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University College Cork, Ireland  
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1 **Title:** **Predicting 1-year mortality in older hospitalized patients: external**  
2 **validation of the HOMR model**

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4 **Running title:** **External validation of the HOMR model**

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32 **Abstract**

33

34 **Background**

35 Accurate prognostic information can enable patients and physicians to make better healthcare  
36 decisions. The Hospital-patient One-year Mortality Risk (HOMR) model accurately predicted  
37 mortality risk (concordance [c] statistic 0.92) in adult hospitalized patients in a recent study in North  
38 America. We evaluated the performance of the HOMR model in a population of older inpatients in a  
39 large teaching hospital in Ireland.

40

41 **Design**

42 Retrospective cohort study.

43

44 **Setting**

45 Acute hospital

46

47 **Participants**

48 Patients aged  $\geq 65$  years cared for by inpatient geriatric medicine services from January 1<sup>st</sup>  
49 2013 to March 6<sup>th</sup> 2015 (n = 1654). After excluding those who died during the index  
50 hospitalization (n = 206), and those with missing data (n = 39), the analytical sample  
51 included 1409 patients.

52

53 **Measurements**

54 Administrative data and information abstracted from hospital discharge reports were used  
55 to determine covariate values for each patient. One-year mortality was determined from

56 the hospital information system, local registries, or by contacting the patient's general  
57 practitioner. The linear predictor for each patient was calculated and performance of the  
58 model was evaluated in terms of its overall performance, discrimination, and calibration.  
59 Recalibrated and revised models were also estimated and evaluated.

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61

## 62 **Results**

63 One-year mortality rate after hospital discharge in this patient cohort was 18.6%. The  
64 unadjusted HOMR model had good discrimination (c statistic 0.78; 95% confidence interval  
65 [CI] 0.76 -0.81) but was poorly calibrated and consistently overestimated mortality  
66 prediction. The model's performance was modestly improved by recalibration and revision  
67 (optimism corrected c-statistic 0.8).

68

## 69 **Conclusions**

70 The superior discriminative performance of the HOMR model reported previously was  
71 substantially attenuated in its application to our cohort of older hospitalized patients, who  
72 represent a specific subset of the original derivation cohort. Updating methods improved its  
73 performance in our cohort, but further validation, refinement and clinical impact studies are  
74 required prior to use in routine clinical practice.

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79 **Introduction:**

80 An important principle when caring for an older person with frailty and multi-morbidity is to  
81 align interventions to the patient's condition, preferences, and prognosis.<sup>1</sup> When life  
82 expectancy is limited, strategies to optimize quality of life may be prioritized over invasive  
83 or futile interventions. Discussions about goals of care, however, are often deferred in  
84 frailer older patients because of the uncertainty associated with prognostic estimates.<sup>2</sup> An  
85 accurate method of assessing prognosis could inform and motivate discussions between  
86 physicians and their patients about values, priorities, and therapeutic goals.

87 The Hospital-patient One-year Mortality Risk (HOMR) model has been shown recently to  
88 accurately predict one-year mortality risk in hospitalized patients.<sup>3,4</sup> It is comprised of  
89 covariates that include demographics, co-morbidities, severity of acute illness, and recent  
90 acute hospital care utilization (**Supplementary Appendix S1**). These covariates are  
91 determined at the time of hospital admission using routinely collected health administrative  
92 data. Over 3 million patients aged 18 or older were included in the validation studies in  
93 Ontario and Alberta (Canada), and Boston (United States).<sup>3,4</sup> The HOMR model had a very  
94 high discriminative performance (concordance [c] statistic of 0.89 -0.92) and there was a  
95 less than 1% difference between the observed and expected percentages of deceased  
96 patients at 1 year.

97 To our knowledge, the HOMR model's performance exceeds that of other similar prognostic  
98 models. However, it has not been validated in an exclusively older ( $\geq 65$  years) hospitalized  
99 patient population. The aim of this study was to evaluate the performance of the HOMR  
100 model in a population of older hospitalized patients in a large teaching hospital in Ireland.

101 **Methods:**

102 Data collection

103 The HOMR model was retrospectively applied to all hospitalized patients aged 65 years or  
104 older that were under the care of the specialist geriatric medicine service in Cork University  
105 Hospital from January 1<sup>st</sup> 2013 to March 6<sup>th</sup> 2015. When patients were admitted more than  
106 once during that period, a single hospital admission was chosen at random as the index  
107 hospitalization. Most of the information required to calculate the HOMR model was  
108 obtained using administrative data from the Hospital In-Patient Enquiry system (HIPE -a  
109 national database of coded discharge summaries). The *International Statistical Classification*  
110 *of Diseases and Related Health Problems, Tenth Revision, Australian Modification (ICD-10-*  
111 *AM)*, Australian Classification of Health Interventions (ACHI) and *Australian Coding*  
112 *Standards (ACS)* apply to all activity coded in HIPE in Ireland.<sup>5</sup> Details about home supports  
113 prior to admission as well as provision of home oxygen therapy, which are not routinely  
114 collected by administration staff in Ireland, were obtained from the consultant geriatrician  
115 discharge reports. When information was missing from these sources, the patients' medical  
116 records were reviewed. Covariate values were determined independently by two  
117 researchers with discrepancies resolved through consensus.

118 Deaths within one year of hospital admission were determined by accessing the hospital  
119 clinical information system, an online death notification system (<https://www.RIP.ie>), the  
120 Births, Deaths and Marriages Registry Office in Cork City, and, if required, by contacting the  
121 patient's general practitioner. Unlike the initial HOMR derivation and validation studies,  
122 patients who died during the index hospital admission were not included. There were two  
123 reasons for this. Firstly, geriatrician discharge reports were used to obtain information

124 about home supports for the HOMR model, and these details were generally not included  
125 when the patient died during hospitalization. Secondly, the value of the predictive model,  
126 for the present project, is to calculate 1-year mortality risk after the acute hospital episode.  
127 Predicting in-hospital deaths largely depends on specific clinical factors.

128

### 129 Statistical analysis

130 A sample size that results in at least 100 events, and preferably 200 or more events, is  
131 recommended to externally validate a prognostic model.<sup>6</sup> We estimated that one-year  
132 mortality *after* hospital discharge would very likely exceed 15%,<sup>7, 8</sup> and on that basis  
133 calculated that a sample size of 1400 patients would be required.

134 To validate the HOMR model, the linear predictor for each patient was calculated based on  
135 the coefficient values provided in Appendix E of the original HOMR model development  
136 study.<sup>3</sup> The HOMR model was then evaluated in terms of its overall performance,  
137 discrimination and calibration. The model's overall performance was evaluated using the  
138 Brier score, rescaled to range from 0 to 1, with higher values indicating better performance.<sup>9</sup>  
139 Discrimination, which refers to how well the model distinguishes those with the outcome  
140 from those without the outcome (i.e. death in this case), was measured using the c statistic.  
141 Calibration refers to the agreement between observed outcomes and predicted outcomes  
142 and is usually displayed using a calibration plot. In addition to calibration plots, we also  
143 report the maximum and average difference in predicted versus loess-calibrated  
144 probabilities (E<sub>max</sub> and E<sub>avg</sub>).<sup>10</sup> Finally, we report bootstrapped 95% confidence intervals  
145 for these metrics, based on 500 resampled replicates.<sup>11</sup>

146 To recalibrate the HOMR Model, three additional logistic regression models were  
147 estimated.<sup>12</sup> The first additional model included the HOMR linear predictor, with its  
148 coefficient set to equal 1, and a freely estimated intercept (**Recalibration in the Large**). The  
149 second model then allowed the coefficient on the HOMR linear predictor to be freely  
150 estimated (**Logistic Recalibration**). The third model included the complete set of variables  
151 used in the HOMR model, including the same transformations and interactions, and allowed  
152 their respective coefficients to be freely estimated (**Model Revision**). The performance of  
153 each of these models was assessed using the same metrics used to validate the original  
154 HOMR model. In addition, optimism corrected c-statistic and shrinkage factor were  
155 estimated for the Model Revision using bootstrapping (with 500 re-sampled replicates).

156 All analyses were conducted using R language for statistical computing software,<sup>13</sup> version  
157 3.4.3 (2017-11-30). All data and the code used to analyze it and generate outputs can be  
158 found on the Open Science Framework (<https://osf.io/tv26k/>).

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167 **Results:**

168 Baseline characteristics of study population

169 Between January 1<sup>st</sup> 2013 and March 6<sup>th</sup> 2015, 1654 individual patients aged 65 year or  
170 older were hospitalized under the care of the specialist geriatric service. Of these, 206  
171 patients (12.4%) died during the index hospitalization and therefore were not included in  
172 the analysis. After removing 39 patients with missing outcome data (2.7%), a final sample of  
173 1409 patients was analysed. Of these, 259 (18.4%) died within 1 year of admission to  
174 hospital. The median age of the study patients was 80 years (interquartile range 74 -85), two  
175 thirds were living independently prior to their hospital admission, and 94.5% were admitted  
176 through the emergency department. The baseline characteristics of the study participants  
177 are summarized in **Table 1**.

178

179 HOMR model external validation

180 When the HOMR model was applied directly to the sample of 1409 older patients, it showed  
181 good discrimination (c statistic =0.78). Calibration, however, was poor (see **Figure 1** for  
182 calibration plot) with the model consistently over-estimating mortality at all but the lowest  
183 levels of risk (see **Table 2** for performance metrics).

184

185 Performance of updated HOMR model

186 All three updating methods improved calibration over the original model. Recalibration in  
187 the Large resulted in a lower intercept (-0.42; see **Table 2**) and a significant improvement in

188 model fit over the HOMR model (likelihood ratio test [LRT] Chi-square p value= <0.001).  
189 Logistic Recalibration did not lead to additional improvements in model fit (LRT Chi-square p  
190 value = 0.85), with a recalibration slope of 0.99 (i.e. close to 1). The Brier score and Eavg  
191 were improved by recalibration (**Table 2**). The calibration plot for Recalibration in the Large  
192 (which is virtually identical to the plot for Logistic Recalibration) is shown in **Figure 1**. In  
193 addition to improving calibration, Model Revision also improved discrimination (c statistic  
194 =0.82). The optimism corrected c-statistic for the Model Revision was 0.8, and the shrinkage  
195 factor was 0.91, indicating some overfit. The re-estimated HOMR model, with regression  
196 coefficients, is shown in **Supplementary Appendix S2**.

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208 **Discussion:**

209 This study provides information about the performance of the HOMR model in new  
210 patients, in a different geographical region, when validated by investigators who were not  
211 involved in the model's development. The high discriminative performance reported in the  
212 initial validation studies was substantially attenuated in our older hospitalized cohort and  
213 calibration was found to be poor with the model consistently overestimating mortality risk.  
214 The results illustrate the importance of testing seemingly accurate prediction models in  
215 target populations before applying them in routine practice.

216 There are plausible reasons for the reduced predictive performance in this external  
217 validation study. Firstly, the patients in the present cohort were substantially older (median  
218 age was 80 years versus 59 years in the HOMR derivation cohort; see **Table 1**) and less likely  
219 to be living independently (66.3% versus 83%).<sup>3</sup> Secondly, unlike the initial validation  
220 studies, patients who died during their index hospital admission were excluded. This is likely  
221 to be significant because one of the HOMR covariates, the diagnostic risk score, quantifies  
222 risk of death based on specific admission diagnoses. High scores associated with diagnoses  
223 such as intracerebral haemorrhage and sepsis reflect high risk of death during  
224 hospitalization. This risk may diminish significantly when patients survive the initial days of  
225 their acute hospital episode. Thirdly, it is unclear whether the diagnostic risk scores, which  
226 were derived from a large population of adult patients of all ages, are weighted  
227 appropriately for older hospitalized patients. An admission diagnosis of syncope, for  
228 example, is assigned a diagnostic risk score of -9 which perhaps reflects its usually benign  
229 prognosis in younger adults. Syncope, in older adults however, is associated with reduced  
230 survival.<sup>14</sup> Finally, differences in access and organization of primary care between North

231 America and Ireland may have had an important impact on covariates relating to recent  
232 acute hospital care utilization (i.e. ambulance transfers, emergency department visits,  
233 readmissions).<sup>15,16</sup>

234 Our findings are not surprising: the accuracy of predictive models is often substantially  
235 lower in new patients compared to the accuracy found in patients of the development  
236 population.<sup>17, 18</sup> Rather than simply reject the model, updating methods were used to  
237 improve performance in our older patient cohort. In this study, Recalibration in the Large  
238 (the simplest updating method where just one parameter of the original model [i.e. the  
239 intercept] is adjusted) substantially improved performance. While model revision resulted in  
240 further improvements, this more extensive updating method is less ideal because  
241 parameter estimates are redeveloped on the data of the validation set (a much smaller  
242 sample) and prior information from the larger derivation sample is disregarded.<sup>19</sup>

243 The performance of the recalibrated HOMR model compares favourably to other validated  
244 prognostic models for older hospitalized patients (**Supplementary Appendix S3**).<sup>18, 20-29</sup>  
245 However, it is important to emphasize that an updated HOMR model, just like a newly  
246 developed model, would require testing of its generalizability, as well as its impact on  
247 clinician behaviour and patient outcomes, before it could be recommended for use in  
248 routine clinical practice.<sup>30</sup> Even then, because of inherent unwieldiness, it would need to be  
249 integrated into hospital information systems to ensure usability for practicing physicians.

250 The present study has some limitations. Firstly, the HOMR model was applied and updated  
251 in a single medical centre where patients were cared for by specialist geriatricians. As  
252 discussed, this limits the generalizability of our findings and further validation in other  
253 centres is now required. Secondly, we used the model differently to how it was originally

254 designed by excluding patients who died during their index admission. However, we  
255 contend that the primary purpose of an accurate 1-year mortality prediction in a  
256 hospitalized patient is to help guide decision-making and care-planning *after* the index acute  
257 episode when the patient's condition has stabilized.

258 In conclusion, the exceptional performance of the HOMR model, reported in the North  
259 American validation studies, was substantially attenuated in a cohort of older hospitalized  
260 patients in a large teaching hospital in Ireland. Nevertheless, the performance of the HOMR  
261 model in our older patient cohort was demonstrably good and compares favourably to  
262 other validated non-disease specific mortality prediction tools for older people. Updating  
263 methods improved performance of the HOMR model but further refinement, validation, as  
264 well as clinical impact studies, will be required before the model could be applied  
265 confidently in routine practice.

266

## 267 **Acknowledgements**

### 268 **Conflict of interest**

269 None

### 270 **Author contributions**

271 Curtin, O'Mahony, Gallagher: study concept and design. Doyle: data aggregation. Curtin, O'Donnell:  
272 determination of covariate values. Dahly, van Smeden: statistic analysis. Curtin, O'Mahony,  
273 Gallagher: preparation of manuscript. All authors: critical revision and final approval of manuscript.

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283 **References:**

- 284 1. Steinman MA, Hanlon JT. Managing medications in clinically complex elders: "There's  
285 got to be a happy medium". *JAMA* 2010; 304:1592.
- 286 2. Sleeman KE. End-of-life communication: let's talk about death. *J R Coll Physicians*  
287 *Edinb* 2013; 43:197–9.
- 288 3. van Walraven C. The Hospital-patient One-year Mortality Risk score accurately  
289 predicted long-term death risk in hospitalized patients. *J Clin Epidemiol*. 2014  
290 Sep;67(9):1025-34.
- 291 4. van Walraven C, McAlister FA, Bakal JA, Hawken S, Donzé J. External validation of the  
292 Hospital-patient One-year Mortality Risk (HOMR) model for predicting death within 1  
293 year after hospital admission. *CMAJ*. 2015 Jul 14;187(10):725-33.
- 294 5. Irish Coding Standards, Healthcare Pricing Office, January 2016 ii

- 295 6. Collins GS, Ogundimu EO, Altman DG. Sample size considerations for the external  
296 validation of a multivariable prognostic model: a resampling study. *Stat Med*.  
297 2016;35(2):214-26.
- 298 7. Clark D, Armstrong M, Allen A et al. Imminence of death among hospital inpatients:  
299 Prevalent cohort study. *Palliative Medicine* 2014;28(6):274-279.
- 300 8. Pilotto A, Rengo F, Marchionni N et al. Comparing the prognostic accuracy for all-  
301 cause mortality of frailty instruments: a multicentre 1-year follow-up in hospitalized  
302 older patients. *PLoS One*. 2012;7(1):e29090. doi: 10.1371/journal.pone.0029090.
- 303 9. Steyerberg EW, Vickers AJ, Cook NR et al. Assessing the performance of prediction  
304 models: a framework for traditional and novel measures. *Epidemiology*.  
305 2010;21(1):128-38.
- 306 10. Harrell, FE. *Regression modeling strategies: with applications to linear models,*  
307 *logistic and ordinal regression, and survival analysis*. Cham: Springer; 2015.
- 308 11. Efron B, Tibshirani R. *An introduction to the bootstrap*. Monographs on statistics and  
309 applied probability. New York: Chapman & Hall; 1993.
- 310 12. Vergouwe Y, Nieboer D, Oostenbrink R et al. A closed testing procedure to select an  
311 appropriate method for updating prediction models. *Stat Med*. 2017;36(28):4529-  
312 4539.
- 313 13. R Development Core Team. *R: A language and environment for statistical computing*.  
314 R Foundation for Statistical Computing, Vienna, Austria. 2008. ISBN 3-900051-07-0,  
315 URL <http://www.R-project.org>.
- 316 14. Soteriades ES, Evans JC, Larson MG et al. Incidence and prognosis of syncope. *N Engl*  
317 *J Med* 2002;347:878-85.

- 318 15. Starfield B, Shi L, Macinko J. Contribution of primary care to health systems and  
319 health. *Milbank Q.* 2005;83(3):457–502.
- 320 16. White B, Carney PA, Flynn J, Marino M, Fields S. Reducing hospital readmissions  
321 through primary care practice transformation. *J Fam Pract.* 2014 Feb;63(2):67-73.
- 322 17. Bleeker SE, Moll HA, Steyerberg EW et al. External validation is necessary in  
323 prediction research: a clinical example. *J Clin Epidemiol* 2003;56:826e32.
- 324 18. Monacelli F, Tafuro M, Molfetta L et al. Evaluation of prognostic indices in elderly  
325 hospitalized patients. *Geriatr Gerontol Int.* 2017;17(6):1015-1021.
- 326 19. Janssen K, Moons K, Kalkman C, et al. Updating methods improved the performance  
327 of a clinical prediction model in new patients. *J Clin Epidemiol* 2008; 61: 76–86.
- 328 20. Yourman LC, Lee SJ, Schonberg MA, Widera EW, Smith AK. Prognostic indices for  
329 older adults: a systematic review. *JAMA.* 2012;307(2):182-92.
- 330 21. Teno JM, Harrell FE Jr, Knaus W et al. Prediction of survival for older hospitalized  
331 patients: the HELP survival model. Hospitalized Elderly Longitudinal Project. *J Am*  
332 *Geriatr Soc* 2000;48(Suppl 5): S16-24.
- 333 22. Walter LC, Brand RJ, Counsell SR, et al. Development and validation of a prognostic  
334 index for 1-year mortality in older adults after hospitalization. *JAMA* 2001;285:2987-  
335 94.
- 336 23. Inouye SK, Bogardus ST Jr, Vitagliano G et al. Burden of illness score for elderly  
337 persons: risk adjustment incorporating the cumulative impact of diseases,  
338 physiologic abnormalities, and functional impairments. *Med Care* 2003; 41: 70–83.
- 339 24. Fischer SM, Gozansky WS, Sauaia A, et al. A practical tool to identify patients who  
340 may benefit from a palliative approach: the CARING criteria. *J Pain Symptom*  
341 *Manage* 2006;31:285-92.



- 342 25. Levine SK, Sachs GA, Jin L, et al. A prognostic model for 1-year mortality in older  
343 adults after hospital discharge. *Am J Med* 2007;120:455-60.
- 344 26. Pilotto A, Ferrucci L, Franceschi M, et al. Development and validation of a  
345 multidimensional prognostic index for one-year mortality from comprehensive  
346 geriatric assessment in hospitalized older patients. *Rejuvenation Res* 2008;11:151-61.
- 347 27. Pilotto A, Rengo F, Marchionni N, et al. Comparing the prognostic accuracy for all-  
348 cause mortality of frailty instruments: a multicentre 1-year follow-up in hospitalized  
349 older patients. *PLoS ONE* 2012;7:e29090.
- 350 28. Dramé M, Novella JL, Lang PO, et al. Derivation and validation of a mortality-risk  
351 index from a cohort of frail elderly patients hospitalised in medical wards via  
352 emergencies: the SAFES study. *Eur J Epidemiol* 2008;23:783-91.
- 353 29. Di Bari M, Balzi D, Roberts AT, et al. Prognostic stratification of older persons based  
354 on simple administrative data: development and validation of the “Silver Code,” to  
355 be used in emergency department triage. *J Gerontol A Biol Sci Med Sci* 2010;65:159-  
356 64.
- 357 30. Justice AC, Covinsky KE, Berlin JA. Assessing the generalizability of prognostic  
358 information. *Ann Intern Med* 1999;130:515-24.

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SUPPORTING INFORMATION

Additional Supporting Information may be found in the online version of this article:

**Figure S1.** Covariates used to calculate a patient’s Hospital-patient One-year

Mortality Risk (HOMR) score

**Table S2.** Re-estimated HOMR model with regression coefficients.

**Table S3.** Summary of prognostic models used to predict mortality in hospitalized older patients.

404 **Table 1.** Baseline characteristics of study participants (and how they compare to original  
 405 derivation cohort)  
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Variable	Mean SD	Median [IQR]	(Min, Max)	HOMR derivation cohort
<b>Sex</b>				
Female	800 (56.8%)			61.8%
Male	609 (43.2%)			38.2%
<b>Age</b>	79.3 ± 7.4	80 (74, 85)	(65, 101)	59 (IQR 37 -75)
<b>Living Status*</b>				
Independent	933 (66.2%)			83%
Rehabilitation Unit	33 (2.3%)			0.2%
Homecare	295 (20.9%)			12.1%
Nursing Home	148 (10.5%)			4.5%
<b>Urgency of admission</b>				
Elective	78 (5.5%)			47.4%
ED without Ambulance	498 (35.3%)			25.7%
ED with Ambulance	833 (59.1%)			26.9%
<b>Number of ambulance transfers**</b>	0.3 ± 0.7	0 (0, 0)	(0, 5)	N/A
<b>Admitting Service***</b>				
General Medicine (including geriatric medicine)	1365 (96.9%)			31.4%
General Surgery	3 (0.2%)			11%
Cardiology	17 (1.2%)			6.4%
Orthopedics	8 (0.6%)			8.4%
Gastroenterology/Nephrology/Neurology	16 (1.1%)			4.9%
<b>ICU admission (directly from emergency department)</b>	3 (0.2%)			7.4%
<b>Home O<sub>2</sub>*</b>	0			2.3%
<b>ED Visits**</b>				
0	828 (58.8%)			55.1%
≥1	581 (41.2%)			44.9%
<b>Urgent readmission within 30 days</b>	131 (9.3%)			4.5%
<b>DRS</b>	-1.9 ± 4.8	0 (-1, 0)	(-22, 9)	N/A
<b>CCI****</b>				
0	23.3%			57.8%
1-2	34.2%			21.7%
≥3	42.5%			20.5%

407 Legend: CCI =Charlson Comorbidity Index; DRS = Diagnostic Risk Score; ED = emergency  
 408 department; HOMR = Hospital-patient One-year Mortality Risk; ICU = intensive care unit;  
 409 IQR = interquartile range; N/A = not available; SD = standard deviation. \*Prior to index  
 410 hospitalization. \*\* In 12 months prior to index hospitalization.\*\*\* All patients, after hospital  
 411 admission, were under the care of the specialist geriatric medicine service. \*\*\*\* Not  
 412 adjusted for patient age.

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414 **Figure 1.** Calibration plots of the unadjusted and updated Hospital-patient One year  
415 Mortality Risk (HOMR) models: (A) Original HOMR model; (B) Recalibrated model  
416 (Recalibration in the Large)

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426 **Table 2.** Performance of the unadjusted and updated Hospital-patient One-year Mortality  
427 Risk (HOMR) models.

	HOMR model	Calibration in the Large	Logistic Recalibration	Model Revision
Intercept	0	-0.42	-0.43	-
Slope	1	1	0.99	-
Residual deviance	1139.96	1107.76	1107.73	1046.55
Df	1409	1408	1407	1389
LRT Chisq p-value	-	<0.001	0.85	-
Brier score (rescaled)	0.15 (0.1 to 0.21)*	0.19 (0.13 to 0.25)	0.19 (0.13 to 0.26)	0.23 (0.18 to 0.31)
E <sub>max</sub>	0.103 (0.085 to 0.146)	0.111 (0.03 to 0.225)	0.121 (0.03 to 0.236)	0.017 (0.016 to 0.094)
E <sub>avg</sub>	0.058 (0.046 to 0.072)	0.016 (0.01 to 0.028)	0.017 (0.009 to 0.029)	0.008 (0.005 to 0.016)
c-statistic	0.78 (0.76 to 0.81)	0.78 (0.75 to 0.81)	0.78 (0.76 to 0.81)	0.82 (0.8 to 0.85)
* Bootstrapped 95% confidence intervals				

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429 Df = degrees of freedom; LRT = likelihood ratio test; E<sub>max</sub> = maximum absolute difference in  
430 predicted and calibrated probabilities; E<sub>avg</sub> = average absolute difference in predicted and  
431 calibrated probabilities.

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