

## Population-based Health Services Research in the Era of Big Data

Leighton Chan, MD, MPH  
Chief, Rehabilitation Medicine  
Department  
Clinical Center  
NIH

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## Disclosures

- No financial disclosures

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## A "new" era: BIG DATA

- Advances in computing power-IBM Watson
- Increasing data capture- EMR
- We can use these data to:
  - Provide "decision support" to providers
  - Inform policy

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### Types of Data

- Structured: highly organized data containing pre-defined elements with standardized relationships to one another (e.g., data in a database)
- Unstructured: data that is not structured in a pre-defined manner
  - Clinical notes, Faxed documents
  - **Anything written in narrative**
- **Majority of medical data is unstructured**

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### Where Does Data Come From?

- Primary Data – generated for research purposes, including national surveys and disease registries
- Secondary Data – Secondary data is administrative/billing/encounter data
  - Often generated with utilization in mind
  - Enough data to make meaningful population-base conclusions

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### Common Sources of Secondary Data

- Populations:
  - Medicare (54 million)
  - Integrated health systems (e.g., Kaiser, 10 million)
  - Medicaid (55 million)
  - Pharmacies
- Billing /encounter/administrative data
  - Electronic Medical Record (RMR)

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### Why Study Medicare Patients?

- Largest purchaser of health care in the world
  - 54 million enrollees
  - \$613 billion in expenditures in 2014
- The percentages
  - **Almost 16% of U.S. budget outlays**
  - 22% of all health care dollars in US
  - 26% of hospital spending
  - 22% of nursing home spending
  - 22% of physician billings
- Single data system

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### Who are Medicare patients?

- 83% age > 65
- <1% ESRD
- 16% disabled
- 20% in an HMO

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### Medicare

- FFS beneficiaries health care costs ~\$8,000/yr
- Costs/beneficiary rise ~7 percent/yr
- Part A trust fund depletion projection: 2030

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### Organization of Medicare Data: Files

- Hospital stays
- Physician visits (inpt & outpt)
  - specialty
  - experience
- SNF, DME, & Home Health
- Hospital level data: size, non-profit status, staffing, etc.

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### Organization of Medicare Data: Variables

- Patient demographics:
  - age, sex, race, zip code
- Primary Diagnosis(ICD-9)
- Associated co-morbidities
- Procedure codes - CPT-4 & HCPCs

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### Organization of Medicare Data: Variables

- Hospitalization and Rehospitalization
- Sentinel Events
- Length of Stay
- Disposition
- Mortality
- Pharmacy use
- Costs

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### Benefits of Medicare Data

- Pre-existing data
  - less expensive
  - less time
- large numbers of cases
  - Generalizability
- Links to other data
  - Zip codes, SSN
- Accurate measure of resource use
- Can measure “effectiveness”

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### Limitations of Medicare data

- Lots of limitations...
  - Limited data on severity of illness
  - Not generalizable to the US working population
  - Coding and billing errors/bias
  - Limited outcome measures of interest
    - No QOL, Patient Satisfaction, functional assessment, illness severity

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### Limitations

- Studies limited to non-experimental design (observational studies)
- Difficult to avoid selection bias
- Impossible to control for all possible confounders (eg. severity of illness & functional status)
- HMO patients are excluded
- Cost of obtaining the data
- Administrative overhead

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### How can I get data access?

- Medicare administrative/billing/encounter data
  - <http://www.resdac.org/about-resdac/our-services>
  - Available through CCW Data Enclave

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### Types of Studies using Medicare data

- Monitoring secular trends
- Measuring disparities
  - Race, ethnicity, SES, geographic variation
- Supporting the evaluation of specific conditions, treatments or procedures

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### Monitoring Secular Trends

- Examine changes in health care over time
- Take advantage of “Natural Experiments”
  - Examine the impact of policy changes
  - e.g., Epidural Steroid Injections for Back Pain
    - 14,000 recently exposed to contaminated steroids

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### Medicare patients 2002-2006

- Nonspecific backache 60.3%
- Degenerative changes 14.7%
- Sciatica 11.8%
- Spinal Stenosis 7.3%

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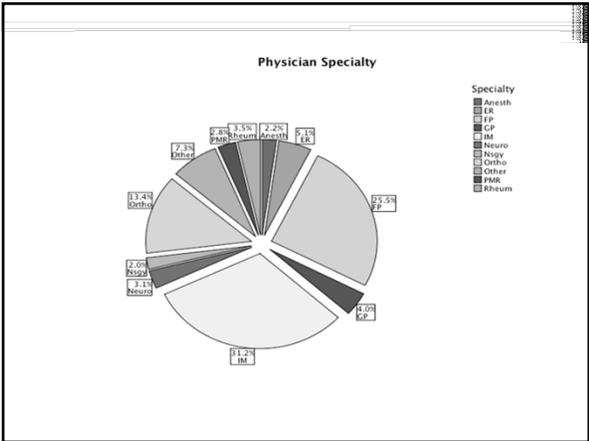
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### LBP Costs

- Deyo, MEPS
- Costs are very high (\$86B)
- Mean adjusted costs
  - 1997 \$4,695 (95% CI, \$4,181-\$5,209)
  - 2005 \$6,096 (95% CI, \$5,670-\$6,522)
  - 30% increase in costs
  - Self-reported measures of mental health, physical functioning, work or school limitations, and social limitations among adults with spine problems were worse in 2005 than in 1997.

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Definitions

Epidural Steroid Injections

Transforaminal



lumbar

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**Are ESIs Effective in LBP?**

Conflicting data on effectiveness of ESIs

- 18-90% success rates
- Few good quality studies (Freidly, 2014)
- No consistency in methods
  - Patient selection
  - Technique used
  - Definition of success
- Recent incidents confirm that the risks of the procedure are greater than suspected

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Methods

- Retrospective Cohort Study
- Medicare claims data
- 1995-2006, 5%-20% sample of physician bills
- Cohorts defined by CPT and ICD-9 codes
  - 62311 Caudal or interlaminar
  - 64483 Transforaminal
  - 64475 Facet Injection
- LBP dx from ICD-9 codes
- Physician specialty from UPIN

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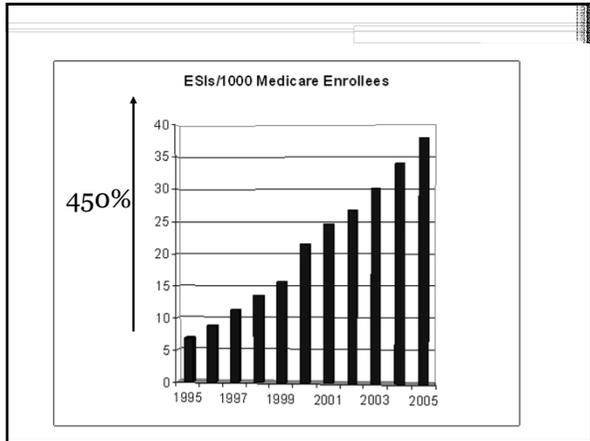
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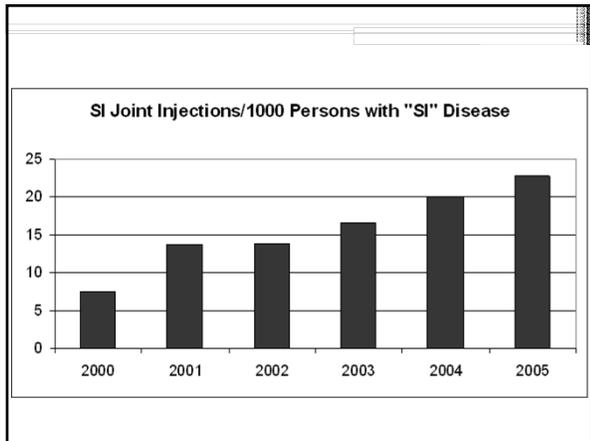
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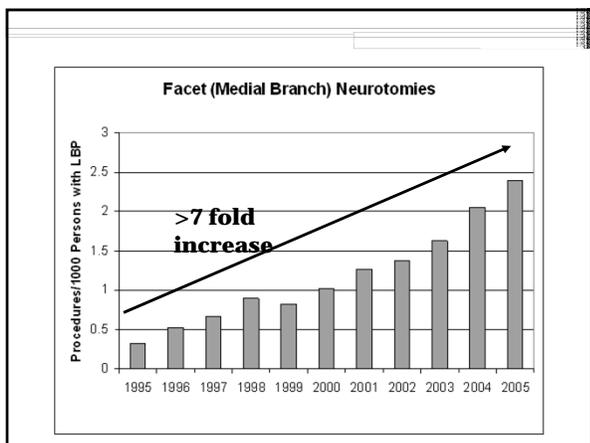
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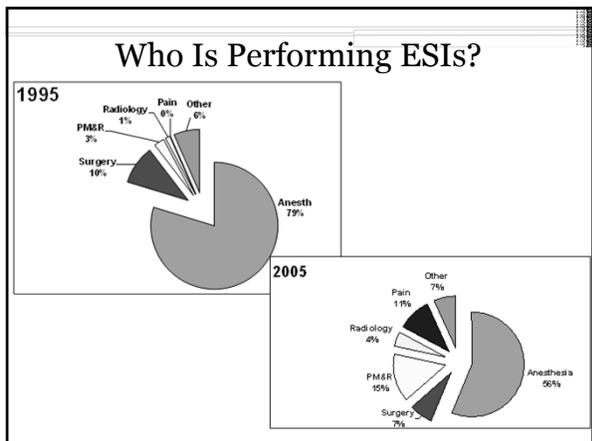
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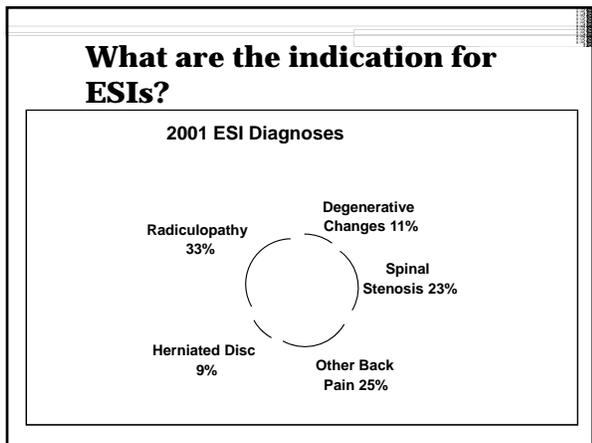
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How much has this increase cost Medicare?

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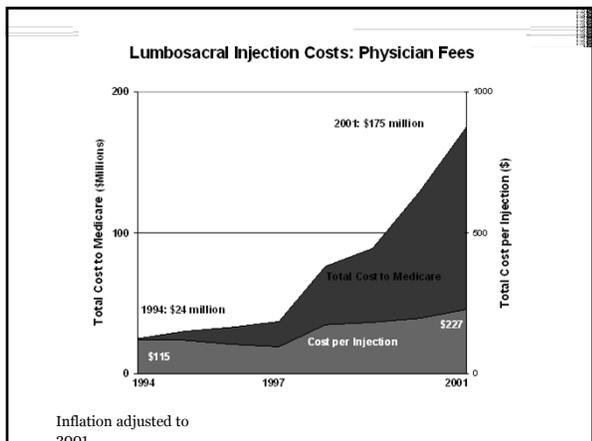
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**Total Estimated Costs**

Physician Professional Fees	\$175 million
+	
<u>Facility Fees</u>	<u>\$275 million</u>
<b>Total Cost to Medicare</b>	<b>= \$450 million</b>

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- Where ESIs are Performed?**
- Outpatient Hospital Clinics
  - Physician Offices
  - Ambulatory Surgical Centers

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### Ambulatory Surgery Centers (ASCs)

Most Medicare certified ASCs are: (n=5,000)

- privately owned
- for profit
- urban locations

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### Ambulatory Surgery Centers (ASCs)

- Supposed to reduce costs by avoiding hospital overhead
- Majority owned by local physician investors
- The Stark self-referral law (1989 Social Security Act) does not apply to ASCs
  - MDs can invest in ASCs and increase revenue by receiving ASC facility payments

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*Ambulatory Surgery Center Symposium • Baltimore, Maryland*

**The Backbone of a Healthy ASC: Chronic Spinal Pain Management as a Revenue Strategy**

*8 am - 5 pm, Wednesday, July 18, 2007*  
*Hosted by Kimberly-Clark & GE Healthcare*

GE Healthcare

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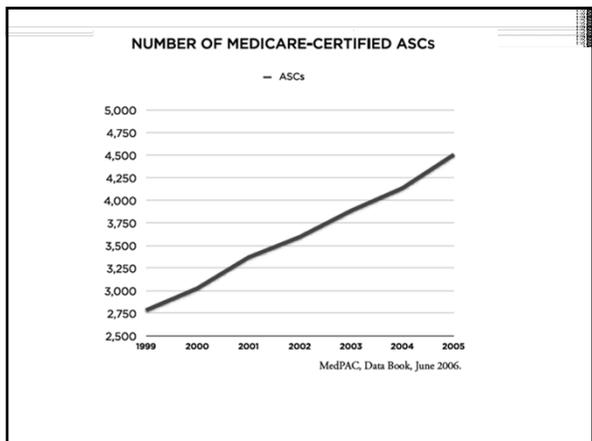
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### ASC Advantages

- More convenient locations, shorter wait times
- Medicare coinsurance is lower than in hospitals
  - (\$9 difference in 2004)
- Customized environments, specialized staffing
- Customer friendly

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### ESIs at ASCs: 1995-2005

1995: 13% of ESIs performed at ASCs

2005: 29% of ESIs performed at ASCs

Facility Type	Percentage
Outpatient Hospitals	53%
Ambulatory Surgery Centers	29%
Physician Offices	18%

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### Results

ASC ESI Facility Payment\*

1995: \$7.5 million  
2005: \$101 million  
>1200% increase

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### Conclusions

- Lots of growth in ESI
- Growth associated with shift in “injectionists”
- Growth associated ASC growth
- Significant cost increases for Medicare
- Do patients benefit?

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### Measuring geographic variation

- Tom Wennberg & Alan Gittelsohn
- Examine procedure rates in different geographic areas
- If rates differ this suggests inequity or inefficiency in practice

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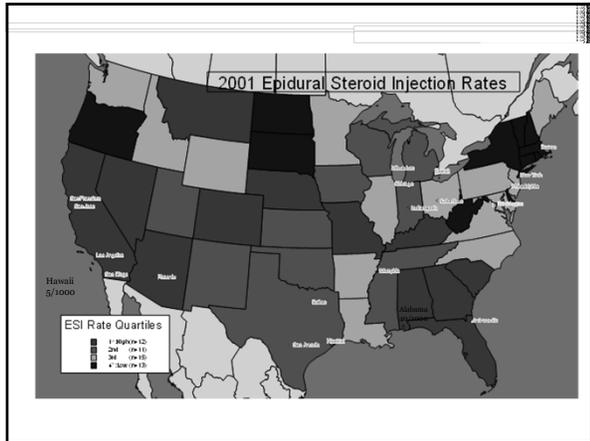
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### Geographic Variations

Health Referral Regions (HRR):

- Smaller geographic regions
- Defined by Dartmouth's Atlas for Health Care (<http://www.dartmouthatlas.org/>)
- 306 HRRs across the country
- Defined by where most of the cardiovascular and neurosurgery is performed

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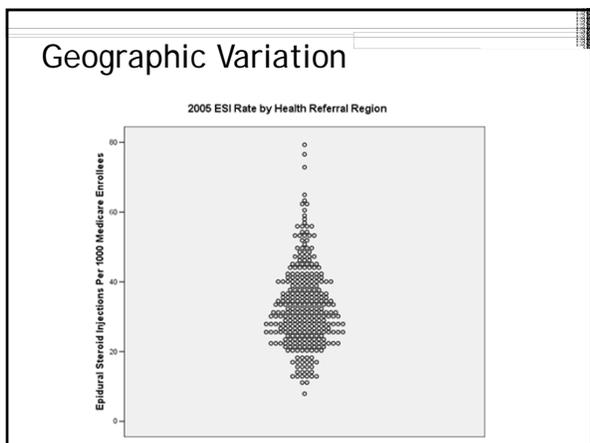
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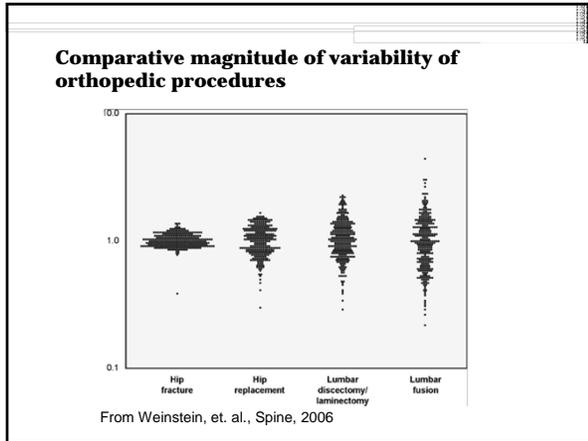
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### 2005 Geographic Variations: Health Referral Regions:

- 9-fold difference in ESIs/1000 patients
  - 7.9/1000 in Honolulu, HI
  - 103.6/1000 in Palm Springs, CA

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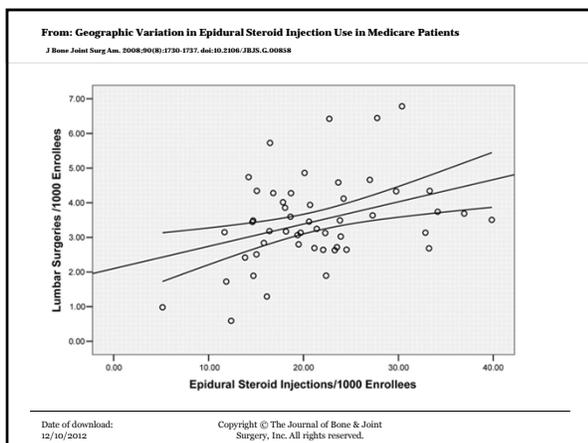
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## Geographic Variations Summary

1. Large geographic variations in ESI use
2. High ESI rates are not associated with lower surgery rates
3. High ESI rates are moderately associated with “injectionist” supply

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## Limitations

- Only study those over age 65 in Medicare
  - No young active workers
  - No HMO patients
- Possible errors in diagnosis/billing codes
- Which ESI rate is right?
  - No data on pain relief
  - No data on return to work
  - No data on functional improvement

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## Unanswered Questions

- Are ESIs effective?
  - How do we select the ideal patients for ESIs?
  - How many should we be doing?
  - How often should we be doing them?
  - Should we be doing them with other treatments? (i.e. multidisciplinary approach)

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### Bariatric Surgical Procedures Mortality Study

- Objective:
  - Evaluate the risk factors of early mortality among Medicare beneficiaries (age, gender, surgeon experience)
  - Determine relative risk of death among older patients
- Retrospective cohort design using Medicare physician bills, (1996-2002), 16,155 cases

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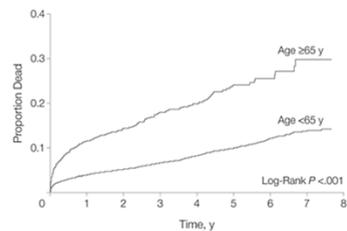
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Survival After Bariatric Surgery by Age Group



Age, y	No. at Risk	1	2	3	4	5	6	7	8
≥65	1517	1350	1126	708	453	282	150	52	
<65	14638	14062	12486	8647	5866	3842	2174	759	

Flum, D. R. et al. JAMA 2005;294:1903-1908.

Copyright restrictions may apply.

JAMA

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### Mortality Rate After Bariatric Surgery, by Age and Sex

Table 2. Mortality Rate After Bariatric Surgery, by Age and Sex

Age Category (y) and Sex	No.	Mortality Rate, %		
		30 Days	90 Days	1 Year
<25				
Women	150	0.7	1.3	2.0
Men	53	0.0	1.9	1.8
Subtotal	203	0.7	1.5	2.0
25-34				
Women	1341	0.8	1.3	2.5
Men	488	2.1	3.3	4.3
Subtotal	1827	1.1	1.8	3.0
35-44				
Women	3288	1.0	1.5	2.7
Men	1121	3.2	3.7	5.6
Subtotal	4409	1.5	2.0	3.4
45-54				
Women	4214	1.1	1.8	3.1
Men	1191	4.5	5.4	7.7
Subtotal	5405	1.9	2.6	4.1
55-64				
Women	2126	2.0	2.5	4.7
Men	668	2.1	3.1	6.9
Subtotal	2794	2.0	2.7	5.2
65-74				
Women	1039	2.6	3.4	6.2
Men	342	5.8	8.2	12.9
Subtotal	1381	3.4	4.6	7.6
≥75				
Women	85	18.8	28.2	40.0
Men	51	19.6	35.3	51.0
Subtotal	136	19.1	30.9	44.1
Total	16155	2.0	2.8	4.6

Copyright restrictions may apply.

Flum, D. R. et al. JAMA 2005;294:1903-1908.

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### Conclusions

- Medicare Claims data is widely used in outcomes research
- The data has significant advantages and disadvantages
- The importance of this data will increase as the US demographics change and Medicare enrollment accelerates

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### CCW Data Enclave

- CMS developed virtual data access for investigators through a new data enclave
- Cost determined by the number of licenses (seats) in the enclave, and not by the amount of data requested
- Users are assigned a dedicated workspace within the CCW Virtual Data Enclave where they can directly access approved CMS data and run analyses in SAS
- Users may:
  - Upload external files to their Data Enclave workspace for use with CMS data
  - Download aggregate, statistical files to their workstations

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### NLP: The Next Big Thing

- Unstructured data
  - There is a lot!
  - Medical history
  - Large numbers of patients
  - Machine learning methods: identify patterns, trends, and long-term changes
- Need input from clinician and a linguist
- Successful pre-processing critical

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## NLP Application to HF

- Identification of Framingham HF criteria in PCP notes
- Based on Unstructured Information Management Architecture (UIMA) framework
- Partnership between IBM T.J. Watson Research Center, Geisinger Medical Center, and Sutter Health

Source: R.J. Byrd, et al., Automatic identification of heart failure diagnostic criteria, using text analysis of clinical notes from electronic health records, Int. J. Med. Inform. (2013), <http://dx.doi.org/10.1016/j.ijmedinf.2012.12.005>

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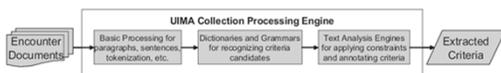
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## NLP Application to HF



- Iterative process: cardiologist, linguist, and coders in partnership
  - Cardiologist and linguist jointly review case files for key words and linguistics
  - Linguist builds NLP tools
  - Joint review of outcomes; extraction improvement
  - Coders create a “gold standard” for comparison

Source: R.J. Byrd, et al., Automatic identification of heart failure diagnostic criteria, using text analysis of clinical notes from electronic health records, Int. J. Med. Inform. (2013), <http://dx.doi.org/10.1016/j.ijmedinf.2012.12.005>

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## Promising Results

- High accuracy in identification of Framingham HF criteria
  - Few false negatives: successfully identified 90% of true positives
  - Few false positives: >92% of cases labeled positive were true positives
- Demonstrates PC notes can be successfully extracted
- Shows potential for early identification methods

Source: R.J. Byrd, et al., Automatic identification of heart failure diagnostic criteria, using text analysis of clinical notes from electronic health records, Int. J. Med. Inform. (2013), <http://dx.doi.org/10.1016/j.ijmedinf.2012.12.005>

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