**Supplementary Material**

**A Hierarchical Meta-Analytical Approach to Western European Dietary Transitions in the First Millennium AD**

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**Further Statistical Information**

A combination of base R functions, the A2R function, and packages ‘ggdendro’, ‘ape’, ‘factoextra’, ‘cluster’, ‘NbClust’ and ‘ggplot2’ (see code for details) were used to run the hierarchical clustering and visualize the outputs (Lamarange, 2006; Kaufman & Rousseeuw, 2009; Charrad et al., 2014; de Vries & Ripley, 2016; Kassambara & Mundt, 2017; R Development Core Team, 2017; Maechler et al., 2019; RStudio Team, 2019; Wickham, 2019; Grolemund & Wickham, 2020).

A mixture of various statistical and graphical methods for determining the optimal number of clusters was employed, thirty of which are automatically computed as part of the “NbClust” package, and the other graphical indices were generated using a combination of “NbClust” and “factoextra” packages in R (Charrad et al., 2014; Kassambara, 2017; Kassambara & Mundt, 2017). All indices were used for every UML iteration, and the majority rule adhered to (optimal number of clusters determined by agreement of the highest number of indices) to avoid user determination. The pre-sets for all indices were kept (generally this also means a 95% confidence interval if they were used by the index, see code and “NbClust” documentation for mathematical details), and the algorithm run for the clustering method used (Ward2 hierarchical).

**Hierarchical Clustering “NbClust” outputs**

**Bone**

NbClust(data = EMEUboneclean, diss = NULL, distance = "euclidean", min.nc = 2, max.nc = 15, method = "ward.D2")

\*\*\* : The Hubert index is a graphical method of determining the number of clusters.

 In the plot of Hubert index, we seek a significant knee that corresponds to a

 significant increase of the value of the measure i.e the significant peak in Hubert

 index second differences plot.

\*\*\* : The D index is a graphical method of determining the number of clusters.

 In the plot of D index, we seek a significant knee (the significant peak in Dindex

 second differences plot) that corresponds to a significant increase of the value of

 the measure.

\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*

\* Among all indices:

\* 3 proposed 2 as the best number of clusters

\* 8 proposed 3 as the best number of clusters

\* 2 proposed 4 as the best number of clusters

\* 1 proposed 5 as the best number of clusters

\* 6 proposed 6 as the best number of clusters

\* 1 proposed 7 as the best number of clusters

\* 1 proposed 12 as the best number of clusters

\* 1 proposed 15 as the best number of clusters

 \*\*\*\*\* Conclusion \*\*\*\*\*

\* According to the majority rule, the best number of clusters is 3

\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*

$All.index

 KL CH Hartigan CCC Scott Marriot TrCovW TraceW Friedman Rubin Cindex DB Silhouette Duda

2 2.9470 1923.879 1552.1379 -22.9149 3595.199 28062699 10559187.3 5648.984 1.3085 1.4650 0.1413 1.4502 0.3921 0.5151

3 5.2031 2098.406 1291.8626 -42.5995 5804.395 37025991 3765891.2 4107.801 2.1228 2.0147 0.1388 1.0617 0.4075 0.6043

4 1.1856 2265.962 966.0241 -38.5583 8121.882 37602469 1738443.2 3130.121 3.4543 2.6440 0.1565 1.0465 0.3121 0.5344

5 1.5564 2337.445 868.9175 -36.8777 9827.143 38914172 1151233.5 2537.343 4.6931 3.2617 0.1441 1.0428 0.3162 0.5629

6 0.1082 2436.193 337.8742 -34.5102 11286.202 39389006 999386.8 2096.652 5.9249 3.9472 0.1183 1.1218 0.3068 0.6733

7 1.4673 2251.894 367.1101 -39.2452 12000.497 45114845 707889.5 1938.203 6.6749 4.2699 0.1106 1.1897 0.2896 0.5654

8 1.3385 2153.608 357.8757 -41.9811 12646.659 50408444 677554.7 1780.053 7.3405 4.6493 0.1221 1.1786 0.2866 0.6735

9 1.1280 2091.884 324.2138 -43.8069 13311.730 54328058 677271.5 1638.139 8.1065 5.0521 0.1205 1.1299 0.2902 0.5711

10 2.0277 2040.953 348.1011 -45.3730 13966.314 57260534 512580.7 1518.902 8.9695 5.4487 0.1156 1.1308 0.2811 0.5685

11 2.1568 2026.036 345.6806 -45.9072 14668.331 58476296 378339.8 1400.805 9.9641 5.9080 0.1138 1.0910 0.2821 0.4325

12 2.0891 2027.022 329.8978 -45.9650 15291.359 59866562 370837.8 1292.565 10.8585 6.4028 0.1462 1.0017 0.2826 0.6694

13 1.2932 2033.633 328.1841 -45.8458 15957.638 59813276 287846.6 1196.890 11.9718 6.9146 0.1411 1.0205 0.2557 0.6409

14 0.2107 2051.260 244.2454 -45.3911 16548.071 60147063 285571.4 1108.703 12.9476 7.4646 0.1323 1.0586 0.2523 0.5438

15 1.7699 2034.476 246.7738 -45.9523 17020.621 61596685 281030.2 1046.725 13.8212 7.9066 0.1260 1.0494 0.2570 0.5299

 Pseudot2 Beale Ratkowsky Ball Ptbiserial Frey McClain Dunn Hubert SDindex Dindex SDbw

2 1146.7191 0.9407 0.3673 2824.4922 0.4729 -0.4888 0.3803 0.0067 2e-04 6.3540 0.9403 1.4088

3 1910.0016 0.6546 0.4087 1369.2671 0.5423 1.7266 0.3885 0.0072 2e-04 4.5541 0.8232 0.8481

4 816.4711 0.8704 0.3940 782.5302 0.4589 0.0132 0.9319 0.0040 2e-04 4.4837 0.7153 0.9543

5 1518.3939 0.7763 0.3723 507.4687 0.4816 0.6693 0.9502 0.0040 3e-04 4.0522 0.6508 0.7618

6 465.7589 0.4847 0.3528 349.4420 0.4437 0.4731 1.3848 0.0040 3e-04 4.2693 0.5742 0.6447

7 214.4304 0.7658 0.3308 276.8862 0.4345 0.0040 1.5027 0.0040 3e-04 4.9696 0.5426 0.5867

8 142.5110 0.4831 0.3132 222.5067 0.4371 -0.0846 1.4936 0.0044 3e-04 4.8725 0.5256 0.5206

9 491.1249 0.7498 0.2985 182.0154 0.4397 0.4829 1.4809 0.0044 3e-04 4.6677 0.5135 0.4678

10 202.6979 0.7563 0.2857 151.8902 0.4331 0.0175 1.5512 0.0044 3e-04 4.6145 0.4920 0.4626

11 356.9464 1.3075 0.2748 127.3459 0.4349 -0.1083 1.5427 0.0044 3e-04 4.3367 0.4798 0.4260

12 641.5641 0.4935 0.2652 107.7137 0.4367 2.3670 1.5319 0.0058 3e-04 5.5693 0.4732 0.4464

13 359.1052 0.5594 0.2565 92.0684 0.3687 0.2772 2.2394 0.0058 4e-04 7.0510 0.4486 0.4399

14 575.4163 0.8376 0.2487 79.1931 0.3624 0.3663 2.3322 0.0058 4e-04 7.1806 0.4299 0.4010

15 187.1673 0.8829 0.2413 69.7817 0.3544 0.0838 2.4430 0.0058 4e-04 7.1968 0.4162 0.3780

$All.CriticalValues

 CritValue\_Duda CritValue\_PseudoT2 Fvalue\_Beale

2 0.6110 775.3291 0.3905

3 0.6360 1669.3758 0.5197

4 0.6012 621.6597 0.4189

5 0.6259 1168.4713 0.4602

6 0.6021 634.3506 0.6160

7 0.5345 243.0072 0.4654

8 0.5383 252.2106 0.6171

9 0.5853 463.2995 0.4727

10 0.5312 235.6094 0.4699

11 0.5326 238.6958 0.2713

12 0.6133 819.1438 0.6105

13 0.5844 455.9063 0.5717

14 0.5876 481.4464 0.4330

15 0.5126 200.6259 0.4144

$Best.nc

 KL CH Hartigan CCC Scott Marriot TrCovW TraceW Friedman Rubin Cindex DB Silhouette

Number\_clusters 3.0000 6.000 6.0000 2.0000 4.000 6 3 3.0000 4.0000 6.0000 7.0000 12.0000 3.0000

Value\_Index 5.2031 2436.193 531.0433 -22.9149 2317.486 5251004 6793296 563.5026 1.3315 -0.3629 0.1106 1.0017 0.4075

 Duda PseudoT2 Beale Ratkowsky Ball PtBiserial Frey McClain Dunn Hubert SDindex Dindex SDbw

Number\_clusters 6.0000 6.0000 2.0000 3.0000 3.000 3.0000 1 2.0000 3.0000 0 5.0000 0 15.000

Value\_Index 0.6733 465.7589 0.9407 0.4087 1455.225 0.5423 NA 0.3803 0.0072 0 4.0522 0 0.378

$Best.partition TOO MANY TO PRINT

**Dentine**

NbClust(data = EMEUdentineclean, diss = NULL, distance = "euclidean", min.nc = 2, max.nc = 15, method = "ward.D2")

\*\*\* : The Hubert index is a graphical method of determining the number of clusters.

 In the plot of Hubert index, we seek a significant knee that corresponds to a

 significant increase of the value of the measure i.e the significant peak in Hubert

 index second differences plot.

\*\*\* : The D index is a graphical method of determining the number of clusters.

 In the plot of D index, we seek a significant knee (the significant peak in Dindex

 second differences plot) that corresponds to a significant increase of the value of

 the measure.

\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*

\* Among all indices:

\* 1 proposed 2 as the best number of clusters

\* 11 proposed 3 as the best number of clusters

\* 2 proposed 4 as the best number of clusters

\* 5 proposed 5 as the best number of clusters

\* 2 proposed 11 as the best number of clusters

\* 1 proposed 13 as the best number of clusters

\* 1 proposed 15 as the best number of clusters

 \*\*\*\*\* Conclusion \*\*\*\*\*

\* According to the majority rule, the best number of clusters is 3

\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*

$All.index

 KL CH Hartigan CCC Scott Marriot TrCovW TraceW Friedman Rubin Cindex DB Silhouette Duda

2 1.1605 689.8837 638.3127 -3.0678 1164.951 943438.6 512552.084 1067.3651 1.9708 1.7426 0.1490 1.1517 0.4481 0.4261

3 2.6473 900.1366 253.6577 -2.3540 1970.244 893803.0 92376.167 632.6639 3.9210 2.9399 0.1860 0.7636 0.4883 0.5277

4 0.7343 847.7568 307.3965 -4.1147 2462.697 936265.0 91811.213 496.8547 5.7963 3.7435 0.2032 0.8730 0.4005 0.6008

5 1.0312 922.5099 119.0435 -1.4182 3000.736 820792.8 36394.359 373.1251 8.5692 4.9849 0.1680 0.9714 0.3386 0.6702

6 1.0541 855.7673 96.4745 -3.7506 3272.885 882355.4 22899.105 330.6215 10.5059 5.6258 0.1540 1.1333 0.2984 0.6277

7 1.3558 802.7278 91.9402 -5.7153 3483.187 958153.5 14718.625 299.3955 12.1124 6.2125 0.1442 1.1617 0.2933 0.4261

8 1.9342 768.8166 95.4013 -7.0374 3623.368 1076532.1 14011.121 272.3009 12.9927 6.8307 0.1390 1.0359 0.2830 0.6240

9 0.8749 753.3544 80.4051 -7.6688 3840.429 1079138.0 8810.811 246.7924 15.0569 7.5367 0.1321 1.1063 0.2787 0.4945

10 2.5513 736.1811 83.6286 -8.3866 3959.482 1172345.9 7775.685 226.9967 15.8773 8.1940 0.1264 1.0674 0.2896 0.6703

11 6.6935 730.2941 82.3841 -8.6536 4093.848 1227897.2 7708.636 208.1007 17.0057 8.9380 0.1171 1.0821 0.2998 0.5143

12 0.1012 730.0500 89.0134 -8.6907 4231.375 1260623.2 6410.307 190.9973 18.2310 9.7384 0.1633 1.0967 0.2933 0.4115

13 0.5441 740.6428 93.8351 -8.2839 4379.846 1261393.5 6026.755 174.1311 19.6721 10.6816 0.2065 1.0337 0.2956 0.5413

14 1.2512 759.9423 84.2959 -7.5343 4561.080 1204142.0 5887.249 157.9826 21.9124 11.7734 0.1913 1.0063 0.2988 0.5232

15 1.6569 775.7033 72.4795 -6.9416 4712.309 1175055.7 5004.047 144.6826 23.7635 12.8557 0.1802 0.9768 0.3089 0.3920

 Pseudot2 Beale Ratkowsky Ball Ptbiserial Frey McClain Dunn Hubert SDindex Dindex SDbw

2 507.7796 1.3433 0.4536 533.6826 0.4960 -0.5753 0.4751 0.0062 0.0007 3.9937 0.8394 1.2743

3 307.0376 0.8926 0.4689 210.8880 0.6042 1.1814 0.4414 0.0090 0.0011 2.9269 0.7184 0.6612

4 365.4913 0.6633 0.4280 124.2137 0.5918 1.4329 0.5445 0.0106 0.0012 2.9958 0.6352 0.5551

5 180.1015 0.4907 0.3997 74.6250 0.5044 1.6433 1.0051 0.0105 0.0013 3.3165 0.5475 0.5778

6 132.8464 0.5904 0.3700 55.1036 0.4357 0.6402 1.4856 0.0105 0.0014 4.5300 0.5036 0.4619

7 290.8936 1.3405 0.3461 42.7708 0.4183 1.5417 1.6717 0.0105 0.0014 4.5532 0.4793 0.5807

8 70.5056 0.5975 0.3266 34.0376 0.3855 0.2080 2.0231 0.0105 0.0014 4.5331 0.4476 0.6078

9 151.2832 1.0153 0.3104 27.4214 0.3838 0.4343 2.0624 0.0105 0.0014 4.3006 0.4303 0.4894

10 89.5206 0.4892 0.2963 22.6997 0.3753 0.3896 2.1756 0.0105 0.0014 4.8752 0.4102 0.4409

11 30.2145 0.9156 0.2841 18.9182 0.3621 0.0127 2.3532 0.0105 0.0015 4.7917 0.3952 0.4127

12 70.0885 1.4018 0.2734 15.9164 0.3629 0.0078 2.3400 0.0148 0.0015 4.8309 0.3876 0.3185

13 130.5143 0.8420 0.2640 13.3947 0.3641 0.3873 2.3210 0.0190 0.0015 4.5056 0.3772 0.2832

14 122.1056 0.9045 0.2557 11.2845 0.3503 0.1081 2.4950 0.0190 0.0015 4.6258 0.3560 0.2872

15 105.4624 1.5284 0.2480 9.6455 0.3501 0.2101 2.4658 0.0190 0.0015 4.7841 0.3452 0.2635

$All.CriticalValues

 CritValue\_Duda CritValue\_PseudoT2 Fvalue\_Beale

2 0.5549 302.3658 0.2616

3 0.5488 281.9660 0.4101

4 0.5767 403.7767 0.5153

5 0.5530 295.7861 0.6124

6 0.5175 208.8197 0.5545

7 0.5146 203.7829 0.2628

8 0.4555 139.8775 0.5510

9 0.4802 160.2064 0.3635

10 0.4998 182.1721 0.6135

11 0.2585 91.8049 0.4055

12 0.3361 96.7755 0.2511

13 0.4841 164.1092 0.4318

14 0.4701 151.0575 0.4060

15 0.3867 107.8309 0.2206

$Best.nc

 KL CH Hartigan CCC Scott Marriot TrCovW TraceW Friedman Rubin Cindex DB

Number\_clusters 11.0000 5.0000 3.000 5.0000 3.0000 5.0 3.0 3.0000 5.0000 5.0000 11.0000 3.0000

Value\_Index 6.6935 922.5099 384.655 -1.4182 805.2928 177034.9 420175.9 298.8919 2.7728 -0.6005 0.1171 0.7636

 Silhouette Duda PseudoT2 Beale Ratkowsky Ball PtBiserial Frey McClain Dunn Hubert SDindex Dindex

Number\_clusters 3.0000 4.0000 4.0000 2.0000 3.0000 3.0000 3.0000 1 3.0000 13.000 0 3.0000 0

Value\_Index 0.4883 0.6008 365.4913 1.3433 0.4689 322.7946 0.6042 NA 0.4414 0.019 0 2.9269 0

 SDbw

Number\_clusters 15.0000

Value\_Index 0.2635

$Best.partition

 CND\_01 CND\_02 CND\_03 CND\_04 CND\_05 CND\_06 CND\_07 CND\_08 CND\_09 CND\_10 CND\_11 CND\_12 CND\_13 CND\_14 CND\_15 CND\_16

 1 1 1 1 1 1 1 2 1 1 2 2 2 2 2 2

 CND\_17 CND\_18 CND\_19 CND\_20 CND\_21 CND\_22 CND\_23 CND\_24 CND\_25 CND\_26 CND\_27 CND\_28 CND\_29 CND\_30 CND\_31 CND\_32

 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2

 CND\_33 CND\_34 CND\_35 CND\_36 CND\_37 CND\_38 CND\_39 CND\_40 CND\_41 CND\_42 CND\_43 CND\_44 CND\_45 CND\_46 CND\_47 CND\_48

 2 2 2 2 2 2 2 2 1 2 2 2 2 2 1 1

 CND\_49 CND\_50 CND\_51 CND\_52 CND\_53 CND\_54 CND\_55 CND\_56 CND\_57 CND\_58 CND\_59 CND\_60 CND\_61 CND\_62 CND\_63 CND\_64

 1 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2

 CND\_65 CND\_66 CND\_67 CND\_68 CND\_69 CND\_70 CND\_71 CND\_72 CND\_73 CND\_74 CND\_75 CND\_76 CND\_77 CND\_78 CND\_79 CND\_80

 2 2 2 1 1 1 2 2 2 1 2 2 1 2 1 1

 CND\_81 CND\_82 CND\_83 CND\_84 CND\_85 CND\_86 CND\_87 CND\_88 CND\_89 CND\_90 CND\_91 CND\_92 CND\_93 CND\_94 CND\_95 CND\_96

 1 2 2 1 1 1 1 1 1 1 1 1 1 2 2 2

 CND\_97 CND\_98 CND\_99 CND\_100 CND\_101 CND\_102 CND\_103 CND\_104 CND\_105 CND\_106 CND\_107 CND\_108 CND\_109 CND\_110 CND\_111 CND\_112

 2 2 2 1 2 2 1 1 1 2 1 1 1 1 1 1

CND\_113 CND\_114 CND\_115 CND\_116 CND\_117 CND\_118 CND\_119 CND\_120 CND\_121 CND\_122 CND\_123 CND\_124 CND\_125 CND\_126 CND\_127 CND\_128

 1 1 1 1 1 1 1 1 1 2 2 2 2 1 1 2

CND\_129 CND\_130 CND\_131 CND\_132 CND\_133 CND\_134 CND\_135 CND\_136 CND\_137 CND\_138 CND\_139 CND\_140 CND\_141 CND\_142 CND\_143 CND\_144

 2 1 1 1 2 2 2 1 1 1 2 2 2 1 2 1

CND\_145 CND\_146 CND\_147 CND\_148 CND\_149 CND\_150 CND\_151 CND\_152 CND\_153 CND\_154 CND\_155 CND\_156 CND\_157 CND\_158 CND\_159 CND\_160

 1 1 1 1 2 2 2 1 1 1 2 2 2 1 1 1

CND\_161 CND\_162 CND\_163 CND\_164 CND\_165 CND\_166 CND\_167 CND\_168 CND\_169 CND\_170 CND\_171 CND\_172 CND\_173 CND\_174 CND\_175 CND\_176

 1 1 1 2 1 1 1 1 1 1 1 1 1 1 1 2

CND\_177 CND\_178 CND\_179 CND\_180 CND\_181 CND\_182 CND\_183 CND\_184 CND\_185 CND\_186 CND\_187 CND\_188 CND\_189 CND\_190 CND\_191 CND\_192

 2 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1

CND\_193 CND\_194 CND\_195 CND\_196 CND\_197 CND\_198 CND\_199 CND\_200 CND\_201 CND\_202 CND\_203 CND\_204 CND\_205 CND\_206 CND\_207 CND\_208

 1 1 1 1 1 1 1 1 1 1 1 1 1 1 2 1

CND\_209 CND\_210 CND\_211 CND\_212 CND\_213 CND\_214 CND\_215 CND\_216 CND\_217 CND\_218 CND\_219 CND\_220 CND\_221 CND\_222 CND\_223 CND\_224

 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1

CND\_225 CND\_226 CND\_227 CND\_228 CND\_229 CND\_230 CND\_231 CND\_232 CND\_233 CND\_234 CND\_235 CND\_236 CND\_237 CND\_238 CND\_239 CND\_240

 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1

CND\_241 CND\_242 CND\_243 CND\_244 CND\_245 CND\_246 CND\_247 CND\_248 CND\_249 CND\_250 CND\_251 CND\_252 CND\_253 CND\_254 CND\_255 CND\_256

 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1

CND\_257 CND\_258 CND\_259 CND\_260 CND\_261 CND\_262 CND\_263 CND\_264 CND\_265 CND\_266 CND\_267 CND\_268 CND\_269 CND\_270 CND\_271 CND\_272

 1 1 1 1 1 1 1 1 1 1 1 1 1 2 1 1

CND\_273 CND\_274 CND\_275 CND\_276 CND\_277 CND\_278 CND\_279 CND\_280 CND\_281 CND\_282 CND\_283 CND\_284 CND\_285 CND\_286 CND\_287 CND\_288

 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1

CND\_289 CND\_290 CND\_291 CND\_292 CND\_293 CND\_294 CND\_295 CND\_296 CND\_297 CND\_298 CND\_299 CND\_300 CND\_301 CND\_302 CND\_303 CND\_304

 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1

CND\_305 CND\_306 CND\_307 CND\_308 CND\_309 CND\_310 CND\_311 CND\_312 CND\_313 CND\_314 CND\_315 CND\_316 CND\_317 CND\_318 CND\_319 CND\_320

 1 1 1 1 1 1 1 1 1 1 1 1 1 1 2 1

CND\_321 CND\_322 CND\_323 CND\_324 CND\_325 CND\_326 CND\_327 CND\_328 CND\_329 CND\_330 CND\_331 CND\_332 CND\_333 CND\_334 CND\_335 CND\_336

 1 1 2 1 1 2 1 2 1 1 2 1 1 1 2 2

CND\_337 CND\_338 CND\_339 CND\_340 CND\_341 CND\_342 CND\_343 CND\_344 CND\_345 CND\_346 CND\_347 CND\_348 CND\_349 CND\_350 CND\_351 CND\_352

 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1

CND\_353 CND\_354 CND\_355 CND\_356 CND\_357 CND\_358 CND\_359 CND\_360 CND\_361 CND\_362 CND\_363 CND\_364 CND\_365 CND\_366 CND\_367 CND\_368

 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1

CND\_369 CND\_370 CND\_371 CND\_372 CND\_373 CND\_374 CND\_375 CND\_376 CND\_377 CND\_378 CND\_379 CND\_380 CND\_381 CND\_382 CND\_383 CND\_384

 1 1 2 1 1 1 1 1 1 1 1 1 1 1 1 1

CND\_385 CND\_386 CND\_387 CND\_388 CND\_389 CND\_390 CND\_391 CND\_392 CND\_393 CND\_394 CND\_395 CND\_396 CND\_397 CND\_398 CND\_399 CND\_400

 2 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1

CND\_401 CND\_402 CND\_403 CND\_404 CND\_405 CND\_406 CND\_407 CND\_408 CND\_409 CND\_410 CND\_411 CND\_412 CND\_413 CND\_414 CND\_415 CND\_416

 1 1 1 1 1 1 1 1 1 1 1 2 1 1 1 1

CND\_417 CND\_418 CND\_419 CND\_420 CND\_421 CND\_422 CND\_423 CND\_424 CND\_425 CND\_426 CND\_427 CND\_428 CND\_429 CND\_430 CND\_431 CND\_432

 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1

CND\_433 CND\_434 CND\_435 CND\_436 CND\_437 CND\_438 CND\_439 CND\_440 CND\_441 CND\_442 CND\_443 CND\_444 CND\_445 CND\_446 CND\_447 CND\_448

 1 2 1 1 1 1 1 1 1 1 1 1 1 1 1 1

CND\_449 CND\_450 CND\_451 CND\_452 CND\_453 CND\_454 CND\_455 CND\_456 CND\_457 CND\_458 CND\_459 CND\_460 CND\_461 CND\_462 CND\_463 CND\_464

 1 1 1 1 1 1 1 1 1 2 1 1 1 1 3 1

CND\_465 CND\_466 CND\_467 CND\_468 CND\_469 CND\_470 CND\_471 CND\_472 CND\_473 CND\_474 CND\_475 CND\_476 CND\_477 CND\_478 CND\_479 CND\_480

 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3

CND\_481 CND\_482 CND\_483 CND\_484 CND\_485 CND\_486 CND\_487 CND\_488 CND\_489 CND\_490 CND\_491 CND\_492 CND\_493 CND\_494 CND\_495 CND\_496

 3 3 3 3 3 3 3 3 3 3 3 3 3 2 2 2

CND\_497 CND\_498 CND\_499 CND\_500 CND\_501 CND\_502 CND\_503 CND\_504 CND\_505 CND\_506 CND\_507 CND\_508 CND\_509 CND\_510 CND\_511 CND\_512

 2 1 2 1 1 1 2 2 2 2 2 2 2 2 2 2

CND\_513 CND\_514 CND\_515 CND\_516 CND\_517 CND\_518 CND\_519 CND\_520 CND\_521 CND\_522 CND\_523 CND\_524 CND\_525 CND\_526 CND\_527 CND\_528

 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2

CND\_529 CND\_530 CND\_531 CND\_532 CND\_533 CND\_534 CND\_535 CND\_536 CND\_537 CND\_538 CND\_539 CND\_540 CND\_541 CND\_542 CND\_543 CND\_544

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CND\_545 CND\_546 CND\_547 CND\_548 CND\_549 CND\_550 CND\_551 CND\_552 CND\_553 CND\_554 CND\_555 CND\_556 CND\_557 CND\_558 CND\_559 CND\_560

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CND\_561 CND\_562 CND\_563 CND\_564 CND\_565 CND\_566 CND\_567 CND\_568 CND\_569 CND\_570 CND\_571 CND\_572 CND\_573 CND\_574 CND\_575 CND\_576

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CND\_577 CND\_578 CND\_579 CND\_580 CND\_581 CND\_582 CND\_583 CND\_584 CND\_585 CND\_586 CND\_587 CND\_588 CND\_589 CND\_590 CND\_591 CND\_592

 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2

CND\_593 CND\_594 CND\_595 CND\_596 CND\_597 CND\_598 CND\_599 CND\_600 CND\_601 CND\_602 CND\_603 CND\_604 CND\_605 CND\_606 CND\_607 CND\_608

 2 2 2 2 2 2 2 1 1 1 1 1 1 1 1 1

CND\_609 CND\_610 CND\_611 CND\_612 CND\_613 CND\_614 CND\_615 CND\_616 CND\_617 CND\_618 CND\_619 CND\_620 CND\_621 CND\_622 CND\_623 CND\_624

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CND\_625 CND\_626 CND\_627 CND\_628 CND\_629 CND\_630 CND\_631 CND\_632 CND\_633 CND\_634 CND\_635 CND\_636 CND\_637 CND\_638 CND\_639 CND\_640

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CND\_641 CND\_642 CND\_643 CND\_644 CND\_645 CND\_646 CND\_647 CND\_648 CND\_649 CND\_650 CND\_651 CND\_652 CND\_653 CND\_654 CND\_655 CND\_656

 2 2 2 2 2 2 2 1 1 1 2 2 2 2 2 2

CND\_657 CND\_658 CND\_659 CND\_660 CND\_661 CND\_662 CND\_663 CND\_664 CND\_665 CND\_666 CND\_667 CND\_668 CND\_669 CND\_670 CND\_671 CND\_672

 2 1 2 2 2 2 2 2 2 2 2 1 1 1 1 1

CND\_673 CND\_674 CND\_675 CND\_676 CND\_677 CND\_678 CND\_679 CND\_680 CND\_681 CND\_682 CND\_683 CND\_684 CND\_685 CND\_686 CND\_687 CND\_688

 1 2 2 1 1 1 1 1 1 2 2 2 2 2 2 2

CND\_689 CND\_690 CND\_691 CND\_692 CND\_693 CND\_694 CND\_695 CND\_696 CND\_697 CND\_698 CND\_699 CND\_700 CND\_701 CND\_702 CND\_703 CND\_704

 2 2 2 2 2 2 1 1 1 1 1 1 1 1 2 1

CND\_705 CND\_706 CND\_707 CND\_708 CND\_709 CND\_710 CND\_711 CND\_712 CND\_713 CND\_714 CND\_715 CND\_716 CND\_717 CND\_718 CND\_719 CND\_720

 2 1 2 2 1 1 1 1 1 2 1 1 1 1 2 2

CND\_721 CND\_722 CND\_723 CND\_724 CND\_725 CND\_726 CND\_727 CND\_728 CND\_729 CND\_730 CND\_731 CND\_732 CND\_733 CND\_734 CND\_735 CND\_736

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CND\_737 CND\_738 CND\_739 CND\_740 CND\_741 CND\_742 CND\_743 CND\_744 CND\_745 CND\_746 CND\_747 CND\_748 CND\_749 CND\_750 CND\_751 CND\_752

 2 2 2 1 1 1 1 1 1 1 1 1 2 2 1 1

CND\_753 CND\_754 CND\_755 CND\_756 CND\_757 CND\_758 CND\_759 CND\_760 CND\_761 CND\_762 CND\_763 CND\_764 CND\_765 CND\_766 CND\_767 CND\_768

 1 1 1 1 2 2 2 2 2 2 2 2 2 2 2 1

CND\_769 CND\_770 CND\_771 CND\_772 CND\_773 CND\_774 CND\_775 CND\_776 CND\_777 CND\_778 CND\_779 CND\_780 CND\_781 CND\_782 CND\_783 CND\_784

 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2

CND\_785 CND\_786 CND\_787 CND\_788 CND\_789 CND\_790 CND\_791 CND\_792 CND\_793 CND\_794 CND\_795 CND\_796 CND\_797 CND\_798 CND\_799 CND\_800

 2 2 2 2 2 2 1 1 1 1 1 1 1 2 2 2

CND\_801 CND\_802 CND\_803 CND\_804 CND\_805 CND\_806 CND\_807 CND\_808 CND\_809 CND\_810 CND\_811 CND\_812 CND\_813 CND\_814 CND\_815 CND\_816

 1 1 1 1 1 2 1 2 2 2 2 2 1 1 1 2

CND\_817 CND\_818 CND\_819 CND\_820 CND\_821 CND\_822 CND\_823 CND\_824 CND\_825 CND\_826 CND\_827 CND\_828 CND\_829 CND\_830 CND\_831 CND\_832

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CND\_833 CND\_834 CND\_835 CND\_836 CND\_837 CND\_838 CND\_839 CND\_840 CND\_841 CND\_842 CND\_843 CND\_844 CND\_845 CND\_846 CND\_847 CND\_848

 1 1 2 2 2 1 1 2 2 2 2 1 1 1 1 2

CND\_849 CND\_850 CND\_851 CND\_852 CND\_853 CND\_854 CND\_855 CND\_856 CND\_857 CND\_858 CND\_859 CND\_860 CND\_861 CND\_862 CND\_863 CND\_864

 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1

CND\_865 CND\_866 CND\_867 CND\_868 CND\_869 CND\_870 CND\_871 CND\_872 CND\_873 CND\_874 CND\_875 CND\_876 CND\_877 CND\_878 CND\_879 CND\_880

 1 1 1 1 1 1 1 2 2 2 2 1 3 3 1 1

CND\_881 CND\_882 CND\_883 CND\_884 CND\_885 CND\_886 CND\_887 CND\_888 CND\_889 CND\_890 CND\_891 CND\_892 CND\_893 CND\_894 CND\_895 CND\_896

 1 1 1 1 1 1 1 1 1 1 1 1 1 1 3 1

CND\_897 CND\_898 CND\_899 CND\_900 CND\_901 CND\_902 CND\_903 CND\_904 CND\_905 CND\_906 CND\_907 CND\_908 CND\_909 CND\_910 CND\_911 CND\_912

 1 1 1 1 1 3 1 1 1 1 1 1 1 1 1 1

CND\_913 CND\_914 CND\_915 CND\_916 CND\_917 CND\_918 CND\_919 CND\_920 CND\_921 CND\_922 CND\_923 CND\_924 CND\_925 CND\_926 CND\_927 CND\_928

 1 1 2 2 1 1 1 1 1 1 1 1 1 2 1 1

CND\_929 CND\_930 CND\_931

 1 2 1

**BEST Tests**

BEST (Bayesian Estimation Supersedes the t-test) tests were used to compare between groups; these were run with R package “BEST” (Kruschke, 2013). The BEST test uses Markov-chain Monte-Carlo (MCMC) sampling to generate posterior predictive distributions for group data. In Bayesian statistics, posterior predictive distributions (PPDs), and therefore the means of these distributions, are distributions of possible unobserved values which have been predicted based on the observed or ‘real’ data put into the model (Kruschke, 2013, 2014). An important point is that the results are drawn from the PPD generated from the MCMC and not the inputted data directly. For more details on the test and how it works and see Kruschke (2013).

**Outputs**



Supplementary Figure 1. BEST test output for c. 200 bc–ad 450 (group 1) vs c. ad 400-790 (group 2) bone $δ$13Ccoll values for England (all sexes).



Supplementary Figure 2. BEST test output for c. 200 bc–ad 450 (group 1) vs c. ad 400–790 (group 2) bone $δ$15Ncoll values for England (all sexes).



Supplementary Figure 3. BEST test output for c. ad 350–790 (group 1) vs c. ad 790–1200 (group 2) bone $δ$13Ccoll values for England (all sexes).



Supplementary Figure 4. BEST test output for c. ad 350–790 (group 1) vs c. ad 790–1200 (group 2) bone $δ$15Ncoll values for England (all sexes).

**R code**

*.R file upload not supported on Editorial assistant, see research compendium for full code, data, outputs and associated licenses.*

Leggett, S. 2021. *Compendium of R code and data for Tackling Early Medieval Dietary Transitions Using a Hierarchical and Multi-Isotope Approach*. https://doi.org/10.17605/OSF.IO/6B8MZ

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