

NIH Public Access

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Arch Intern Med. Author manuscript; available in PMC 2014 June 05.

Published in final edited form as:

Arch Intern Med. 2010 November 22; 170(21): 1940–1942. doi:10.1001/archinternmed.2010.410.

Predicting Hip and Major Osteoporotic Fractures Using Administrative Data

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Background

The Fracture Risk Assessment tool (FRAX) was released in 2008 by the World Health Organization (WHO) [1]. The FRAX algorithm uses bone mineral density (BMD), and 11 additional clinical and physiological risk factors to estimate a person's 10 year probability of hip and other major osteoporotic fracture [2]. The latter is defined by WHO as a hip, clinical vertebral, distal forearm or humerus fracture. Ensrud et al., using risk prediction models including only age and BMD or age and fracture history [3], concluded that these few risk factors predicted 10 year risk of hip and other major osteoporotic fractures as well as FRAXbased models. We have performed a similar evaluation using administrative claims data, which do not include information on BMD. We derived and examined several fracture risk prediction models to determine if demographics, history of fracture, and comorbidities, all identifiable within administrative claims data, could be used to predict hip fracture and major osteoporotic fractures as well as models with additional clinical information or models derived from FRAX. This type of prediction model might be useful for large health plans to target higher-risk individuals for more aggressive screening efforts including BMD testing.

Methods

We performed a retrospective cohort study using the Medicare Current Beneficiary Survey (MCBS), a rotating panel in-home survey of approximately 12,000 community or institutional dwelling beneficiaries linked to Medicare claims data, for the years 1999–2005. The MCBS can provide national estimates for the U.S. Medicare population due to its

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unique multi-stage sampling design. Eligible subjects for this analysis were: $age \ge 65$ years, always having Medicare part A and B coverage, having one year of baseline data and two years of follow up data. For analyses of each type of fracture, beneficiaries with any claims for the particular fracture during the baseline were excluded.

We used inpatient and outpatient administrative claims data to obtain demographic, baseline comorbidity and fracture histories, and MCBS survey data to obtain information on height, weight, activities of daily living, body mass index (BMI), current smoking status, osteoporosis drug usage and glucocorticoid usage. Alcohol status and fracture history were obtained from both claims and survey data. Because the MCBS does not contain information regarding family history of hip fractures, we used population-based data [4] to simulate this risk factor according to previously published methods [5].

We used multivariable logistic regression modeling to evaluate the predictive ability of models with varying degrees of complexity. The c-statistic, a measure of area under the receiver operating characteristic (ROC) curve, was reported and compared across models. To provide statistically valid inferences and account for sampling, we used survey logistic regression for the analysis [6]. To obtain the weighted c statistic and its 95% confidence interval, we applied bootstrapping methods reported by Izrael [7].

Results

Of the more than 12,000 beneficiaries eligible for evaluation of risk of hip fracture and other major osteoporotic fracture, 187 experienced a hip fracture and 430 had a major osteoporotic fracture (Table 1). In the analysis of hip fracture, the sex-specific, weighted c-statistic was 0.74 for the model using only administrative claims data containing demographic, fracture history and comorbidities, which minimally changed to 0.75 when we added the extra variables from MCBS. The c-statistic for the model that used FRAX score only (using BMI) was 0.64. The analysis of major osteoporotic fractures found similar patterns with modestly lower c statistics. The c statistics were numerically higher in men than in women, and higher in African Americans than Caucasians, but confidence intervals were wide.

Comments

Our results indicate that simple models based on administrative claims data are useful for predicting hip and major osteoporotic fractures. Although BMD and BMI were not available in claims data, our models generated using only administrative data yielded comparable results compared to more complex models with clinical risk factors or FRAX without BMD. This result is consistent with those reported by Ensrud et al [3], and our c statistics are comparable with their results, including models with BMD. Because the follow up time in MCBS was limited to 2 years, we could not assess the calibration of the risk prediction models, only their discrimination. However, our well defined cohort is generalizable to the US. Medicare population. Our findings suggesting that administrative data alone can risk-stratify patients to identify those that should be considered higher priorities for further fracture risk assessment including BMD testing, have implications for screening at a population level by health plans with ready access to administrative data.

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Acknowledgments

Funding/Support: This research was supported by a contract between UAB and Amgen, Inc. Only the authors from UAB had access to the Medicare data used. The analysis, presentation, and interpretation of the results were solely the responsibility of the authors.

References

- Unnanuntana A, Gladnick BP, Donnelly E, Lane JM. Current Concepts Review The Assessment of Fracture Risk. J Bone Joint Surg Am. 2010; 92:743–53. [PubMed: 20194335]
- 2. [Accessed Jun 23, 2010] FRAX WHO Fracture Risk Assessment Tool. http://www.shef.ac.uk/ FRAX/tool.jsp?locationValue=9
- 3. Ensrud KE, Lui L, Taylor BC, Schousboe JT, et al. A comparison of prediction models for fractures in older women. Is more better? Arch intern Med. 2009; 169 (22):2087–2094. [PubMed: 20008691]
- Curtis JR, McClure LA, Delzell E, Howard VJ, et al. Population-based fracture risk assessment and osteoporosis treatment disparities by race and gender. J Gen Intern Med Med. 24(8):956–62.
- Dawson-Hughes B, Looker AC, Tosteson ANA, Johansson H, et al. The potential impact of new national osteoporosis foundation guidance on treatment patterns. Osteoporos Int. 2010; 21:41–52. [PubMed: 19705046]
- An, AB. Performing logistic regression on survey data with the new SURVEYLOGISTIC procedure. Proceedings of the twenty-seventh annual SAS user group international conference; 2002. paper 258–27
- Izrael, D.; Battaglia, AA.; Hoaglin, DC.; Battaglia, MP. SAS macros and tools for working with weighted logistic regression models that use survey data. Proceedings of the twenty-eighth annual SAS user group international conference; 2003. paper 275–28

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Table 1

Weighted C statistics in the predicting hip and major osteoporotic fractures. 12, 413 beneficiaries were eligible for hip fracture analysis with 187 identified hip fractures while 12,337 beneficiaries were eligible for major osteoporotic fracture analysis with 430 identified major osteoporotic fractures.

	Model One [†]	Model Two [‡]	Model Three $\dot{t}^{\dot{T}}$	Model Four
	demographic, fracture history, Comorbidity	demographic, fracture history, Comorbidity [*] and extra variables ^{**} from Survey	Model two+ FRAX score for hip fracture (for hip fracture outcome) or FRAX score for major osteoporotic fracture (for major fracture outcome)	Only FRAX score for hip fracture (for hip fracture outcome) or FRAX score for major osteoporotic fracture (for major fracture outcome)
Hip fracture is the o	utcome of interest			
All subjects	0.74 (0.70–0.77)	0.75(0.72–0.78)	0.75 (0.72–0.78)	0.64 (0.60–0.68)
Gender				
Female	0.71(0.67–0.75)	0.73(0.68–0.77)	0.73 (0.68–0.77)	0.66 (0.62–0.70)
Male	0.78 (0.73–0.83)	0.81 (0.75–0.85)	0.81 (0.75–0.85)	0.67 (0.60–0.73)
Ethnicity				
Caucasian	0.74 (0.70–0.78)	0.75 (0.72–0.79)	0.75 (0.72–0.79)	0.64 (0.60–0.67)
African American	0.74 (0.50-0.93)	0.81 (0.50-0.94)	0.81 (0.50-0.95)	0.70 (0.57–0.81)
Major osteoporotic t	racture**** is the outcome of interest			
All subjects	0.71 (0.69–0.73)	0.72 (0.69–0.74)	0.72 (0.70–0.74)	0.55 (0.53–0.58)
Gender				
Female	0.67 (0.65-0.70)	0.68 (0.65–0.71)	0.69 (0.66–0.71)	0.64 (0.61–0.66)
Male	0.71 (0.67–0.76)	0.75 (0.71–0.78)	0.75 (0.71–0.79)	0.67 (0.62–0.72)
Ethnicity				
Caucasian	0.71 (0.68–0.73)	0.71 (0.69–0.74)	0.72 (0.70–0.74)	0.54 (0.51–0.56)
African American	0.74 (0.50–0.85)	0.78 (0.66-0.88)	0.78 (0.67–0.88)	0.52 (0.44–0.63)
* Comorbidity is coded	as dichotomous: 1,Have any of the gluc	coorticoid related disease, bone disease, car	ncer, depression, diabetes, fall related disease, othe	er heart disease or renal disease; 0, otherwise.

** The extra variables from the survey included body mass index (BMI), activity of daily living (ADL) and instrumental activity of daily living while BMI was derived from self reported weight and height;

*** WHO defined major fracture including hip, clinical vertebral, distal forearm, and humerus for FRAX

[†] Logit (Hip Fracture) = -5.5487 + 0.5909(Age 70_74) + 0.7710 (Age 75_79) + 1.0513 (Age 80_84) + 2.0719 (Age 85_89) + 2.3560 (Age 90plus) - 0.4015 (African American) - 0.6153(Male) + 0.7380(Baseline Fracture) + 0.3830 (Baseline Comorbidity)

Logit (Major Fracture) = -4.5842 + 0.5112(Age 70_74) + 1.0129 (Age 75_79) + 1.3373 (Age 80_84) + 1.8804 (Age 85_89) + 2.0844 (Age 90plus) - 0.7225 (African American) - 0.8138(Male) + 1.2146(Baseline Fracture) + 0.4028 (Baseline Comorbidity)

Logit (Major Fracture) = -4.6038 + 0.4907(Age 70_74) + 0.9785 (Age 75_79) + 1.2894 (Age 80_84) + 1.8103 (Age 85_89) + 1.9624 (Age 90plus) - 0.7806 (African American) - 0.7844(Male) + ⁷ Logit (Hip Fracture) = -5.1061 + 0.5747(Age 70_74) + 0.7397 (Age 75_79) + 0.9847 (Age 80_84) + 1.9628 (Age 85_89) + 2.1978 (Age 90plus) - 0.4404 (African American) - 0.5592(Male) + 0.7204(Baseline Fracture) + 0.3463 (Baseline Comorbidity) - 0.0178 (BMI) - 0.0041 (ADL) + 0.1791 (IADL)

1.1905(Baseline Fracture) + 0.3595 (Baseline Comorbidity) + 0.0004 (BMI) – 0.005 (ADL) + 0.1906 (IADL)

 $^{\uparrow\uparrow}$ Logit (Hip Fracture) = -5.1435 + 0.5536(Age 70_74) + 0.6586 (Age 75_79) + 0.8568 (Age 80_84) + 1.8108 (Age 85_89) + 2.0499 (Age 90plus) - 0.3516 (African American) - 0.6362(Male) + 0.6362(Male Logit (Major Fracture) = -4.7421 + 0.4641(Age 70_74) + 0.8654 (Age 75_79) + 1.1004 (Age 80_84) + 1.5980 (Age 85_89) + 1.7747 (Age 90plus) - 0.5796 (African American) - 1.0428(Male) + 0.8654 (Age 70_74) + 0.8654 (Age 70_ 0.6513(Baseline Fracture) + 0.3414 (Baseline Comorbidity) - 0.0169 (BMI) - 0.0032 (ADL) + 0.1754 (IADL) + 0.0185 (FRAX Score) .0016(Baseline Fracture) + 0.3495 (Baseline Comorbidity) + 0.0004 (BMI) – 0.004 (ADL) + 0.1860 (IADL) + 0.0258 (FRAX Score)