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State Health Access Reform Evaluation

shadac
State Health Access Data Assistance Center

Prospective Benefit Design
for the Medicaid Expansion Population:
The Predictive Capacity of Self-Reported Health Measures

October 16, 2013

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Introduction & Overview

About SHARE

State Health Access Reform Evaluation (SHARE)

- National Program of the Robert Wood Johnson Foundation

- Part of the Foundation's Coverage Team

- Operates out of the State Health Access Data Assistance Center (SHADAC)

- 33 research grants awarded since 2008

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Grant Support

Robert Wood Johnson Foundation

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Today's Speaker

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Predicting High-Need Cases among New and Returning Adult Medicaid Enrollees:
The Promise of Self-Reported Health Measures

SHARE Webinar, October 16, 2013

Lindsey Leininger

Assistant Professor, University of Illinois-Chicago

Division of Health Policy and Administration

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Acknowledgements

Collaborators
- Donna Friedsam, Tom DeLeire, and Kristen Voskuil (Wisconsin study)
- Marguerite Burns and Laura Wherry (national survey data study)

Funder
- RWJF SHARE initiative

Disclaimer

Findings/conclusions do not necessarily reflect the opinion of the Robert Wood Johnson Foundation or the Wisconsin Department of Health Services.

Research Objective

- Test the usefulness of self-reported health (SRH) measures in informing program design for adults in Medicaid
  - Focus: childless adult population and parents

- Key test of usefulness: how well a model prospectively classifies "at risk" individuals
  - Application: case finding
  - Outcomes of interest: high ER utilization; hospitalization; high cost

Preview of Results

- Predictive models incorporating SRH measures demonstrate acceptable predictive performance for use in case-finding applications
  - Performance approaches that achieved with claims and/or encounter-based algorithms

- Collecting self-reported health measures at application is a promising practice with respect to building predictive models for new and returning Medicaid enrollees

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Background and Motivation

- CBO estimates that ACA will lead to 13 million new individuals entering into Medicaid/CHIP beginning in 2014

- Steady state estimates suggest that expansion population will churn between Medicaid, exchanges, and group market

- Resulting issue: "no history"

- Consequences: inability to prospectively profile "no history" population
    - Case finding

leveraging IBM text analytics to mitigate risk in healthcare

how big data analytics reduced Medicaid re-admissions

Medicaid Analytics Promote Effective Care and Better Outcomes

Identify High-Risk and Impactable Medicaid Beneficiaries for Care and Disease Management

Managing the Medicaid Enrollment Surge Starts Today

Predictive analytics help states plan and create targeted programs for 2014

States have an abundance of data. Even as they work on connecting systems, a variety of data exists today in Medicaid systems and related health and human services. Predictive analytics can be an important strategy in planning for 2014 populations. Predictive modeling uses data-driven decision-support tools to estimate an individual's future potential health care costs[7] and is viewed as a viable tool to help states make educated estimates about future enrollment needs.

Medicaid Best Buys: Using Predictive Modeling to Pinpoint "High-Opportunity" Medicaid Beneficiaries

Data Analysis Considerations to Inform Medicaid Health Home Program Design

TECHNICAL ASSISTANCE BRIEF

JUNE 2012

Quote #1:

"If available, use risk scores or predictive modeling to identify the population at high medical risk and likely well-suited for enrollment in a health home."

Quote #2:

"Data from health risk assessments are also valuable in identifying people at high risk."

BADGERCARE+

July 1, 2008
Waiver Proposal

Low-income childless adults are the most chronically uninsured people in Wisconsin. They are individuals and married couples between the ages of 19 and 64 who are not pregnant, disabled, or qualified for any other Medicaid, Medicare or SCHIP program. They have income that does not exceed 200% of the federal poverty level (FPL) and do not have any children under age 19 under their care. While 60% of them work, they do not have access to employer subsidized insurance. With the expansion of BadgerCare Plus, an estimated 81,000 uninsured childless adults will have access to affordable health insurance beginning January 1, 2009.

Target population: **81,000** uninsured childless adults. Roll-out: 2009

Childless adults enrolled in BadgerCare Plus will have access to basic health care services including primary and preventive care and generic drugs in the form of a Core benefit plan. Childless adults will pay nominal co-payments for non-institutional services and $5 for generic drugs. The Core benefit will be much less comprehensive than traditional Medicaid. An employer or other public entity

Basic "Core" Benefit

Expanding BadgerCare Plus to childless adults will be budget neutral, as required for an 1115(a) waiver of federal law.

NOT an entitlement. Enrollment suspended 10/2009.

Budget neutrality required

The benefit for childless adults is not an entitlement. Therefore, Wisconsin will maintain the flexibility to manage the childless adults benefit within the state's overall DSH allocation during each year of the waiver.

Please check the box for any medical condition that John has right now.

☐ Asthma   ☐ Emphysema

☐ Cancer   ☐ Heart Problems

☐ COPD (Chronic Obstructive   ☐ High Blood Pressure
Pulmonary Disease)

☐ Depression   ☐ Stroke

☐ Diabetes

* Does John feel that he/she has a problem with his/her use of alcohol or   ○ Yes ○ No
drugs?

* In the last two years, has John been hospitalized or had other medical   ○ Yes ○ No
care for emotional or psychiatric reasons?

* Does John take more than 5 prescription medications?   ○ Yes ○ No

* Does John use tobacco?   ○ Yes ○ No

* Does John have a regular doctor?   ○ Yes ○ No

* Does John have a regular clinic or hospital?   ○ Yes ○ No

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You told us that John has asthma.

* Has John been to the emergency room in the past 12 months because of asthma?   ○ Yes ○ No
* Has John been hospitalized in the past 12 months because of asthma?   ○ Yes ○ No

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Innovation

- Collecting self-reported health measures at the time of enrollment
  - Novel use of Medicaid enrollment systems

- No empirical evidence (to our knowledge) about quality of resulting data

- Potential benefits large
  - Low marginal cost relative to other modes

Hypothesis

- H_1: In using a combination of self-reported health and sociodemographic measures collected at application, Medicaid programs could build their own models that perform at the level of accepted quality thresholds

Data and Sample

- Merged administrative enrollment and claims data (CARES + InterChange)

- Sample filters
  - Entered coverage between July – October 2009
  - Enrolled for at least 1 full year (> 90%)
  - Completed an HNA
    - 64% of all Core Plan members entering coverage during this time period

- *N* = 34,087

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Outcomes

- Any inpatient stay (9%)

- Top decile ER utilization (3 or more visits)

- Top cost decile (> $6360)

- Correlations:

	Inpatient	ER	Cost
Inpatient	1		
ER	0.2639	1	
Cost	0.5687	0.2640	1

Predictors

- Baseline block of sociodemographic predictors from CARES
  - Age, age ^ 2, sex
  - Race, Hispanic ethnicity, income

- Six blocks of HNA predictors
  - Conditions
  - Behaviors
  - Prescriptions
  - Access to care
  - Previous year's utilization
  - All HNA measures

Methodology

- Test of discriminative ability: c – statistic

- What is the c – statistic?!
  - Plot of sensitivity (true positive rate) versus 1 – specificity (false positive rate)
  - Ranges between 0.5 – 1
  - Threshold: > 0.7 is "acceptable"

Descriptive Statistics

- Mean age: 42

- Female: 51%

- Income distribution
  - 60% below 100% FPL
  - 80% below 138% FPL

- Race/ethnicity
  - 78% white
  - 4% Hispanic

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More Descriptive Statistics

- Approximately ½ of sample report having at least one condition
  - Most prevalent: high blood pressure, depression, asthma, diabetes
- 37% report tobacco use
- 10% take 5+ prescription drugs
- 7% had a condition-specific ER visit or hospitalization in the past year

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Results

	High ER	Any Hosp	High Cost
Demographics (baseline)	0.667	0.592	0.610
	(0.654, 0.681)	(0.578, 0.606)	(0.597, 0.624)
Baseline + conditions	0.712 **	0.649 **	0.694 **
	(0.699, 0.725)	(0.634, 0.663)	(0.681, 0.708)
Baseline + behaviors	0.689 **	0.616 **	0.621 **
	(0.676, 0.703)	(0.602, 0.630)	(0.608, 0.634)
Baseline + prescriptions	0.692 **	0.626 **	0.678 **
	(0.679, 0.706)	(0.612, 0.641)	(0.665, 0.692)
Baseline + access	0.668	0.600 **	0.630 **
	(0.655, 0.682)	(0.587, 0.613)	(0.617, 0.642)
Baseline + past yr	0.709 **	0.629 **	0.649 **
	(0.670, 0.722)	(0.615, 0.642)	(0.635, 0.662)
Baseline + all HNA	0.738 **	0.670 **	0.715 **
	(0.725, 0.750)	(0.657, 0.683)	(0.702, 0.728)

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Benchmark: VT Claims Study*

Table 2

Area Under the Receiver Operating Characteristics (ROC) Curve, Evaluated at the 90th Percentile of Cost

Model	Area	95 Percent Confidence Intervals	
		Lower Bound	Upper Bound
CDPS	0.69	0.67	0.70
DCG	0.75	0.74	0.76
ACG-PM™	0.79	0.78	0.80

NOTES: The ROC curve plots sensitivity against 1–Specificity. CDPS is Chronic Illness and Disability Payment System. DCG is Diagnostic Cost Groups. ACG-PM™ is Adjusted Clinical Groups, Predictive Model™.

SOURCE: Office of Vermont Health Access: Medicaid claims data from State fiscal years 2005-2006.

- *Baseline + HNA specification : 0.715 (0.702, 0.728)*

*Citation: Weir, S., G. Aweh, and R.E. Clark. 2008. "Case Selection for a Medicaid Chronic Care Management Program." *Health Care Financing Review* 30(1): 61-74.

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Important Limitations

- Non-universal administration of HNA

- HNA omitted several of most predictive self-reported health measures
  - GSRH
  - Functional/activity limitations
  - All-cause utilization over past year

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KEY QUESTION:
What measures should be included in HNA?

Data, Sample, and Outcome Measures

- 1997-2008 rounds of National Health Interview Survey (NHIS) linked with 1998-2009 rounds of the Medical Expenditure Panel Survey (MEPS)

- Sample chosen to approximate the ACA adult Medicaid expansion population
  - n = 6,615 adults ages 19-64 with family incomes < 138% FPL

- Outcome measures: any inpatient visit; top ER utilization decile (2+); top cost decile

Study Design

Baseline Predictors: NHIS interview

t_{-1} t_0 t_1

12-Month Utilization: First year MEPS
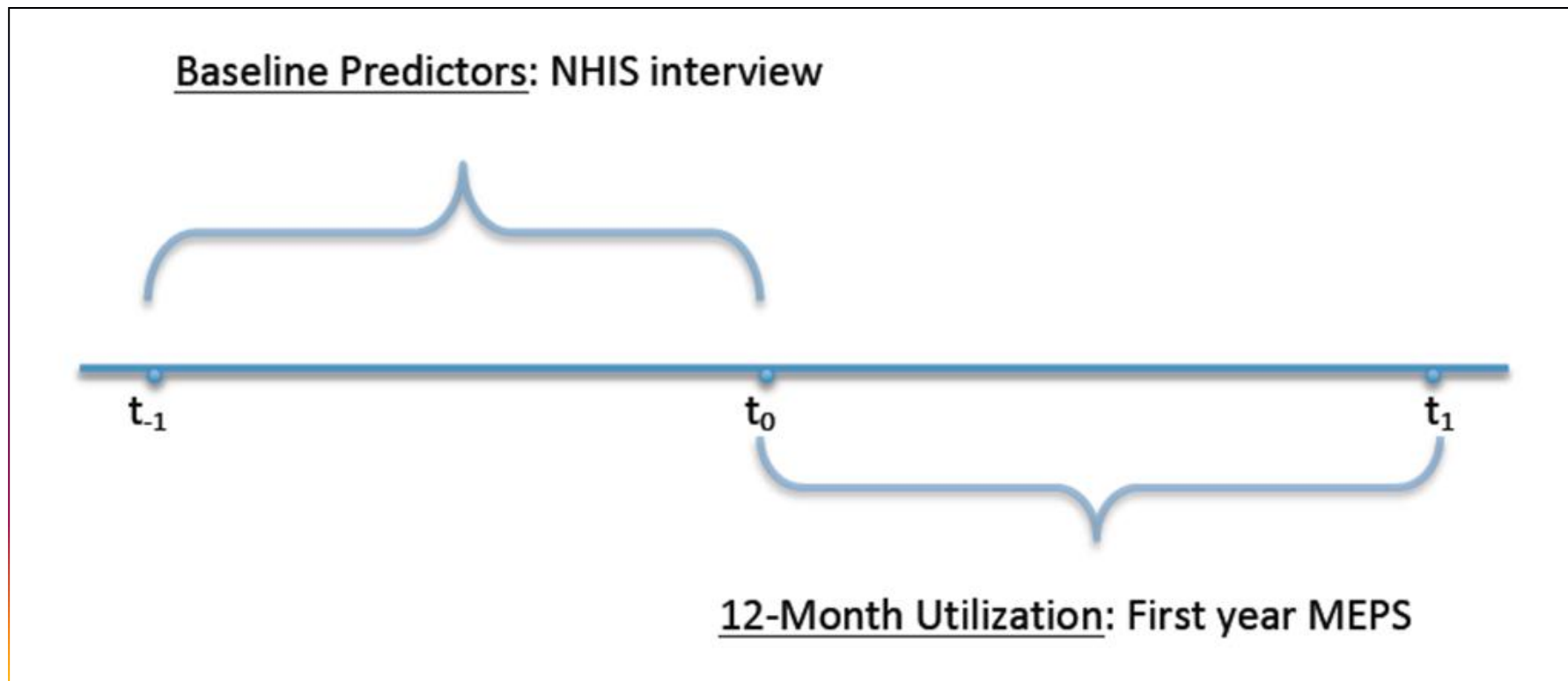
Predictors

- Baseline: sociodemographic characteristics collected as part of the Medicaid application

- Candidate domains:

  - Presence of health conditions

  - Mental health

  - Access to care

  - Health-related behaviors

  - Health-related quality of life

  - Prior year's medical care utilization

Results

	High ER	Any Hospitalization	High Cost
Model 1: Baseline	0.600	0.663	0.690
	(0.555, 0.649)	(0.606, 0.678)	(0.647, 0.729)
Model 2: Baseline + conditions	0.654**	0.686*	0.705
	(0.599, 0.685)	(0.629, 0.701)	(0.664, 0.743)
Model 3: Baseline + mental health	0.603	0.664	0.699
	(0.564, 0.658)	(0.610, 0.683)	(0.634, 0.742)
Model 4: Baseline + access	0.610	0.669	0.693
	(0.568, 0.658)	(0.595, 0.669)	(0.653, 0.734)
Model 5: Baseline + behaviors	0.629	0.674	0.693
	(0.567, 0.660)	(0.609, 0.683)	(0.648, 0.736)
Model 6: Baseline + HRQOL	0.644**	0.697**	0.729**
	(0.600, 0.690)	(0.633, 0.704)	(0.687, 0.772)
Model 7: Baseline + prior utilization	0.676**	0.706**	0.746**
	(0.615, 0.705)	(0.652, 0.732)	(0.706, 0.780)

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	(0.615, 0.705)	(0.652, 0.732)	(0.706, 0.780)

Results:
Conditions + HrQOL + Prior Year Utilization

- ER outcome: 0.703

- Hospitalization outcome: 0.711

- Cost outcome: 0.751

Conclusions

- Nationally representative data replicate findings from WI case study
  - SRH measures are adequately predictive of utilization and cost outcomes to comprise predictive tool

- Optimal SRH measures for predictive purposes:
  - Prior year's health care utilization
  - Health-related quality of life (general health status + activity limitations)
  - Checklist of chronic conditions

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Limitations

- Achieving universal completion can be tricky

- Predictive modeling **≠** a silver bullet that perfectly predicts high-need!!

- Must recognize that HNAs often serve several purposes

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Ending on a hopeful note…

- It is encouraging that a simple, self-reported health screener can predict the need for case management among Medicaid-eligible adults!
    - No proprietary algorithms needed
    - Strongly believe that agencies can implement this in-house
- We are willing to share the items comprising the best-performing domains with anyone who wants them – for free! We are also willing to consult with interested non-profit and public sector stakeholders who want to implement an HNA for predictive purposes – for free!

Question & Answer

Submit questions using the chat feature on the left-hand side of the screen.

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Prospective Benefit Design for the Medicaid Expansion Population: The Predictive Capacity of Self-Reported Health Measures

- Direct inquiries to Carrie Au-Yeung at butle180@umn.edu

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