Predicted 10-year risk of CVD is influenced by the risk equation adopted.

Running Title: Comparisons of CVD risk equations

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Abstract

Background: Validated risk equations are currently recommended to assess individuals to determine those at 'high risk' of cardiovascular disease (CVD). However, there is no longer a risk 'equation of choice'.

Aim: This study compared four commonly used CVD risk equations.

Design and Setting: Cross-sectional analysis of individuals who participated in a workplace-based risk assessment in Carmarthenshire, South Wales.

Method: Analysis of 790 individuals (474 females, 316 males) with no prior diagnosis of CVD or diabetes. 10-year CVD risk was predicted by entering the relevant variables into the QRISK2, Framingham Lipids, Framingham BMI and JBS2 risk equations.

Results: The Framingham BMI and JBS2 risk equations predicted a higher absolute risk than both QRISK2 and Framingham Lipids and CVD risk increased concomitantly with age irrespective of which risk equation was adopted. Only a small proportion of females (0%-2.1%) were predicted to be at high risk of developing CVD using any of the risk algorithms. The proportion of males predicted at high risk ranged from 5.4% (QRISK2) to 20.3% (JBS2). Following age stratification, few differences were observed in males in regards to isolated risk factors, although a greater proportion of males aged ≥50 years were predicted to be at 'high risk' independent of risk equation used.

Conclusions: Different risk equations can influence the predicted 10-year CVD risk of individuals. More males were predicted at 'high risk' using the JBS2 or Framingham BMI equation. Consideration should also be given to the number of isolated risk factors, especially in younger adults when evaluating CVD risk.

How this fits in

Up until February 2010 the 'equation of choice' of NICE to determine CVD risk was the Framingham Risk Equation with the guidance now encouraging healthcare professionals to adopt the equation that they deem 'most appropriate'. This research compares four commonly used CVD risk equations in the United Kingdom and examines the number of individuals predicted at 'high risk'. The JBS2 and Framingham BMI equations predicted a higher proportion of individuals at 'high risk' of CVD than the Framingham Lipids or QDiabetes risk algorithms. Furthermore, despite changes in absolute risk prediction following age stratification in all of the equations, there are very few differences in isolated risk factors.

Introduction

Cardiovascular disease (CVD) remains the leading cause of mortality in the United Kingdom with latest statistics documenting that almost one third of all deaths are currently attributed to the condition [1]. Current United Kingdom government guidelines implemented through the National Institute for Health and Care Excellence (NICE) advocate risk assessment of individuals aged between 40 – 74 years to identify those at 'high risk' (≥20% 10-year risk of developing CVD, [2]). Early identification of individuals at elevated risk is essential so that lifestyle modification or pharmacological interventions can be prescribed to alleviate the risk of disease [3]. It is recommended that validated equations should be used to assess CVD risk and up until February 2010, the Framingham Risk Equation [4] was the 'equation of choice' before this endorsement was withdrawn [2]. The amended NICE guidelines now encourage healthcare professionals to use the cardiovascular risk equation that they feel most appropriate [2, 5].

Previous research has highlighted differences in false-positive rates (at a 20% threshold) between six widely cited CVD risk algorithms [6], despite these differences the screening performance of the six were similar. It was concluded that age remains the most dominant predictor in CVD events despite individual risk factors being present [6]. This observation is somewhat surprising, especially as 80% of all premature coronary heart disease in males can be attributed to the combination of smoking, hypertension and high levels of total cholesterol (>5.2 $mmol.l^{-1}$) [7]. In further terms of CVD risk factors there is evidence that a multifactorial strategy treating glycaemic control, lipid profiles and blood pressure together through either medication or behavioural therapy has been shown to be highly effective in reducing cardiovascular mortality compared to conventional treatment [8].

An important consideration is that statin therapy is recommended as part of the management strategy for the primary prevention of CVD for adults at high risk of developing CVD [2, 9]. Treatment should be initiated with simvastatin (40 mg) in those adults who have a 20% or greater 10-year risk of developing CVD [2]. Therefore, any differences between predicted risk equations could have a number of implications in regards to the correct treatment of individuals (i.e. either over- or under-prescribing of statins as a primary treatment) and the associated costs of medications.

Thus, the aim of this study was to primarily compare four commonly used CVD risk equations when the same individual dataset was applied and also examine if isolated risk factors translated to 'high risk' of CVD.

Methods

Study Population

All participants in this study were employees of either the local health board or steel workers within the Welsh region of Carmarthenshire who had received a CVD risk assessment as part of the established Prosiect Sir Gâr workplace-based initiative [10]. The initiative was introduced in 2009 and data collection for this study took place between 2009 and 2012. All current employees over the age of 40 years (if Caucasian), or 25 years (if South Asian) with no prior diagnosis of CVD or diabetes were invited to participate in the project. In total, 790 employees accepted the invitation of a health assessment, of which 474 were females and 316 males. This study was approved by Dyfed Powys Local Research Ethics Committee (reference number: 11/WA/0101).

Baseline Measurements and Risk Prediction Equations

According to a standard operational policy (SOP) all recruited individuals attended a standardised health assessment appointment with an occupational health nurse which lasted 30-40 minutes. During the session, demographic (date of birth, gender, postcode of residence) and anthropometric (body mass, height) data were collected. Systolic and diastolic blood pressure, pulse rate and rhythm, smoking status, family and medical histories were also recorded. Blood samples were also collected via capillary puncture and analysed immediately for total cholesterol (TC), high-density-lipoprotein cholesterol (HDL) and triglycerides (Cholestech LDX® System, Alere Inc., Orlando, USA). 10-year predicted CVD risk was calculated by entering the relevant variables into the QRISK2 [11], Framingham Lipids [12], Framingham BMI [12] and the Joint British Societies 2 (JBS2, [13]) risk equations.

Data Analysis

The focus of our analysis within this study was to compare four validated and routinely used CVD risk equations. Within the analysis we chose to stratify the samples by age. Statistical analysis was performed using SPSS software (version 19, SPSS Inc, Chicago, USA) with significance set at $P<0.05$. Normality of data was assessed by one-sample Kolmogorov-Smirnov test. Homogeneity of variance was determined by Levene's statistic and one-way analysis of variance (ANOVA) with post-hoc Bonferroni or Tamhane's T2 correction factor used to locate any differences within groups. Chi-square analysis with alpha set at 0.05 was performed to analyse discrete data variables. Diastolic blood pressure data are represented as mean ± SD. BMI, systolic blood pressure, triglyceride concentrations, QRISK2, Framingham Lipids and Framingham BMI scores did not have a normal distribution. These datasets were consequently log transformed for analysis and represented as the geometric mean and approximate standard deviation. Age, TC:HDL Ratio and JBS2 scores did not have a normal distribution following log transformation and this data is represented as median and interquartile range. Kruskal-Wallis and Mann-Whitney tests were used to analyse JBS2 data.

Results

All age baseline analysis

Table 1 profiles the baseline risk characteristics and predicted all age 10-year CVD risk of the two gender cohorts. Although no statistical comparisons were made between the genders the table clearly illustrates a number of interesting observations. Despite the two cohorts being of similar age, BMI values, systolic and pressure blood pressure readings, lipid profiles (TC:HDL ratio), triglyceride concentrations and 10-year predicted CVD risk in each of the equations are all greater in the male cohort compared to the females. There were also a greater proportion of male individuals that reported to be current smokers and who were presently prescribed anti-hypertensive medication. Furthermore, in each of the gender cohorts the all age predicted CVD risk value was different dependent on which risk equation was adopted.

10-year CVD risk prediction following age stratification

Figure 1 and Table 2 illustrate the 10-year predicted CVD risk for QRISK2, Framingham Lipids, Framingham BMI (Figure 1) and JBS2 (Table 3) following age stratification of the data into five pre-determined age ranges (<45 years, 45-49 years, 50-54 years, 55-59 years and ≥60 years). Figure 1 demonstrates that predicted 10-year CVD risk increased concomitantly with age in each of the risk equations for both genders. Female predicted risk increased from [0.8±0.2% to 8.1±1.3% (QRISK2), 1.4±0.3% to 5.0±0.8% (Framingham Lipids), 2.6±0.4% to 9.6±1.2% (Framingham BMI)], respectively. In the male cohort, CVD risk estimation increased from 2.8±0.8% to 16.0±2.1% (QRISK2), increased from 5.3±1.2% to 16.4±2.5% (Framingham Lipids) and increased from 6.7±1.1% to 22.1±1.8%

(Framingham BMI). In addition, at each age range, the Framingham BMI risk equation predicted individuals to be at a higher risk than either the QRISK2 or Framingham Lipids algorithms. In the male cohort the Framingham Lipid equation also predicted individuals at a higher risk than QRISK2 up until 60 years old. Of interest, in the female cohort, in the two youngest age ranges (<45 years and 45-49 years) Framingham Lipids estimated risk to be higher than QRISK2, however, in the latter two age ranges (55-59 years and ≥60 years) this relationship was reversed. In Table 2, the JBS2 median and interquartile ranges are displayed. The female predicted risk again increased concomitantly with age from 2[1–3]% to 8.5[7–14]% and the male cohort predicted risk increased from 7[4–11]% to the peak value of 20[12–25]% in the 55–59 years age range.

Individuals predicted at different risk classifications

Table 3 illustrates individuals categorised by low, intermediate or high 10-year CVD risk following adoption of the four different equations. The number of women predicted at high risk was relatively low irrespective of which risk equation was adopted. The JBS2 equation predicted the greatest number of women at high risk (10 individuals) but this still only equated to 2.1% of the female cohort. Of note, no females were predicted to be at high risk when the Framingham Lipids risk score was used. However, both the Framingham BMI and JBS2 tools resulted in a greater number of females at intermediate risk and less at low risk than either QRISK2 or Framingham Lipids. The JBS2 equation also predicted more females at intermediate risk and less at low risk than the Framingham BMI. Within the male cohort, the same relationship was observed with the Framingham BMI and JBS2 equations predicted more males at intermediate and less at lower risk than the two other equations. The QRISK2 algorithm predicted the greatest number of males at low risk and this proportion was

significantly lower than all the three other algorithms. Unlike the female cohort, the differences in numbers of male individuals predicted at high risk are clearly apparent. The male JBS2 discrepancies in high risk prediction are most prominent with 1 in 5 males categorised at high risk compared to 1 in 20, 1 in 12 and 1 in 8 using QRISK2, Framingham Lipids and Framingham BMI, respectively.

Analysis of isolated risk factors and 'high risk' individuals following age stratification

Table 4 details the examination of isolated risk factors and amount of individuals predicted to be at 'high risk' of 10-year CVD following age stratification which further uncovered a number of interesting observations. In the female cohort, there was a greater prevalence of females with high concentrations of total cholesterol from 50 years onwards; however, this was not reflected in a larger proportion of females observed to have dyslipidaemia. In all groups beside the <45 years, over one in five females were found to have systolic hypertension, however only the JBS2 risk equation predicted any differences in 'high risk' females in the latter two age groups (55-59 years and ≥60 years). In the male cohort, the only differences in isolated risk factors were observed in a greater prevalence of systolic hypertension after 55 years and in high total cholesterol concentrations in the 55-59 years compared to the 50-54 years. Despite very few differences in isolated risk factors a higher proportion of males were predicted to be at 'high risk' of CVD in older age groups (50-54 years, 55-59 years, ≥60 years) in each of the four risk equations.

Discussion

Summary

This study compared CVD risk prediction when the same dataset was applied to four commonly used risk equations. The major finding from this investigation is that the adoption of the JBS2 or Framingham BMI equation predicts more individuals at both absolute risk and 'high risk' than either QRISK2 or Framingham Lipids. This observation was more evident in male prediction using either the Framingham BMI or JBS2 risk equations where 13.6% and 20.3% of males, respectively, were predicted to be at high risk of CVD compared to only 8.2% (Framingham BMI) or 5.4% (QRISK2). Therefore, up to a four-time greater costing related to statin prescription would be associated if the Framingham BMI or JBS2 risk equations were used instead of QRISK2. In addition, more males were predicted to be at 'high risk' of CVD in the older age groups despite very few differences in prevalence of isolated risk factors. Thus, it appears that age remains more important than isolated risk factors when determining those individuals at 'high risk' irrespective of which risk equation adopted.

Strengths and Limitations

One of the major strengths of this research is that the study population is based on an undiagnosed cohort, representative of the working demographic in Carmarthenshire, South Wales. If not for the Prosiect Sir Gâr initiative, this data would not be routinely available. All of the risk engines in this study accounted for gender, age, systolic blood pressure with all but the Framingham BMI equation incorporating TC:HDL ratio. Therefore, it was feasible to make comparisons between the four prediction tools. The Framingham BMI equation requires the least clinical measurements of the four equations compared with only systolic blood pressure incorporated in the prediction algorithm. Another merit to the Framingham

BMI is that a number of CVD risk factors such as elevated non-HDL cholesterol, reduced HDL cholesterol and hypertension are influenced by obesity [14] and furthermore, obesity is an independent risk factor for fatal coronary events [15]. We acknowledge that there are other risk equations available that may have been pertinent to our dataset. For example, the Scottish ASSIGN [16] prediction model or the SCORE [17] equation based on a European population could have been relevant to our population. One of the advantages of the ASSIGN model is the inclusion of social deprivation; however this deprivation is based on Scottish postcodes and would have not been applicable to our Welsh dataset which is why the QRISK2 model was chosen instead which also incorporates social deprivation. The risk equations that we chose to compare in this study also account for non-fatal CVD unlike the SCORE equation which is why we chose not to include this risk equation in our analysis. The only other limitation to this research could be that the cohort used may possibly be perceived as small, however even in our cohort we still uncovered differences when making comparisons between the CVD risk algorithms.

Comparisons with Existing Literature

In regards to predicting absolute risk, validation studies have reported that the Framingham equation can over-estimate risk by up to 5% in men and shows poor calibration with women in comparison to QRISK2 [18]. Therefore, it is unsurprising that we also observed differences in terms of numbers of individuals in different risk categories. However, in terms of absolute risk we observed only a 2.5% higher estimation when comparing Framingham Lipids and QRISK2 in male individuals. Comparisons between males using QRISK2 and Framingham BMI resulted in the 5% higher prediction in the latter risk equation which may suggest some reliance on lipid profiles in more accurate CVD risk estimation. Although, the average male JBS2 median value is also 5% greater than the QRISK2 score and both the

Framingham BMI and JBS2 female average risk estimates are double that of QRISK2. An interesting point to raise is that in relative terms, the older risk engines predicted risk to be higher than the more recent or updated equations. Healthcare professionals should account for this when determining which equation that they deem 'most appropriate'. However, despite these observations, research has reported that six cardiovascular risk algorithms performed equally well in terms of screening performance even when differences in false-positive rates between the equations were witnessed [6]. Of which, three of the risk equations (QRISK2, Framingham General Cardiovascular Risk Profile (Framingham Lipids, Framingham BMI)) analysed in that research were adopted in this study, further justifying their selection. It appears that all the risk equations adopted in our study have their own individual merits for selection, however the reported better accuracy in regard to absolute risk in the QRISK2 model following independent validation [18], may enhance this risk equation for prioritisation in our Welsh population.

Implications for Research and/or Practice

Therefore, from the observations in our study and the strong evidence in regards to better accuracy, the QRISK2 model should be recommended for use in primary care in the Welsh population in terms of primary prevention of CVD. The added benefit to the QRISK2 model is that it is updated annually with the latest available routinely collected data from England and Wales. The variations in estimation of absolute risk could lead to "over-treatment", where individuals are treated when their risk is substantially lower and vice-versa. In both these scenarios there is a financial implication, be it, by an increase in emergency admissions for individuals that believed they were at 'low' or 'intermediate' risk or through statin treatments that are not required. One of the major disadvantages of CVD risk prediction models is that the most heavily weighted variable in their algorithms is age [6, 19] which

explains how we observed an increase in predicted CVD risk concomitant with age with all the risk algorithms despite very little differences in the prevalence of isolated risk factors. The shortcoming to this approach is that younger individuals (males <50 years, females <65 years) with a number of risk factors for developing cardiovascular disease may not reach the thresholds required to be prescribed medication to reduce their risk [20]. An importance consideration in males as premature CHD is primarily caused by the combination of systolic hypertension, high concentrations of total cholesterol and smoking [7]. The other limitation to the heavy weighting for age is that older individuals with a single risk factor for CVD would score above the thresholds and be recommended for pharmacological intervention. It could be argued that management of isolated risk factors rather than treatment initiated at an absolute predicted risk value is more important. It will be interesting in time to observe whether the emergence of 'lifetime' risk models such as the QIntervention and the in development JBS3 risk equations will improve CVD prediction and primary treatment. Unlike some Type 2 diabetes prediction models which include other lifestyle factors such as physical activity [21, 22] and/or dietary habits [21], CVD equations only account for smoking. Such factors if included in CVD risk prediction would provide the opportunity for more relevant advice to be provided to individuals for lifestyle changes which could reduce CVD risk.

Funding

This work was part-funded by the European Social Fund (ESF) through the European Union's Convergence programme administered by the Welsh Government. Prosiect Sir Gâr received funding contributions from TATA, Hywel Dda Health Board (Diabetes Charitable Fund and Carmarthenshire Charitable Fund), Carmarthenshire County Council and the following pharmaceutical companies; Takada, Lilly, Sanofi-Aventus, Boehringer-Ingelheim, Pfizer and AstraZeneca.

Competing interests

All authors wish to declare no conflict of interest resulting from the findings of this study.

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Tables and Figures

Table 1. Baseline risk characteristics of female and male cohorts.

Risk Variable	Females (n=474)	Males (n=316)
Age (years)[†]	49 [44 – 54]	49 [44 – 53]
BMI (kg.m^{-2})[#]	26.6 ± 1.9	28.1 ± 1.7
Systolic Blood Pressure (mmHg)[#]	125 ± 6	128 ± 5
Diastolic Blood Pressure (mmHg)	82 ± 9	84 ± 9
TC: HDL Ratio[†]	3.2 [2.7 – 4.0]	4.4 [3.6 – 5.7]
Triglycerides (mmol.l^{-1})[#*]	1.24 ± 0.27	1.87 ± 0.47
Family History of CVD	98 (20.7)	66 (20.9)
Current Smoker	46 (9.7)	52 (16.5)
Prescribed Anti-hypertensive Medication	24 (5.1)	26 (8.2)
QRISK2 (%)[#]	2.3 ± 0.9	5.8 ± 1.9
Framingham Lipids (%)[#]	2.6 ± 0.7	8.2 ± 2.1
Framingham BMI (%)[#]	4.8 ± 1.2	10.7 ± 2.4
JBS2 (%)[†]	5 [2 – 8]	11 [7 – 17]

Data expressed as means ± SD with discrete data represented as numbers with percentage of gender in brackets [#] log transformed data, geometric mean and approximate standard deviation reported [†] data not normally distributed following log transformation, median and interquartile range reported. [*] Triglyceride data only available for some individuals, (Females n=437, Males n=251).

Table 2. Changes in risk score predicted by JBS2 equation following age stratification.

	Age Group				
	<45 years	**45 – 49 years**	**50 – 54 years**	**55 – 59 years**	**≥60 years**
Females (n = 474)	2 [1 – 3]%	4 [3 – 6]%[a]	7 [4 – 9]%[a,b]	8 [5 – 12]%[a,b,c]	8.5 [7 – 14]%[a,b,c]
Males (n = 316)	7 [4 – 11]%	10 [7 – 14]%[a]	14.5 [10 – 19]%[a,b]	20 [12 – 25]%[a,b,c]	19 [13.5 – 23.5]%[a,b,c]

Data represented as median and interquartile range. [a] denotes difference from <45 years ($P<0.05$), [b] denotes difference from 45 – 49 years ($P<0.05$), [c] denotes difference from 50 – 54 years ($P<0.05$).

Table 3. Proportion of individuals categorised by risk category (low (<10%), intermediate (10-19.9%) or high (≥20%)) following prediction by different CVD risk equations.

		QRISK2	Framingham Lipids	Framingham BMI	JBS2
Females (n = 474)	**Low Risk (n, %)**	455 (96.0)	463 (97.7)	423 (89.2)[a,b]	390 (82.3)[a,b,c]
	Intermediate Risk (n, %)	17 (3.6)	11 (2.3)	48 (10.2)[a,b]	74 (15.6)[a,b,c]
	High Risk (n, %)	2 (0.4)	0 (0.0)	3 (0.6)	10 (2.1)[a,b]
Males (n = 316)	**Low Risk (n, %)**	226 (71.5)	201 (63.6)[a]	147 (46.5)[a,b]	23 (38.9)[a,b]
	Intermediate Risk (n, %)	73 (23.1)	89 (28.2)	126 (39.9)[a,b]	129 (40.8)[a,b]
	High Risk (n, %)	17 (5.4)	26 (8.2)	43 (13.6)[a,b]	64 (20.3)[a,b,c]

Data represented as numbers with percentage of gender in brackets. [a] denotes difference from QRISK2 (P<0.05), [b] denotes difference from Framingham Lipids (P<0.05), [c] denotes difference from Framingham BMI (P<0.05).

Table 4. The prevalence of isolated risk factors and proportion of individuals categorised as 'high risk' following age stratification.

FEMALES (n=474)	**<45 years**	**45 – 49 years**	**50 – 54 years**	**55 – 59 years**	**≥ 60 years**
	n = 126	**n = 132**	**n = 110**	**n = 72**	**n = 34**
Body Mass Index ≥30 $kg.m^{-2}$	27 (21.4)	38 (28.8)	33 (30.0)	11 (15.3)[b,c]	7 (20.6)
Body Mass Index 25 – 29.9 $kg.m^{-2}$	44 (34.9)	45 (34.1)	43 (39.1)	29 (40.3)	14 (41.2)
Total Cholesterol ≥5.20 $mmol.l^{-1}$	22 (17.5)	35 (26.5)	44 (40.0)[a,b]	33 (45.8)[a,b]	16 (47.1)[a,b]
TC:HDL Ratio ≥6	0 (0.0)	4 (3.0)[a]	4 (3.6)[a]	3 (4.2)[a]	1 (2.9)
Systolic Blood Pressure ≥140 mmHg	7 (5.6)	29 (22.0)[a]	29 (26.4)[a]	18 (25.0)[a]	8 (23.5)[a]
Diastolic Blood Pressure ≥90 mmHg	18 (14.3)	28 (21.2)	23 (20.9)	10 (13.9)	6 (17.6)
Current Smoker	12 (9.5)	14 (10.6)	12 (10.9)	5 (6.9)	3 (8.8)
QRISK2 ≥20%	0 (0.0)	0 (0.0)	0 (0.0)	2 (2.8)	0 (0.0)
Framingham Lipids ≥20%	0 (0.0)	0 (0.0)	0 (0.0)	0 (0.0)	0 (0.0)
Framingham BMI ≥20%	0 (0.0)	1 (0.8)	0 (0.0)	2 (2.8)	0 (0.0)
JBS2 ≥20%	0 (0.0)	1 (0.8)	2 (1.8)	4 (5.6)[a,b]	3 (8.8)[a,b]
MALES (n=316)	**<45 years**	**45 – 49 years**	**50 – 54 years**	**55 – 59 years**	**≥ 60 years**

	n = 89	**n = 98**	**n = 68**	**n = 42**	**n = 19**
Body Mass Index ≥30 $kg.m^{-2}$	27 (30.3)	32 (32.7)	21 (30.9)	15 (35.7)	8 (42.1)
Body Mass Index 25 – 29.9 $kg.m^{-2}$	41 (46.1)	50 (51.0)	36 (52.9)	19 (45.2)	8 (42.1)
Total Cholesterol ≥5.20 $mmol.l^{-1}$	33 (37.1)	40 (40.8)	21 (30.9)	23 (54.8)[c]	7 (36.8)
TC:HDL Ratio ≥6	22 (24.7)	17 (17.3)	14 (20.6)	13 (31.0)	3 (15.8)
Systolic Blood Pressure ≥140 mmHg	11 (12.4)	20 (20.4)	11 (16.2)	16 (38.1)[a,b,c]	9 (47.4)[a,b,c]
Diastolic Blood Pressure ≥90 mmHg	25 (28.1)	33 (33.7)	22 (32.4)	13 (31.0)	5 (26.3)
Current Smoker	20 (22.5)	15 (15.3)	8 (11.8)	7 (16.7)	2 (10.5)
QRISK2 ≥20%	0 (0.0)	2 (2.0)	6 (8.8)[a,b]	5 (11.9)[a,b]	4 (21.1)[a,b]
Framingham Lipids ≥20%	1 (1.1)	4 (4.1)	4 (5.9)	12 (28.6)[a,b,c]	5 (26.3)[a,b,c]
Framingham BMI ≥20%	0 (0.0)	6 (6.1)[a]	10 (14.7)[a]	14 (33.3)[a,b,c]	13 (68.4)[a,b,c,d]
JBS2 ≥20%	8 (9.0)	10 (10.2)	16 (23.5)[a,b]	21 (50.0)[a,b,c]	9 (47.4)[a,b,c]

Data is represented as numbers and proportion of age group in brackets. [a] denotes difference from <45 years age group (P<0.05), [b] denotes difference from 45-49 years age group (P<0.05), [c] denotes difference from 50-54 years age group (P<0.05), [d] denotes difference from 55-59 years age group (P<0.05).

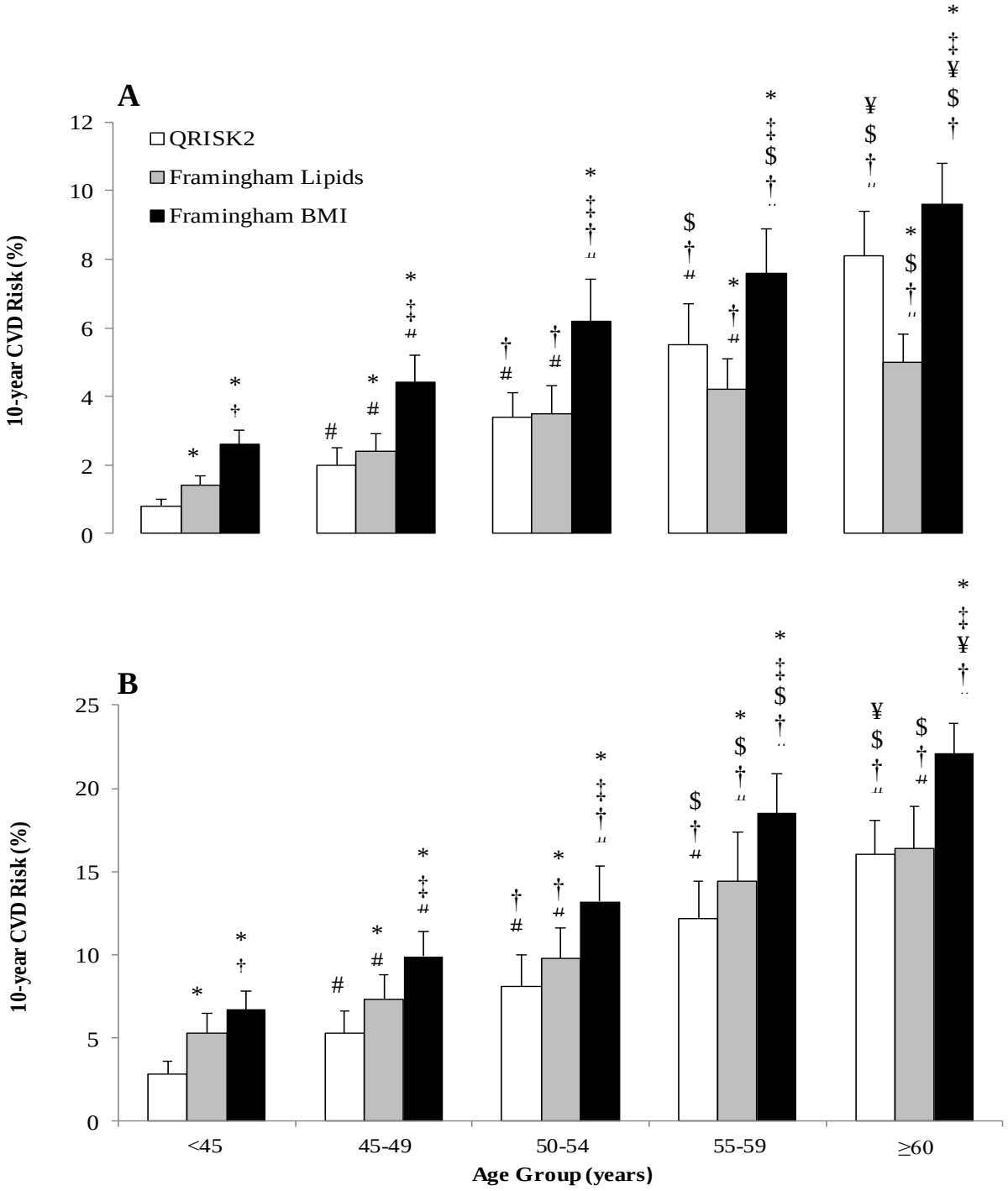

Figure 1. Changes in predicted 10-year CVD risk following age stratification after adoption of QRISK2, Framingham Lipids and Framingham BMI risk equations. (A) illustrates female cohort and (B) illustrates male cohort. * denotes difference from QRISK2 (P<0.05), ‡ denotes difference from Framingham Lipids (P<0.05). # denotes difference from <45 years age group (P<0.05), † denotes difference from 45-49 years age group (P<0.05), $ denotes difference from 50-54 years age group (P<0.05), ¥ denotes difference from 55-59 years age group (P<0.05).