

Identifying Medicare Beneficiaries with Disabilities: Improving on Claims-Based Algorithms

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MATHEMATICA
Policy Research

Motivation

- **Comparative effectiveness research (CER) on disability services is a top priority of the U.S. health care system**
- **Claims data may be a powerful tool for disability CER, but diagnosis codes provide little information on functional status**
- **Claims-based algorithms have limited ability to identify community-dwelling Medicare beneficiaries with disabilities**

Analytic Challenges

- **Not all disability-related conditions generate disability-related claims (Iezzoni 2002)**
- **Disability-related information in claims is far from needed level of detail**
- **Difficult to distinguish between temporary and long-term disability**

Research Questions

- **Can we improve upon claims-based algorithms that identify “disability” by combining them in a predictive model?**
- **How do characteristics and service use differ between beneficiaries correctly and incorrectly classified?**

Data and Methods (1)

- **Use the Medicare Current Beneficiary Survey (MCBS) Access to Care file, including Medicare claims**
- **Create claims-based disability flags and use them in logit models that predict survey-based disability**

Data and Methods (2)

- **Compare predictive performance of flags versus models using receiver operating characteristic (ROC) curves**
- **Compare characteristics and service use of beneficiaries correctly and incorrectly classified**

Study Population (1)

- **Completed MCBS baseline questionnaire in 2003–2006**
- **Community-dwelling at baseline**
- **Not enrolled in Medicare Advantage during baseline year and year after**

Study Population (2)

- **N = 12,415 (weighted = 35.3 million)**
- **Two analytic subgroups:**
 - **Age 18–64 (on SSDI or have ESRD)**
 - **Age 65+**

MCBS Respondents with Disability

Analytic Group	N	Weighted (millions)	3+ ADL	1+ ADL	1+ ADL or IADL
All	12,415	35.3	9.4%	29.4%	45.4%
Age 18–64	2,357	6.0	16.5%	44.0%	70.3%
Age 65+	10,057	29.3	7.9%	26.5%	40.3%

ADL = activities of daily living

IADL = instrumental activities of daily living

Claims-Based Algorithms (0/1 Flags)

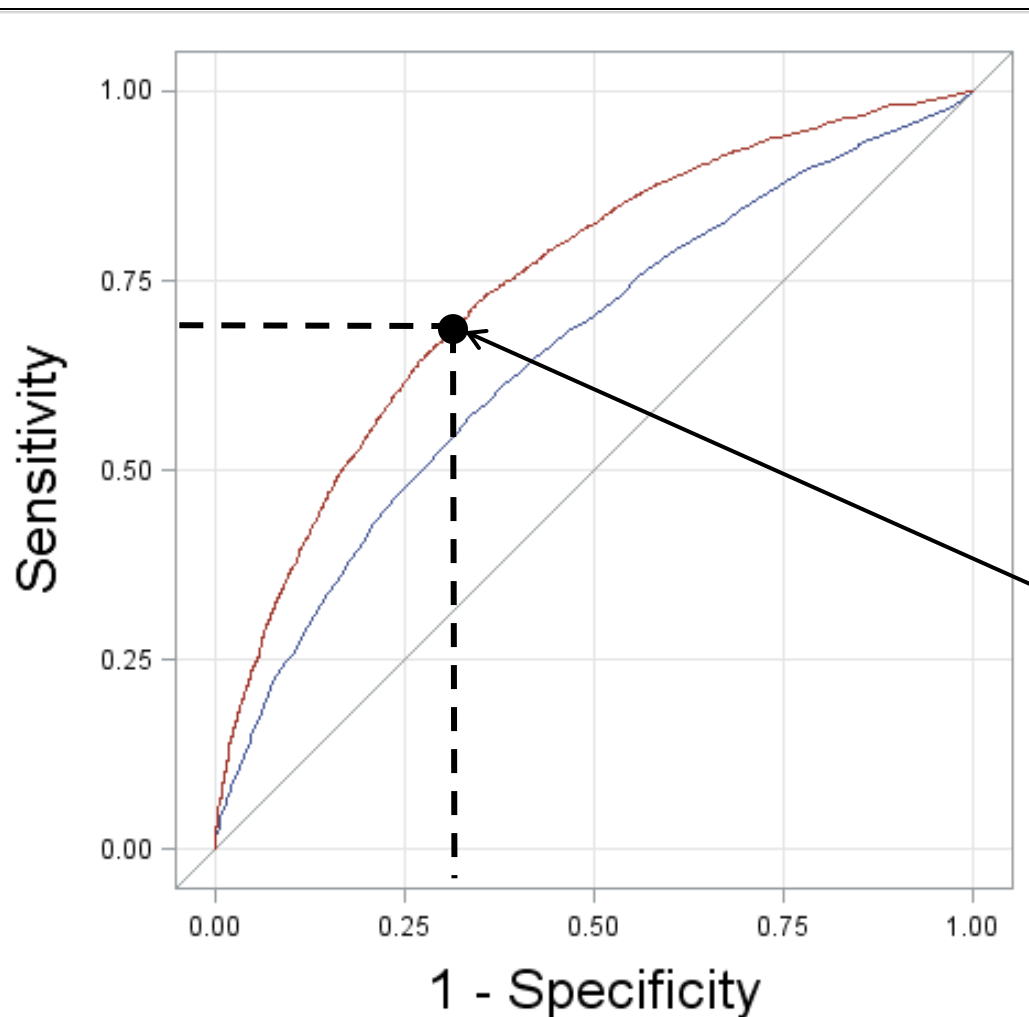
- **SSA Health IT (HIT) business rules**
- **Chronic Illness and Disability Payment System (CDPS)**
- **Access Risk Classification System (ARCS)**
- **ICD-9 codes for psychiatric disorders**
- **ICD-9 codes for dementia and Alzheimer's**
- **ICD-9 codes for intellectual disability**

Logit Model Results

- Age 65+, 1+ ADL limitation

Variable	Odds Ratio	p-Value
Female	1.31	<.001
Age	1.07	<.001
Intellectual disability	4.85	<.001
Psychiatric disorder	1.49	0.119
Dementia and Alzheimer's	2.48	<.001
SSA-HIT	1.26	<.001
ARCS	1.19	<.001
CDPS	2.12	0.025
Dual	2.44	<.001
Medicare entitlement before 65	4.18	<.001
Interaction terms	Yes	Yes

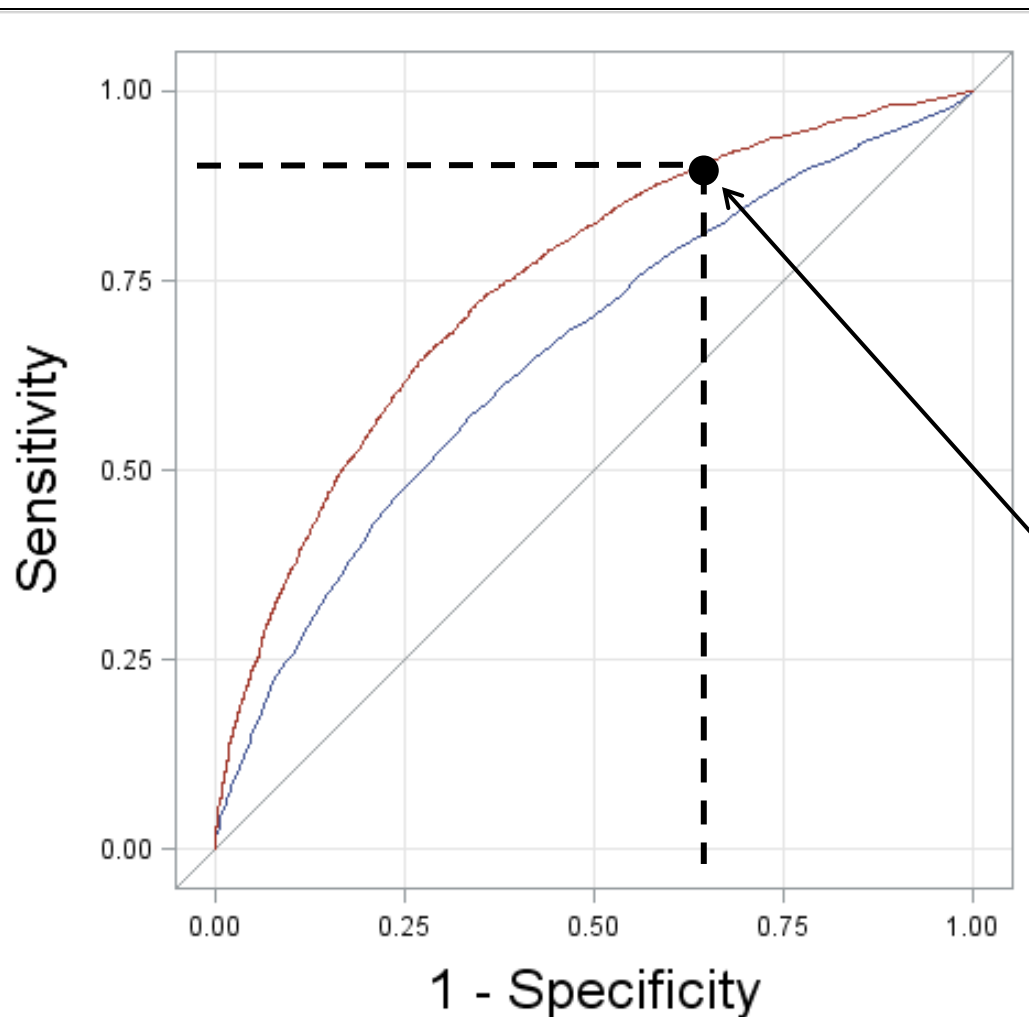
ROC Curves (age 65+, 1+ ADL limitation)



- Y-axis = true positive rate
- X-axis = false positive rate

Disability		1+ ADL	
		Yes	No
Claims	Yes	72%	35%
	No	28%	65%
		100%	100%

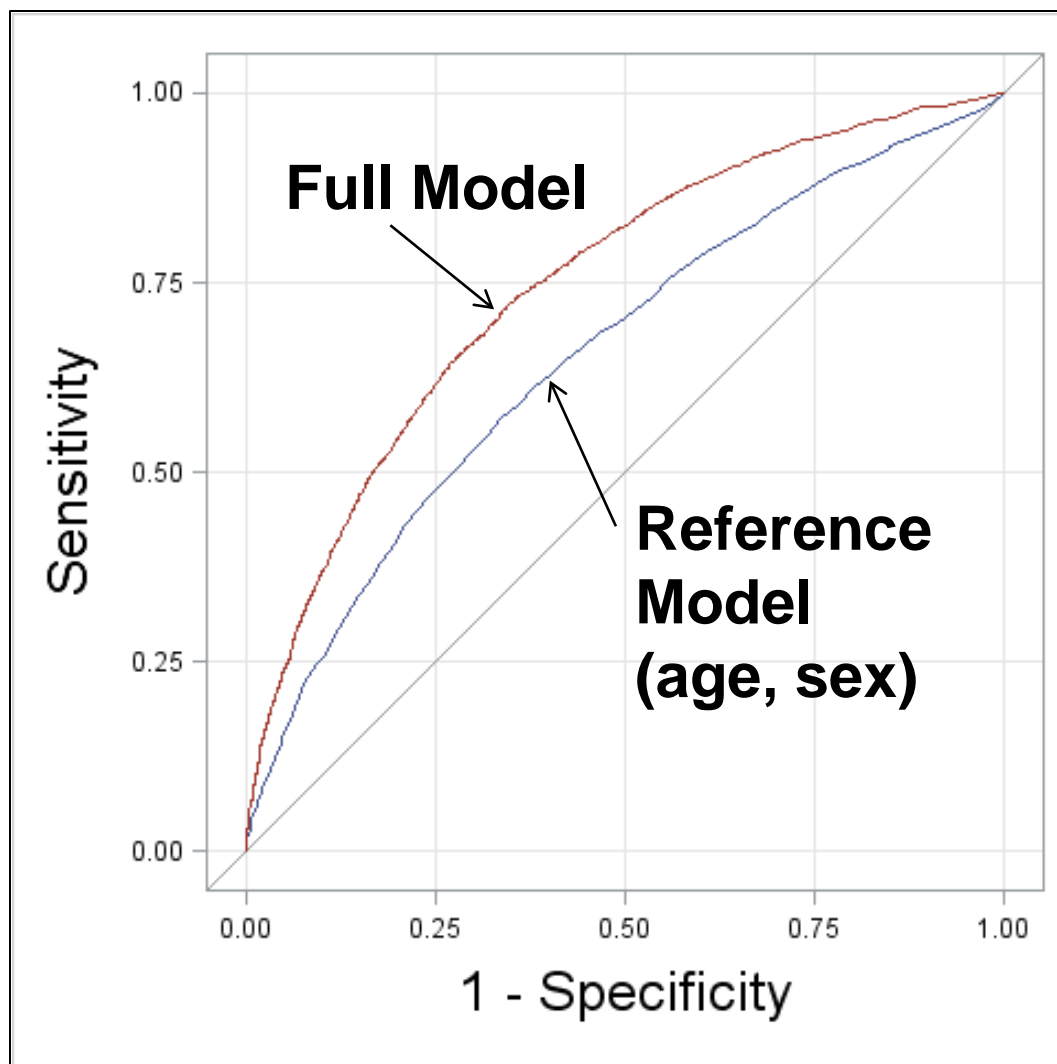
ROC Curves (age 65+, 1+ ADL limitation)



- Y-axis = true positive rate
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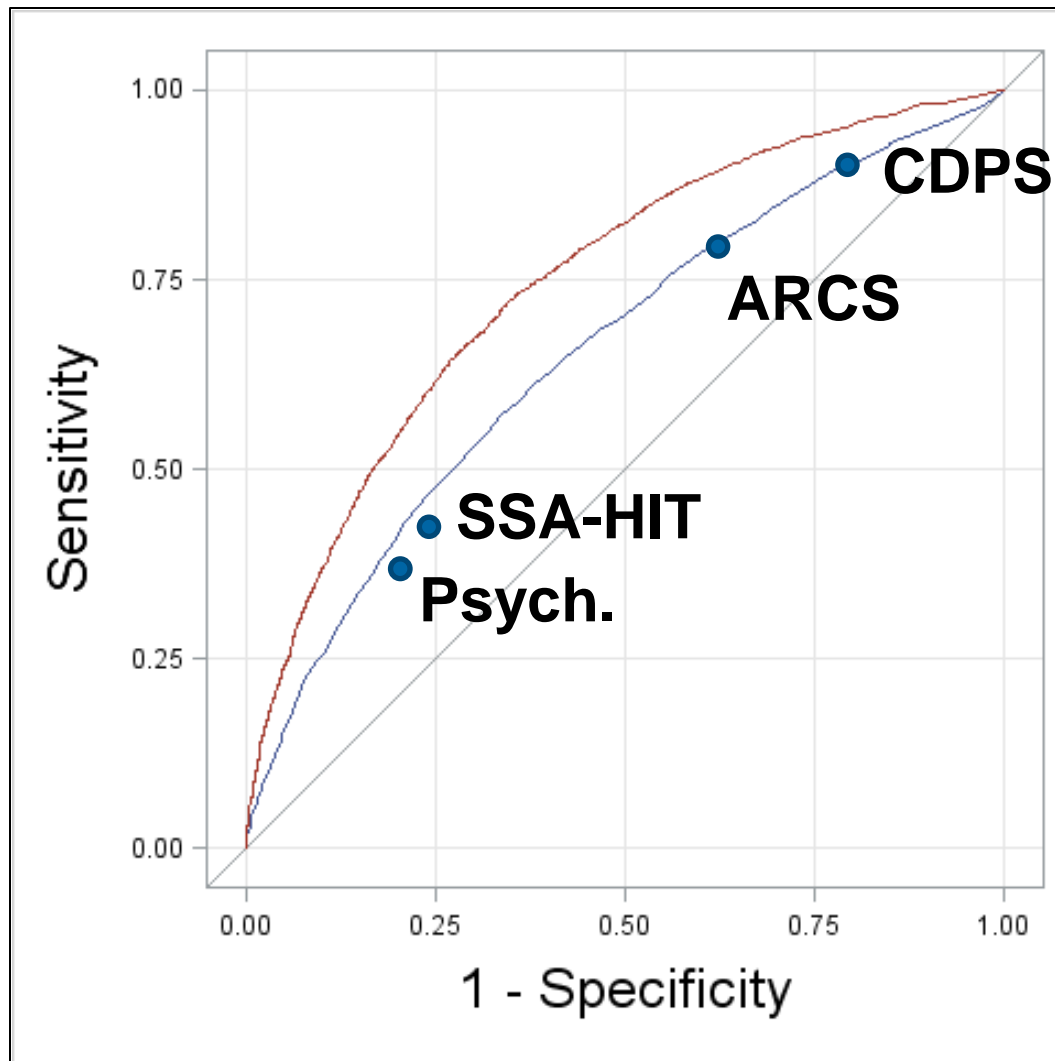
Disability		1+ ADL	
		Yes	No
Claims	Yes	91%	66%
	No	9%	34%
		100%	100%

ROC Curves (age 65+, 1+ ADL limitation)



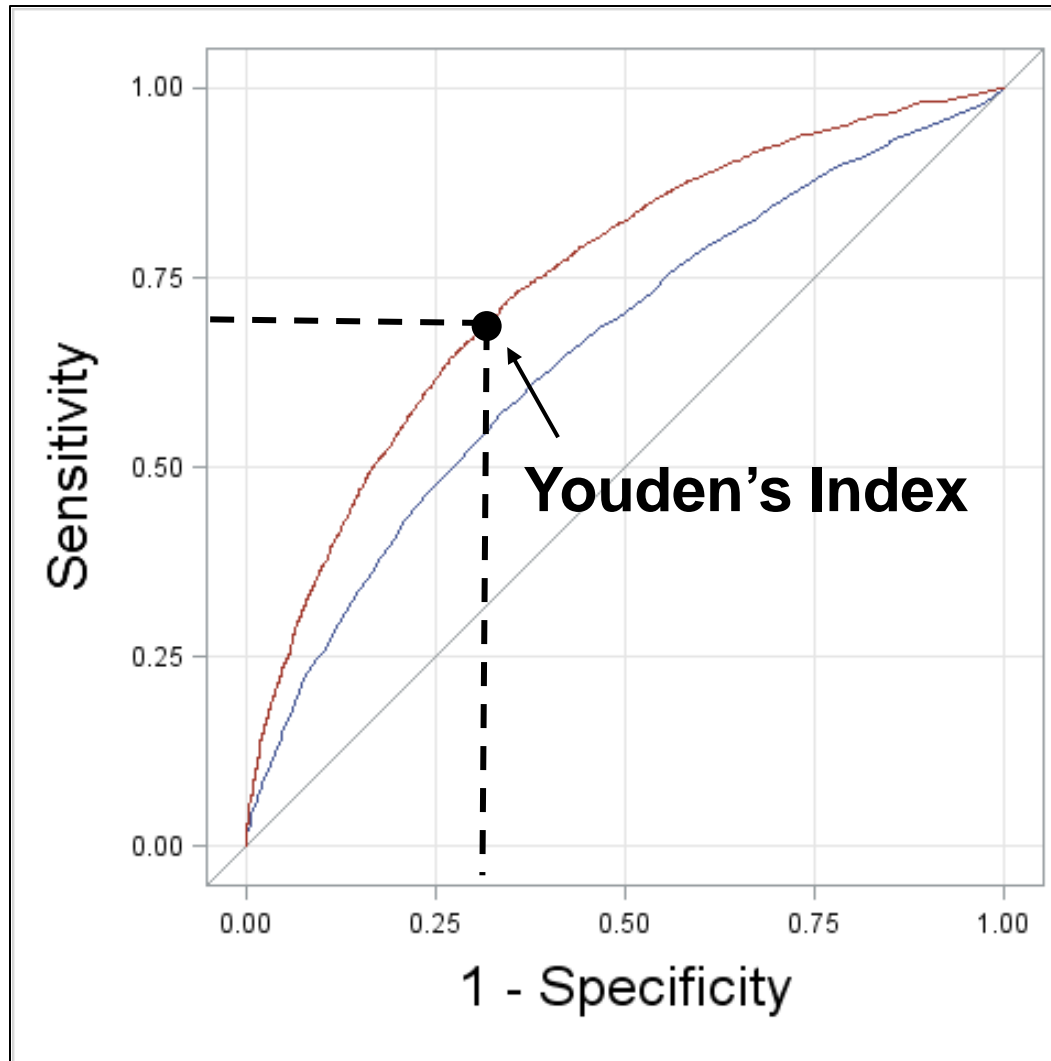
- Y-axis = true positive rate
- X-axis = false positive rate

Comparison to Disability Flags



- Y-axis = true positive rate
- X-axis = false positive rate

Choosing Point on ROC Curve



- Max (true positive rate + true negative rate)

Misclassification Analysis: Age 65+ (1)

- **At optimal point, model picks up 72% of those who report 1+ ADL limitations and 35% of those who report no ADL limitations**
- **False positives are similar to true positives but reflect better health, lower service use**

Misclassification Analysis: Age 65+ (2)

- **False negatives are similar to true negatives but reflect worse health, more obesity**
- **Compared with true positives, false negatives are characterized by obesity, younger ages, and low Medicare expenditures**

Conclusions (1)

- **The models have better predictive performance than individual claims-based disability flags**
- **Predictive performance is better for those age 65 or older than for those age 18 to 64**

Conclusions (2)

- In many ways, false positives are similar to true positives, and false negatives are similar to true negatives
- Who is missed (false negative)?
 - Obese people (age 65+)
 - Dual eligibles (age 18–64)
- Who gets a false alarm (false positive)?
 - Beneficiaries with high service use

Future Research (1)

- **More complete specifications may improve predictive performance of the models**
- **Additional data on service use may also improve performance (e.g., Medicaid services, types of prescriptions, number of home health visits)**

Future Research (2)

- **Inclusion criteria can be tailored for other subgroups and/or disability measures**
- **Other matches of administrative and survey data may facilitate targeting of additional populations (e.g., CDC's NCHS—CMS linked files)**

For More Information

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