Evaluating the Role of Past Clinical Information on Cost Risk Adjustment

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No Disclosures

Collaborators

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Outline

- Risk adjustment
- Overview of Nosos
- Incorporating clinical memory

Risk Adjustment and the VA

- What is risk adjustment?
- Why use risk adjustment?
  - Operations/payment
  - Health services research

Risk Adjustment Systems

- Non-VA Systems
  - Verisk Risk Smart/Risk Solutions (DxCG)
  - Charlson comorbidity index
  - Elixhauser
  - CMS Risk Adjustment Model (V21)
- VA systems
  - CAN score
  - Nosos

Poll

What is your role in the VA?

(Select all that apply)

A. Operations
B. Clinical
C. Research

Poll

Which of these have you worked with?

(Select all that apply)

A. Charlson comorbidity index
B. Elixhauser
C. CMS Risk Adjustment Models
D. CAN score
E. Nosos

Nosos

- Nosos is the Greek word for ‘chronic disease’
- Borrows from CMS risk adjustment
  - Uses CMS V21/V22 Hierarchical Condition Category (HCC) risk score
  - ICD 9/10 codes, age, gender to compute a single risk score
- Adds additional variables, and outperformed CMS risk adjustment models

Nosos Components

- Demographic information
- CMS V21 HCC risk score
- Mental health conditions
- Pharmacy records
- Insurance status
- VA priority status
- VA registry information
- **Nosos only uses information from one single fiscal year**

Nosos: Two Versions

- Concurrent
  - E.g. Uses 2015 FY info to predict 2015 FY costs
  - Explanatory
  - Can be used to measure health system performance
- Prospective
  - E.g. Uses 2015 FY info to predict 2016 FY costs
  - Predictive
  - Can be used to allocate future payments

Interpretation of Nosos

- Nosos produces a single risk score
- Risk scores are centered at 1
- Interpretation
  – Nosos = 1: Annual cost expected to be the national average for VA patients
  – Nosos = 3: Annual cost expected to be three times the national average for VA patients

Can we do better?

- Why rely only on diagnostic information from one fiscal year alone?
- Does adding prior years of diagnostic information improve risk prediction?

Why Clinical Memory Might Help Risk Adjustment?

- Mechanism 1: Additional years may predict intensity of disease
- Mechanism 2: Additional years may fill in "coding gaps"
- Some evidence it may modestly improve risk adjustment for mortality
  - Preen J Clin Epid 2006, Zhang Med Care 1999, Dobbins J Clin Epid 2015

VA coding fidelity

- Peabody et al. Medical Care 2004
  - Standardized patients visited 3 sites
  - Primary diagnosis incorrect for 43% of visits
    - 15% physician made incorrect diagnosis
    - 22% data entered incorrectly

Coding Gaps

- Patients with diagnostic info 2011-2015
- We labeled HCCs as chronic and identified coding gaps
- Conditions that were coded in two end years but not the middle year(s)
- E.g. Patient has HIV coded in 2011, 2012, and 2014 but NOT in 2013

Examples of coding gaps

HCC Indicator	% Patients with Coding Gap
HIV/AIDS	5%
Parkinsons/Huntingtons Dz	8%

Examples of coding gaps

HCC Indicator	% Patients with Coding Gap
HIV/AIDS	5%
Parkinsons/Huntingtons Dz	8%
Dialysis status	11%

Examples of coding gaps

HCC Indicator	% Patients with Coding Gap
HIV/AIDS	5%
Parkinsons/Huntingtons Dz	8%
Dialysis status	11%
Cirrhosis	15%
Congestive Heart Failure	15%
Paraplegia	16%
COPD	17%

Analytic overview

- Two Models
  - Concurrent model
  - Prospective model
- Two Approaches
  - Aggregated HCC risk score
  - Individual HCC risk indicators
- Three Comparisons
  - Base year clinical info (e.g. 2015)
  - Expanded clinical memory (e.g. 2011-2015)
  - Expanded clinical memory with coding gaps imputed
- 5-fold cross-validation used

Results: Concurrent Model

Aggregated HCC risk score

Model	R^2	MSPE
2015	0.6811	1966
2011-2015	0.6794	2144

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Individual HCC risk indicators

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2015	0.7059	1966
2011-2015	0.7033	1831

Results: Concurrent Model

Aggregated HCC risk score

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2015	0.6811	1966
2011-2015	0.6794	2144
2011-2015, gaps imputed	0.6790	2147

Individual HCC risk indicators

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Results: Concurrent Model

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Individual HCC risk indicators

Model	R^2	MSPE
2015	0.7059	1966
2011-2015	0.7033	1831
2011-2015, gaps imputed	0.7074	1805

Results: Prospective Model

Aggregated HCC risk score

Model	R^2	MSPE
2014	0.3336	4295
2011-2014	0.3475	4414

Results: Prospective Model

Aggregated HCC risk score

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Individual HCC risk indicators

Model	R^2	MSPE
2014	0.3508	4181
2011-2014	0.3634	4307

Results: Prospective Model

Aggregated HCC risk score

Model	R^2	MSPE
2014	0.3336	4295
2011-2014	0.3475	4414
2011-2014, gaps imputed	0.3482	4419

Individual HCC risk indicators

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Results: Prospective Model

Aggregated HCC risk score

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Individual HCC risk indicators

Model	R^2	MSPE
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2011-2014	0.3634	4307
2011-2014, gaps imputed	0.3734	4032

Conclusions

- Adding additional years did NOT improve risk adjustment. Why?

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  - Past clinical information is **not useful for predicting costs** (whereas it may be for predicting outcomes)

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  - Past clinical information is **not useful for predicting costs** (whereas it may be for predicting outcomes)
  - For newer adjustment tools (Medicare HCC), the **marginal gain is small**

Conclusions

- Adding additional years did NOT improve risk adjustment. Why?
  - Past clinical information is **not useful for predicting costs** (whereas it may be for predicting outcomes)
  - For newer adjustment tools (Medicare HCC), the **marginal gain is small**
  - **Heterogeneity in disease progression** renders historical ICD data a suboptimal predictor

Conclusions

- Further improvements may require new variables:
  - Socioeconomic status
  - Markers of disease severity (e.g. cancer staging, heart failure/COPD staging)
  - Measures of frailty

Thank You

A New GLM Cost Model for Risk Adjustment

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Disclaimer

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Poll

What models have you used for cost risk adjustment? (Select all that apply)

A. Linear regression of Log-transformed costs
B. Linear regression of Square-root-transformed costs
C. GLM with logarithm link function for mean cost
D. GLM with square-root link function for mean cost
E. Other models

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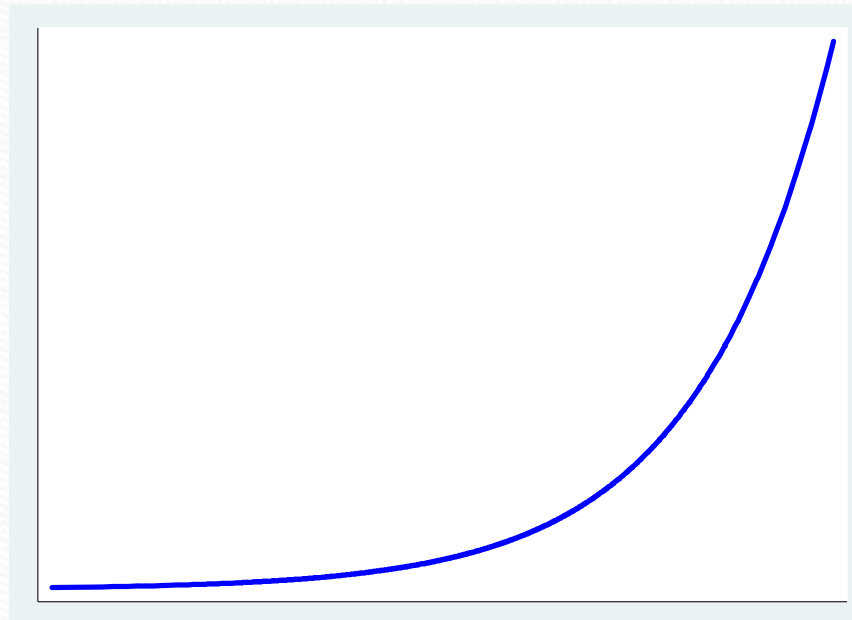
Generalized Linear Models



Generalized Linear Model

$$h(E(y \mid X)) = \beta' X$$

h = Link function that connects conditional mean to linear combination of predictors.

f = Distribution family.

$$y \sim f(y; \theta(X))$$

Estimation by Maximum Likelihood.

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Generalized Linear Model

Example—Log-link function, Gamma family:

$$\ln(E(y \mid X)) = \beta' X$$

$$E(y \mid X) = e^{\beta' X}$$

$$y \sim Gamma(\alpha, \beta)$$

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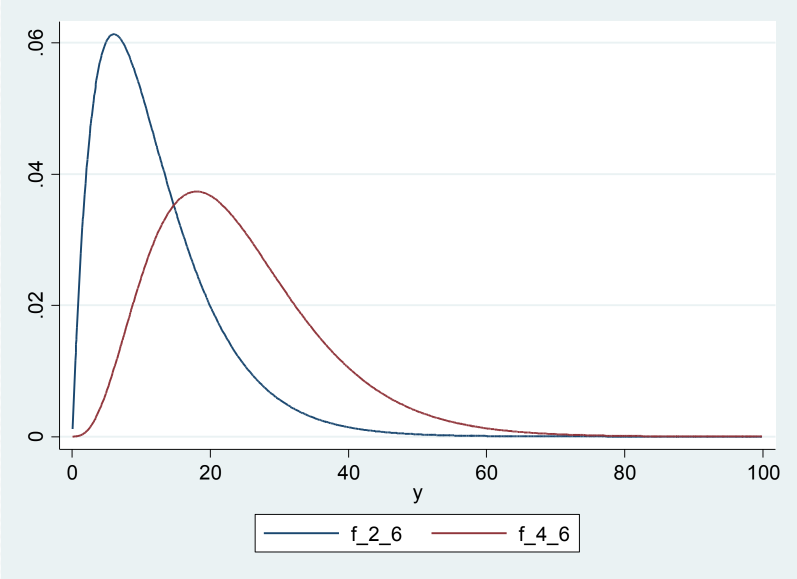
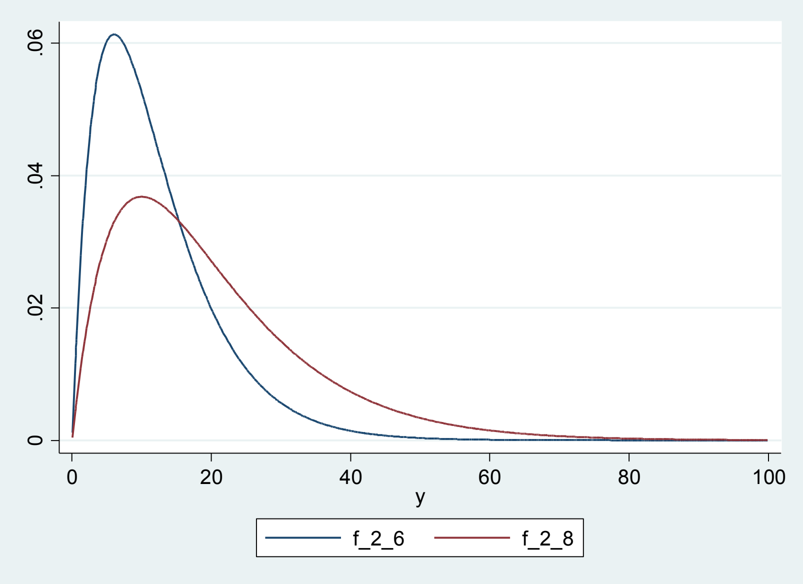
Gamma Distribution

- Shape parameter $\alpha > 0$



- Scale parameter $\beta > 0$



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Mean and Variance

$$E(y) = \alpha \cdot \beta$$

$$V(y) = \alpha \cdot \beta^2$$

Variance proportional to the mean squared:

$$V(y) = \frac{1}{\alpha} \cdot E(y)^2$$

Variance directly proportional to the mean :

$$V(y) = \beta \cdot E(y)$$

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Conditional mean (Regression function)

Regressors influence through the scale parameter

$$E(y \mid x) = \alpha \cdot \beta(x)$$

Regressors influence through the shape parameter

$$E(y \mid x) = \alpha(x) \cdot \beta$$

Regressors influence through both parameters

$$E(y \mid x) = \alpha(x) \cdot \beta(x)$$

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Standard Model (e.g. SAS and STATA GLM programs)

Regressors influence through the scale parameter

$$E(y \mid x) = \alpha \cdot \beta(x)$$

Variance proportional to the mean squared

$$V(y \mid x) = \frac{1}{\alpha} \cdot E(y \mid x)^2$$

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Different Specifications

Standard (e.g. SAS, STATA)

$$E(y\,|\,x) = \alpha \cdot \beta(x)$$

$$V(y\,|\,x) = \frac{1}{\alpha} \cdot E(y\,|\,x)^2$$

Alternative

$$E(y\,|\,x) = \alpha(x) \cdot \beta$$

$$V(y\,|\,x) = \beta \cdot E(y\,|\,x)$$

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Poll

Is misspecification a problem?

A. Yes
B. No
C. Not sure

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Different Specifications

Standard (e.g. SAS, STATA)

$$E(y \mid x) = \alpha \cdot \beta(x)$$

Alternative

$$E(y \mid x) = \alpha(x) \cdot \beta$$

The Problem

$$V(y \mid x) = \frac{1}{\alpha} \cdot E(y \mid x)^2$$

$$V(y \mid x) = \beta \cdot E(y \mid x)$$

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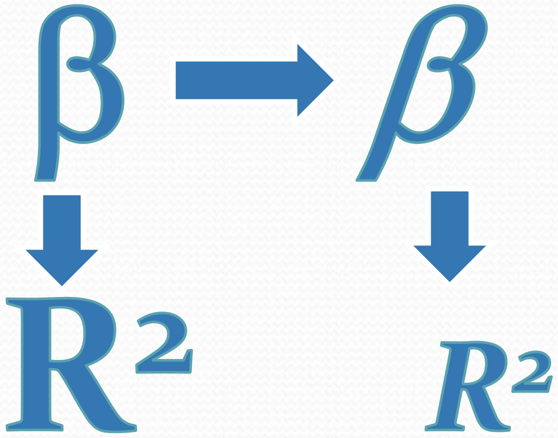
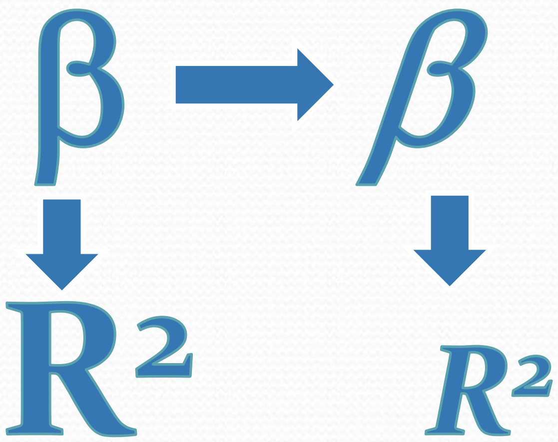
Why is this the problem?

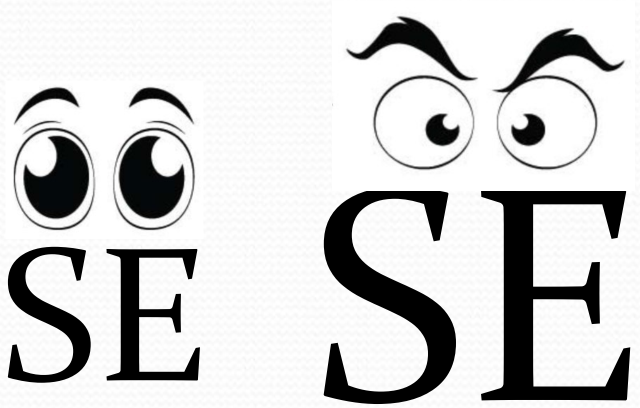
- Maximum Likelihood Estimation
  - Will adjust the **parameter estimates** to match the moment condition (Variance proportional to the Mean squared)



Why is this the problem?

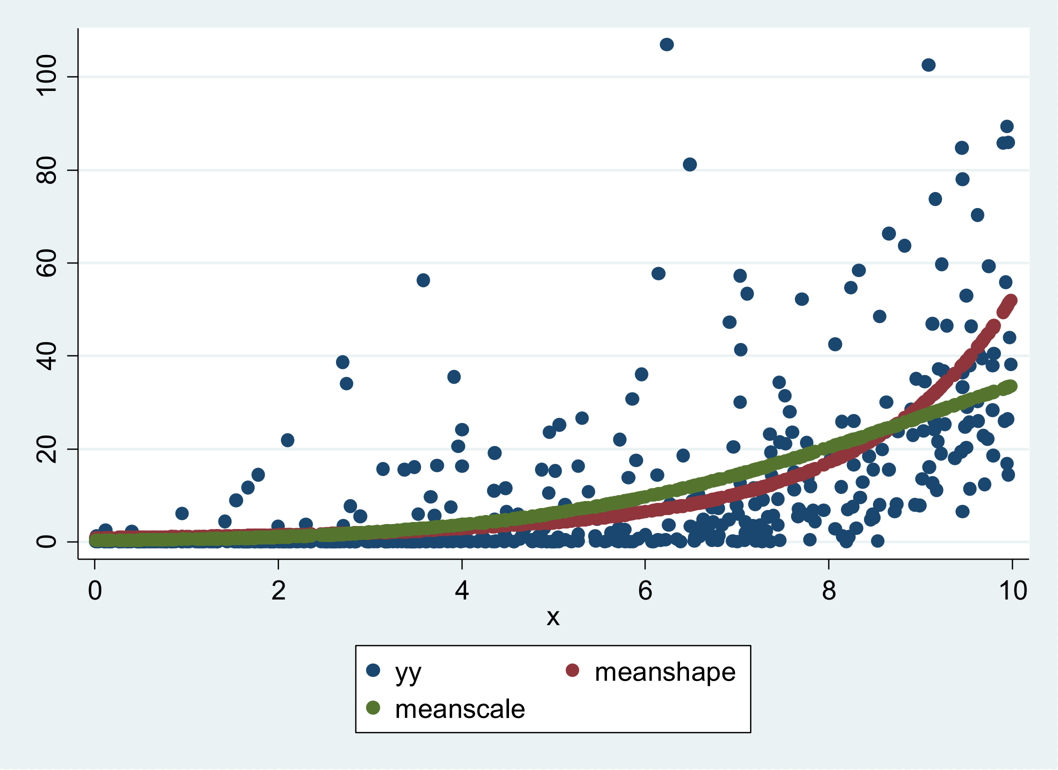
- Maximum Likelihood Estimation
  - Will adjust the **parameter estimates** to match the moment condition (Variance proportional to the Mean squared)
  - **Standard errors** will be affected by misspecification





Monte Carlo Sample

$$E(y \mid x) = \left(\underbrace{e^{0.2 \cdot x + 0.01 \cdot x^2 - 2}}_{\alpha(x)} \right) \cdot \underbrace{e^3}_{\beta}$$



60 Monte Carlo Samples

	Average of coefficient estimates			Average of standard errors	
N	true	bshape	bscale	seshape	sescale
60	0.20	0.20	0.22	0.056	0.158

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Z = 3.0

Z = 1.39

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FY2017 VA Cost Data

GECDAC Core file: VA data from inpatient, outpatient and fee-basis files, cleaned Managerial Cost Accounting costs, enrollment and vital status for 2017. Medicare inpatient, Carrier and certain outpatient claims supplemented VA diagnoses.

Dependent variable: Total CPI adjusted VA cost.

Predictors: Nosos score variables--comprising age, age squared, indicators of being white, being male, having insurance, and being married, priority status group indicators, drug class indicators, mental health CMS hierarchical condition categories (HCC) indicators, and the HCC indicators from the V21 HCC score.

		Never institutional in FY2017				
		Overall	GEC Cohort	HBPC	JFI < 6	JFI ≥6
R^2	GLM-Scale	-19.72	0.38	0.45	-1.98	0.07
	GLM-Shape	0.49	0.60	0.60	0.34	0.36
Max Error	GLM-Scale	56,250	45,850	24,818	17,217	46,152
	GLM-Shape	-8,353	-9,505	-11,892	-1,059	-9,214

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Negative R^2?

$$\hat{R}^2 = R^2 - \frac{\sum (E(y|x) - \hat{y})^2}{\sum (y - \bar{y})^2}$$

Regression model misspecification

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Poll

Do you use STATA as statistical analysis software?

A. Yes

B. No

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How to estimate?
STATA Code

```
program mlfgamma_beta
version 14
args lnf xmean xbeta
quietly {
        tempvar m a b
        g double `m' = exp(`xmean')
        g double `b' = exp(`xbeta')
        g double `a' =`m'/`b'
        replace  `lnf' =
        ln(gammaden(`a', `b', 0, $ML_y1))
} //endquietly
end
```

12 lines of code

```
ml model lf mlfgamma_beta (mean: DEPV = INDV) (beta:)
ml max
```

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Conclusions

- The alternative Gamma GLM model can outperform the standard Gamma GLM

- Of course, other models may perform better in any given situation—need to check.

- NOTE: The alternative implies variance proportional to mean, therefore cannot infer "Not Gamma" from Modified Park Test (lnr2 = a + b*lnyhat: 2 implies Gamma, 1 implies Poisson)

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Thank you!

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