363 the life course beyond the present 10-year estimated risk framework, as recently highlighted in a
364 National Heart Lung and Blood Institute workshop.¹⁸ The Cox proportional hazards model has
365 been the default approach for cardiovascular risk prediction, but its fundamental assumption –
366 that the hazards in both groups compared are proportional – is often erroneous, and commonly

367 reported hazard ratios and risk estimates, such as the ten-year risk estimate from the PCE, are
368 weighted averages of time-varying hazard ratios.¹⁹

369 Current risk calculators provide a fixed window estimate, as opposed to a dynamic
370 trajectory.^{20,5} An incremental enhancement to the existing approach would include the use of
371 time-varying covariates and time-varying effects.^{21,22} The Cox-related approach requires the
372 specification of repeated measures of a particular risk factor, which can be challenging to obtain
373 in practice and is often confounded by frequency of ascertainment. The alternative, using time-
374 varying effects,²² is an improvement, but the interpretation of these estimates is altogether
375 different: each estimate represents the hazard ratio of a particular covariate on risk within a
376 respective finite time interval, whereas our approach describes the average overall hazard for an
377 individual of a particular age at prediction and thus a particular age period, which is more
378 clinically relevant. We emphasize that genomics allows us to predict lifetime risk early and not
379 only premature events. While the PCE tends to capture individuals who have higher rates of
380 known clinical risk factors, genetic risk is largely independent with a broadly uniform
381 distribution of clinical risk factors among varying levels of genetic risk. PCE incorporates age as
382 a constant interaction with time-to-risk models but our study shows that this change is not linear
383 nor easily predictable.^{5,3} Finally, while the advent of machine learning has opened the possibility
384 of deep-learning for predictive algorithms on much larger data sets, interpretable models that can
385 be feasibly incorporated and understood within the confines of a short clinical visit are
386 essential.²³ Future approaches need to account for time-varying effects while also considering the
387 time of assessment. This may require the use of time-varying coefficients,²⁴ multistate models,²⁵
388 and a more nuanced approach to handling time-varying competing risks.²⁶

389 In conclusion, our work highlights three areas in which CAD PRS adds value to current
390 guideline-based clinical risk prediction using the PCE: (i) CAD PRS had the most value in
391 augmenting risk prediction for CAD among individuals younger than 55 years of age. Prior
392 work for CAD has largely examined AUC augmentation with PRS in aggregate of middle-aged
393 or even older participants noting minimal incremental value.^{27,28} (ii) CAD PRS improves
394 precision in risk estimation for individuals within the strata of clinical risk according to the PCE
395 throughout the life course, but that such stratification is highest among individuals under age 55
396 years. (iii) Integration of genomics in risk prediction enables the detection of premature events
397 that are missed by current guideline-supported tools. Collectively, these findings support
398 inclusion of PRS to augment current clinical risk estimation toward better allocation of
399 preventive therapies.^{29,30}

400

401 **Limitations**

402 Our results should be interpreted in the context of potential limitations. First, survival bias is an
403 important limitation with a broad age of inclusion in any volunteer cohort. However, this also
404 reflects the dynamic importance of risk factors when considering event-free individuals at
405 increasing age, which is leveraged in the present study. Second, the two cohorts studied spanned
406 different countries, time periods, and medical guidelines epochs, making absolute estimates
407 between FOS and UKB not directly comparable, but the overall dynamic age-dependent trends
408 were consistent. Third, we do not compare genomic to lifestyle-based “primordial” risk
409 calculators in individuals under the age of 40 year, which would further illuminate the value of
410 genomics in comparison to those measures prior to onset of disease risk factors. Fourth, because
411 this study is predominantly of individuals of European ancestry, additional research is needed to

412 evaluate whether these observations are applicable to other ancestries. CAD PRS has reduced
413 performance in ancestries outside of Europe but cross-ethnic transferability of PRS is improving
414 with more diverse training data and novel methods.³¹

415 **Conclusions**

416 In summary, this study extends current CAD risk prediction models by offering a dynamic
417 framework that also includes genomics toward improved prediction. We show that genomic
418 information adds the most information for young and middle-aged individuals when compared
419 with older individuals for the prediction of CAD events.

420

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523

524 **Figure 1. Dynamic Hazard Ratio of CAD for Genomic and Clinical Risk Factors by Age at**
525 **Estimation**

526
527 The age-specific hazard ratio (HR) for risk of CAD is plotted for multiple risk factors at each age
528 of enrollment (A) between 19 and 57 years in the FOS (N=3,588), and (B) between 40 and 70
529 years in the UK Biobank (N=327,837). The HR is obtained from Cox proportional hazards
530 estimate at each age of enrollment for a standardized unit increase in each of polygenic score,
531 total cholesterol, HDL cholesterol, and systolic blood pressure or a binary indicator for smoking,
532 male sex, and diabetes mellitus (only in the UK Biobank given the low prevalence of diabetes
533 mellitus in FOS). We note the different time periods (1970-2010 and 2007-2021) for FOS and
534 UKB, respectively. The difference in absolute values can thus not be considered as levels of
535 these clinical risk factors varied between populations (Table 1) and between eras. Accordingly,
536 excluding individuals on statins results in a different population in each cohort. No covariates are
537 used in the analysis to isolate the effect of each risk factor separately.

538
539 **HR:** Hazard Ratio; **HDL:** High density lipoprotein, **CAD:** coronary artery disease, **FOS:**
540 Framingham Offspring Cohort, **95% CI:** 95% Confidence Interval.

541

542 **Figure 2. Absolute and Relative Incidence Rate of CAD by Genomic Risk per Age Group**

543
544 In the UK Biobank (N=327,837), three age groups (<55, 55-65, and >65 years) at risk estimation
545 were used to compare the stratification of the observed absolute and relative risk across
546 polygenic score percentile. (A) The absolute risk of CAD increased with increasing polygenic
547 score percentile in all three age groups, and older participants had higher absolute risk of CAD.
548 Absolute risk of CAD ranged from 0.7 to 3.9% in the <55 years age group, 1.9 % to 7.0 % in the
549 55-65 years age group, and 3.3 to 10.4% in the >65 years age group. (B) The polygenic score
550 distribution was similar across three age groups. (C) Relative risk gradient of genomic risk is
551 greatest for younger age groups. The 99th percentile of polygenic score was associated with a
552 5.2-fold increase in risk in the <55 years age group, 3.6-fold increased risk in the 55-65 years age
553 group, and 3.2-fold increase in risk in the >65 years age group.

554
555 **CAD:** coronary artery disease. **PRS:** Polygenic risk score.
556

557 **Figure 3. Cumulative Hazard of Incident CAD by Clinical and Genomic Risk in Three Age**
558 **Groups**

559
560 In the UK Biobank (N=327,837), three age groups (<55, 55-65 and over 65 years) at risk
561 estimation were used to compare the cumulative incidence of CAD by genomic (PRS) and
562 clinical (PCE) risk levels defined as low (bottom quintile), intermediate (middle three quintiles),
563 and high (top quintile) within each age group. We report the cumulative hazard over the
564 observed follow-up time (median 12.2 years). The stratification was highest in the <55 years age
565 group (A), where the cumulative hazard ranged from 0.45% (95% CI 0.23-0.67) for individuals
566 with low PRS and low PCE to 14.6% (95% CI 12.8-15.5) for individuals with high PRS and high
567 PCE. The stratification decreased but persisted in the older age groups (B and C). Here we
568 feature the same Y axis to emphasize differences in *absolute* risk among young, middle and older
569 individuals.

570
571 **CAD:** coronary artery disease, **PRS:** polygenic risk score, **PCE:** Pooled Cohort Equations.
572

573 **Figure 4. Augmenting Risk Prediction of CAD in Early Middle-Age with the Addition of**
574 **PRS**

575
576 In the UK Biobank (N=327,837), we show is the proportion of cumulative CAD events predicted
577 using high genomic risk (PRS in the top quintile), intermediate to high clinical risk (PCE 10-year
578 risk $\geq 7.5\%$) or both at enrollment, by age of estimation. **B.** Mean age of CAD event decreased
579 with increasing PRS (red), from 67.2 (95% CI 66.6-67.8) years in the lowest decile to 64.5 (95%
580 CI 64.1-65.0) years in the highest decile. Conversely, those in the highest PCE decile (blue) had
581 events 13.7 years later in life than those of the lowest PCE. **C.** AUC of a model considering
582 clinical risk only when compared to a combined clinical and genomic risk model for participants
583 in 5-year age strata between ages 40 and 75 years at age of risk estimation. Genomic risk
584 categories are defined as PRS in the top quintile, middle three quintiles, and bottom quintiles.
585 Clinical risk categories are defined by PCE predicted 10-year risk $< 7.5\%$, 7.5-20%, and $> 20\%$.

586
587 **CAD:** coronary artery disease, **PRS:** polygenic risk score, **PCE:** Pooled Cohort Equations. **AUC:**
588 Area Under the Receiver Operator Curve

589
590

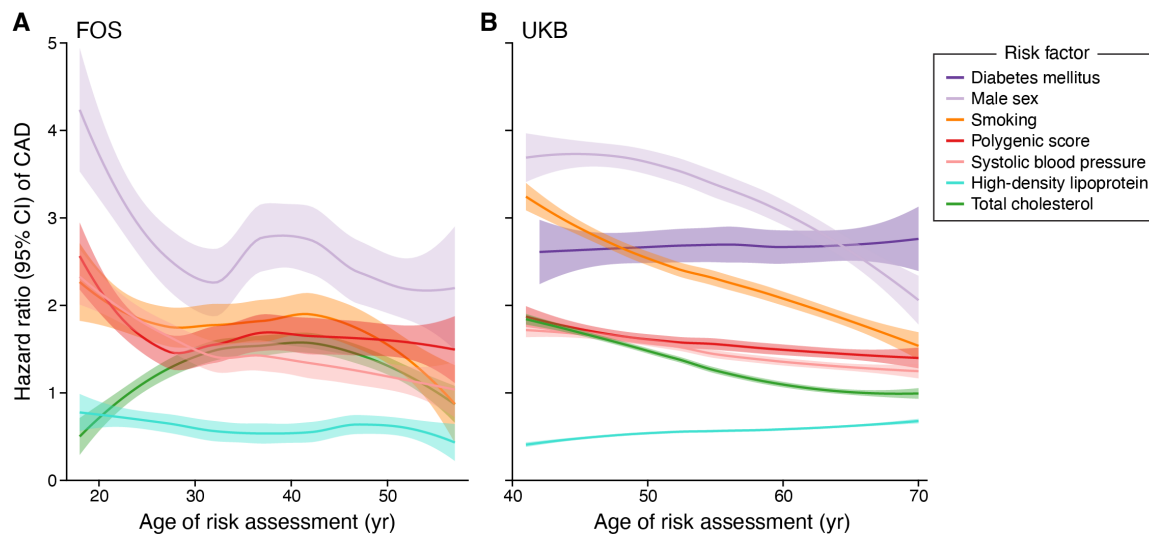
591 **Table 1. Characteristics of Study Participants from the FOS (N=3,588) and UKB**
 592 **(N=327,837)**

Characteristics	FOS (N=3,588)	UKB (N=327,837)
Age at risk estimation, mean (SD), years	35.9 (10.2)	56.1 (8.1)
Female, n (%)	1,828 (50.9)	186,507 (56.9)
White race, n (%)	3,588 (100)	274,927 (83.9)
Incident CAD, n (%)	695 (19.3)	11,190 (3.4)
Follow-up period, median [IQR]	43.7 [38.7-45.3]	12.1 [11.4-12.7]
Diabetes mellitus, n (%)	27 (0.7)	2413 (0.7)
Current smoking, n (%)	1581 (44.1)	33869 (10.3)
Total cholesterol, mean (SD), mg/dL	197 (38.8)	228.6 (41.4)
HDL Cholesterol, mean (SD), mg/dL	52.1 (16.0)	57.2 (14.8)
LDL cholesterol, mean (SD), mg/dL	127 (36.6)	144.0 (31.9)
Triglycerides, mean (SD), mg/dL	99.1 (86.7)	151.9 (90.3)
Diastolic blood pressure, mean (SD), mmHg	78.5 (10.9)	82.8 (11.2)
Systolic blood pressure, mean (SD), mmHg	121 (16.4)	139.7 (20.4)
Taking antihypertensive medication, n (%)	102 (2.8)	41,088 (12.5)
PCE 10-year risk category		
Low or borderline (<7.5%), n (%)	-	207,150 (63.2)
Intermediate (≥7.5 to <20%), n (%)	-	96,775 (29.5)
High (≥20%), n (%)	-	23,912 (7.3)
Genetic data available, n (%)	2,656 (72.5)	327,837 (100.0)
CAD polygenic risk score category		
Low, n (%)	531 (20.0)	65,696 (20.0)
Intermediate, n (%)	1,593 (60.0)	196,750 (60.0)
High, n (%)	532 (20.0)	65,391 (20.0)

593
 594 Characteristics for study participants from the Framingham Offspring Study (FOS) and UK
 595 Biobank are reported for all individuals based on data obtained at enrollment. CAD: coronary
 596 artery disease, PRS: polygenic risk score, PCE: Pooled Cohort Equations, HDL: High-density
 597 lipoprotein cholesterol, LDL: Low-density lipoprotein cholesterol.
 598

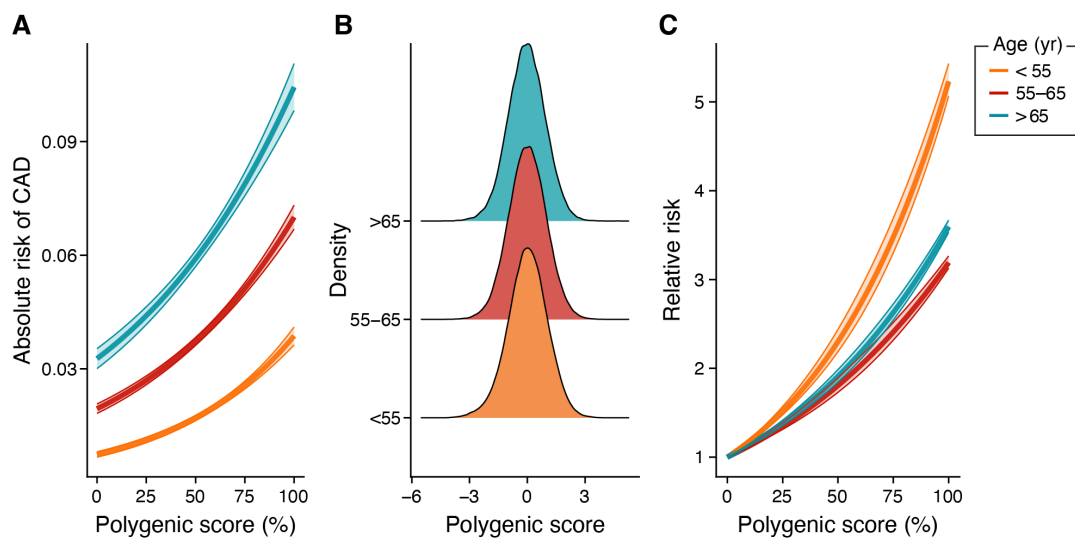
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Figure 1



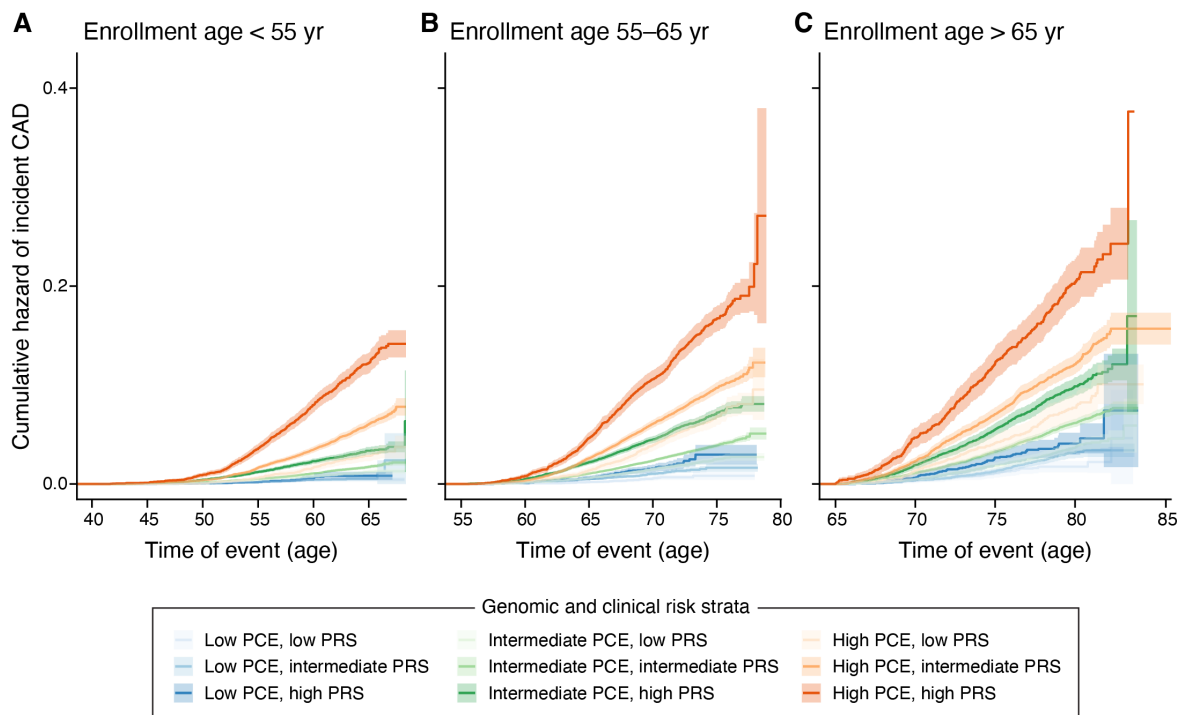
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Figure 2



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Figure 3



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Figure 4

