Changing Healthcare
How can we Harness Predictive Analytics for Patients, Providers and Payers?

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Agenda

1. Introductions
2. Technology-driven Change
4. Actuaries and Predictive Analytics
5. Some Case Examples
7. Questions
Introductions

Ian Duncan, FSA, FIA, FCIA, FCA, MAAA

- Health actuary since 1982; consultant since 1989.
- Founder and former president of PM company, Solucia Consulting (now SCIO Health Analytics) 1998.
- Founder and president, Santa Barbara Actuaries Inc.
- Professor of Actuarial Statistics, University of California Santa Barbara;
- Author of several books and peer-reviewed studies on healthcare management and predictive modeling.
- SOA Board of Directors 2012-5; Massachusetts Health Insurance Exchange board 2007-14.
Technology-driven Change
Technology-driven changes in our lifetimes

Think back over the amazing advances in our lifetimes in technology, medicine, communications – in most industries in fact.

THEN

NOW
Technology-driven changes in our lifetimes

THEN

NOW

A worker from the 1940s would be bewildered by today’s technology
Data has successfully transformed businesses
Data has successfully transformed businesses

What does disruption and transformation of these industries have in common?

**ANSWER**: Through data and technology, activity is transferred to consumers, reducing cost and increasing efficiency and consumer satisfaction.
What has not changed as much?

THEN

NOW

The 1940s worker would feel at home with today’s medical delivery.
Many reasons why we haven’t transformed healthcare

• Medicine is complicated; so are medical data; data is generally big but incomplete.
• The best models aren’t very good yet.
• Professional judgement over-rides analytics.
• We often focus on things that will not produce immediate returns.
• The “Last Mile” Problem.
• The self-management/persistency problem.
• While we have many outcomes studies, it’s hard to know what works.
• It is very difficult to implement and manage an outcome-effective, cost-effective program of sufficient scale.
What hasn’t changed in medicine?

• While medicine has become more technologically-intensive, it is also a very human resource-intensive business.
  • You still have face-to-face (one-on-one) visits to the doctor.
  • Aside from their technology, hospitals are still organized as they were by Florence Nightingale.
• Other industries have used technology to increase consumer power and choice, and to decrease cost. Why not in medicine?

• In part (I submit) because of the way medicine is financed. Either:
  • By large insurance companies, in insurance systems (such as the U.S.) or
  • By national health systems.

• In both cases, decisions are made for the consumer, not by the consumer.
Current Predictive Models aren’t very good

“Most current readmission risk prediction models perform poorly...Efforts to improve their performance are needed.”

....but they are better than humans

- This study assessed the predictions made by:
  - Physicians
  - Case managers
  - Nurses

- “…none of the AUC values were statistically different from chance”

Predictive Modeling in Business helps consumers make better choices, consistent with their long-term goals (cheaper, better products; tailored choices; faster access). The Progressive (and other auto insurers) experience is instructive:

- Progressive (through the use of predictive modeling) identified customers who were classified as high-risk (and assigned to a high-risk pool) but who were predicted to be low-cost.
- Their marketing focused intensely on these customers.
- The company successfully penetrated a profitable market niche.

BUT: They also focused on changing risky behavior in their existing customers.
Which has led to an explosion of devices....

The fair way to pay for car insurance

It is significant that you can change behavior in auto insurance (and benefit from a “fair price”) but not in health insurance.
Since 2015, the National Football League has placed chips under shoulder pads to track exactly where players move. Fans can’t get this data, but teams can. Mr. Hall tells me it can provide “instant analysis to coaches.”
A Failed mHealth Program Offers Lessons Learned For Future Projects

An project to have FQHC patients use an mHealth app to manage their diabetes and hypertension at home collapsed after a few weeks. But researchers say they learned valuable lessons.

- 1/3 of target patients did not download app.
- 12% of patients were regular users.
- Most patients stopped using the app after a few weeks.
- Staff used office visits to train patients in use of smartphones (!).
Why hasn’t data transformed healthcare?

Big Data Mining

A Q&A with one of the leading inventors of tools for medical data analytics.

“I am concerned that it’s all too easy to see the data and say, ‘I’ve been doing big-data analysis for Target and now I can do it for medicine.’ That turns out not to be true. You really need to know something about medicine. If statistics lie, then big data can lie in a very, very big way.”

Isaac Kohane, co-director of the Center for Biomedical Informatics at Harvard Medical Schoo
Change Agents

Payment Reform

Data Analytics

Behavioral Economics
Ultimately, payment reform models in many countries aim to end unlimited healthcare budget growth by transferring financial and clinical outcomes to providers and other risk-takers.

Models include:

- Pay for performance
- Gainsharing
- Accountable Care Organizations
- Bundled Payments
- Patient-centered Medical Homes
- Risk-taking carve-outs
Health Actuaries and Predictive Analytics
Actuaries have been using predictive methods since the profession began.

\[
\mu(x) = \alpha e^{\beta x}
\]

\[
\mu_x = A + B e^x
\]
Actuaries have practiced PM forever....

Identify patterns/segment risks

Develop business rules

Improve decision making

Actuaries have been using predictive methods since the profession began. Examples:

• Mortality Rates (survival functions = parametric predictive models).

![Graph showing fitted models vs. q_x estimates](image)

- **Gompertz**
- **Makeham**

*Estimated probability of a person dying at each age, for the U.S. in 2003 [1].* Mortality rates increase exponentially with age after age 30.
Predictive Analytics Example: Application of Traditional Actuarial (Survival) Models
The Problem

California Office of Self-Insured Work Comp. Plans Medical Reserves
Reserve = Average (past 3 years medical payments) * Future Life Expectancy


Objectives:
1. Test the applicability of the U.S. Life Tables to the Workers’ Comp experience.
2. Determine an appropriate Termination Table for Workers’ Comp Reserves.
   a. Fit models to data using only age as a predictor.
   b. Develop a model using covariates to predict duration of claim
\( \hat{q}_x \) Estimates

- Life Table Estimation \( (q_x) \) for our data
  \[
  \hat{q}_x = \frac{d_x}{l_x - 0.5w_x}
  \]

\( \hat{q}_x \) := Rate of Mortality in Interval \( x \) to \( x + 1 \)
\( d_x \) := Number of Deaths in Interval \( x \) to \( x + 1 \)
\( l_x \) := Number Alive in Interval \( x \) to \( x + 1 \)
\( w_x \) := Number of Deaths + Number Censored in Interval \( x \) to \( x + 1 \)

- Estimates allow us to compare our data with the 2011 U.S. Life Table.
Comparison of 2011 Life Table and Estimates of $q_x$
Gompertz Fitted Model

\[ \hat{q}_x = e^{-7.19859 + 0.08404x} \]

Polynomial Fitted Model

\[ \hat{q}_x = 0.04148 + 1.06074x - 0.15914x^2 + 0.46304x^3 - 0.21410x^4 + 0.40654x^5 + 0.02539x^6 + 0.15662x^7 \]

Quadratic Fitted Model

\[ \hat{q}_x = 0.07755 + 0.72185x + 0.35528x^2 \]

Models selection based on lowest AIC.
Cox Proportional Hazard Models

\( h_{Imputed}(t) \)

\[
= e^{\beta (Entity \ Group) - .000319(Severity)} \\
\times e^{-.00871(Years \ Employed \ at \ DOL) - .532 \ (Gender)} \\
\times e^{-.00144(Body \ Part \ Code) - .007(Age \ at \ DOL)} \\
\times e^{-.000294(Severity*Years \ Employed \ at \ DOL) - .000502*(Severity*Gender)} \\
\times e^{.00883(Gender*Age \ at \ DOL)}
\]

\( h_{No \ Imputation}(t) \)

\[
= e^{\beta (Entity \ Group) + .000223(Severity)} \\
\times e^{-.00775(Years \ Employed \ at \ DOL) - .09736 \ (Gender)} \\
\times e^{-.001989(Body \ Part \ Code) - .00381(Age \ at \ DOL)}
\]
Example: Alternative Payment Model, Predictive Analytics and Behavioral Economics
Accountable Care Organizations

➢ The **Medicare Shared Savings Program** was established by section 3022 of the Affordable Care Act. Congress created this program to better coordinate among providers to ensure quality care for Medicare Fee-For Service beneficiaries and to reduce unnecessary costs.

➢ ACOs share 50% of any savings (projected cost minus actual cost) with Medicare.

➢ Risk adjustment is applied to the comparison population to ensure risk comparability with managed population.
Spending at End-of-Life

12% of Beneficiaries Driving 69% of the Expense

5% of Medicare Beneficiaries die annually.

Second to last year of life represents 13% of the total Medicare FFS spend.

Last year of life represents ~30% of the total Medicare FFS spend.

Other 26%
Over-medicalized death defined as:

- Chemotherapy for cancer patients within 14 days of death
- Unplanned hospitalization within 30 days of death
- More than one emergency department (ED) visit within 30 days of death
- ICU admission within 30 days of death; or
- Life-sustaining treatment within 30 days of death
Cost by Place of Death: Last 6 Months of Life

Figure 5.1.b  Cost by Place of Death and Type for Patients in Last 6 months of life

- Inpatient
- Outpatient
- Hospice
- SNF
- Other
Cost Per Day: Hospital Patients

Figure 5.2.a  Cost per Day – last 3 months of life

Figure 5.2.b  Cost per Day – last 6 months of life
Table 5.5  Medicare Hospice Payment Rates by Type of Service

<table>
<thead>
<tr>
<th>Category</th>
<th>Description</th>
<th>Base payment rate, 2015</th>
<th>Percent of hospice days, 2013</th>
</tr>
</thead>
<tbody>
<tr>
<td>Routine home care</td>
<td>Home care provided on a typical day</td>
<td>$159.34 per day</td>
<td>97.6%</td>
</tr>
<tr>
<td>Continuous home care</td>
<td>Home care provided during periods of patient crisis</td>
<td>$38.75 per hour</td>
<td>0.4</td>
</tr>
<tr>
<td>Inpatient respite care</td>
<td>Inpatient care for a short period to provide respite for primary caregiver</td>
<td>$164.81 per day</td>
<td>0.3</td>
</tr>
<tr>
<td>General inpatient care</td>
<td>Inpatient care to treat symptoms that cannot be managed in another setting</td>
<td>$708.77 per day</td>
<td>1.7</td>
</tr>
</tbody>
</table>

2018 Rates:  $190.55 (Routine Home Care)

By comparison, the 2013 Average Hospital Facility per diem was $1,617.62
Medicare Patients and Deaths (based on 50% of the 5% file)

<table>
<thead>
<tr>
<th>Categories</th>
<th>Members</th>
<th>% of Total Population</th>
<th>PMPM</th>
</tr>
</thead>
<tbody>
<tr>
<td>Survivors</td>
<td>819,189</td>
<td>92.0%</td>
<td>$684.80</td>
</tr>
<tr>
<td>Deceased</td>
<td>71,059</td>
<td>8.0%</td>
<td>$4,323.73</td>
</tr>
<tr>
<td>Appropriate</td>
<td>22,989</td>
<td>2.6%</td>
<td>$2,249.62</td>
</tr>
<tr>
<td>Inappropriate</td>
<td>9,832</td>
<td>1.1%</td>
<td>$3,433.30</td>
</tr>
<tr>
<td>OverMedicalized</td>
<td>38,238</td>
<td>4.3%</td>
<td>$5,797.08</td>
</tr>
<tr>
<td>Total</td>
<td>890,248</td>
<td>100.0%</td>
<td>$975.26</td>
</tr>
</tbody>
</table>

The difference between over-medicalized and appropriate death represents a financial and clinical opportunity. (Inappropriate death also represents an opportunity, although a smaller one).
The PMPMs for members in each category vary across the bands of risk scores. The difference in the costs between those that experience overmedicalized deaths versus those that experience appropriate deaths is greatest in members with risk scores >.95.
Example: Accountable Care Organizations

• The model is accurate in predicting those patients at risk of over-medicalized death.
• The economic model indicates that there are potential gains to the ACO from intervening on this population.
• The quality of care delivered in alternative settings results in less pain or anxiety and fewer side-effects to patients.

What could possibly go wrong with this win-win proposition?

*Hint:* Incentives and Behavioral Economics.

The model overlooks the *last mile problem.*
## Based on Members with Risk Scores >.95

<table>
<thead>
<tr>
<th>Description</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td># of Members (out of 10,000)</td>
<td>341</td>
</tr>
<tr>
<td>% of Members (out of 10,000)</td>
<td>3%</td>
</tr>
<tr>
<td>Over Medicalized Sensitivity</td>
<td>46.0%</td>
</tr>
<tr>
<td>PPV (OM Deaths)</td>
<td>57.9%</td>
</tr>
<tr>
<td># of True Positives (out of 10,000)</td>
<td>197</td>
</tr>
<tr>
<td># of False Positives (out of 10,000)</td>
<td>143</td>
</tr>
</tbody>
</table>

### Estimated Gross Savings

<table>
<thead>
<tr>
<th>Description</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td># of True Positives (a)</td>
<td>197</td>
</tr>
<tr>
<td>Engagement Rate (b)</td>
<td>40%</td>
</tr>
<tr>
<td>Effectiveness Rate (c)</td>
<td>50%</td>
</tr>
<tr>
<td>Potential Savings per True Positive (d), (1)</td>
<td>$15,981</td>
</tr>
<tr>
<td><strong>Estimated Gross Savings (a x b x c x d)</strong></td>
<td>$630,853</td>
</tr>
</tbody>
</table>

### Estimated Net Savings

<table>
<thead>
<tr>
<th>Description</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td># of Members with p&gt;.95 (e )</td>
<td>341</td>
</tr>
<tr>
<td>Engagement Rate (b)</td>
<td>0%</td>
</tr>
<tr>
<td>Cost of Case Management (f)</td>
<td>$940.67</td>
</tr>
<tr>
<td>Total Cost (e x b x f)</td>
<td>$128,234</td>
</tr>
<tr>
<td><strong>Net Savings/(Costs)</strong></td>
<td>$502,619</td>
</tr>
</tbody>
</table>

(1) Difference in costs between OM death and appropriate death, over 6.5 months (PMPM*6.5).
The “Last Mile” Problem

Data/Analytics can identify issues and find opportunities. On their own, they cannot solve the “Last Mile” problem.

The “Last Mile” problem helps to explain why Progressive Insurance, Netflix, Amazon, The Oakland As and others have successfully implemented data analytics and healthcare has not. Consumers either enjoy lower rates (Progressive), better and cheaper players (A’s), a better consumer experience (Amazon), etc.

More End-of-Life Modeling

- Our Hospice dataset contains data on approximately 200,000 patients over 5 years.
- Dataset is unique in that includes *prescription drug data*.
- Hospice patients receive palliative but not curative care, including prescription drugs. Four major drug classes:
  - Analgesics (e.g. morphine)
  - Anti-nausea (e.g. zofran)
  - Anti-cholinergic (e.g. benadryl; dramamine)
  - Anxiolytic (e.g. benzodiazepine)
- Patients receive certain other drugs necessary for survival (e.g. insulin; ACE inhibitors).
- Our hypothesis is that by looking at prescription and dosage of these drugs we can better predict terminal events.

- Method: time-dependent survival modeling.
More End-of-Life Modeling

• Cox model with time-dependent co-variates:

\[ h_i(t|Y_i(t), X_i) = h_0(t)e^{\beta^TX_i+\alpha Y_i(t)} \]

• Sample results:

<table>
<thead>
<tr>
<th>Covariates</th>
<th>Coefficients</th>
<th>Hazard Ratio</th>
<th>Std. Error</th>
<th>P-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gender Male</td>
<td>0.1739</td>
<td>1.1899</td>
<td>0.0052</td>
<td>0.000</td>
</tr>
<tr>
<td>Age at Adm</td>
<td>-0.0085</td>
<td>0.9916</td>
<td>0.0000</td>
<td>0.000</td>
</tr>
<tr>
<td>Risk score</td>
<td>0.1993</td>
<td>1.2206</td>
<td>0.0033</td>
<td>0.000</td>
</tr>
<tr>
<td>Anxiolytic</td>
<td>-0.0315</td>
<td>0.9690</td>
<td>0.0019</td>
<td>0.000</td>
</tr>
<tr>
<td>Antinausea</td>
<td>-0.0330</td>
<td>0.9675</td>
<td>0.0026</td>
<td>0.000</td>
</tr>
<tr>
<td>Analgesic</td>
<td>-0.0454</td>
<td>0.9556</td>
<td>0.0007</td>
<td>0.000</td>
</tr>
<tr>
<td>Anticholinergic</td>
<td>-0.0376</td>
<td>0.9631</td>
<td>0.0029</td>
<td>0.000</td>
</tr>
</tbody>
</table>
More End-of-Life Modeling

Conclusion

**Likely to die earlier:**

- Males (+19%)
- Patients with more co-morbidities (measured through risk score) (+22%)

**Likely to survive longer:**

- Patients with increased dosage of analgesics (+4%)
- Patients with increased dosage of anti-nausea; anti-cholinergic or anxiolytic drugs (+3%)
Example: Big Data
“Big Data”

Plus:

• Unstructured
• Novelty
• Messy
• Machine learning

• External
• New Tools
• Patterns
• Algorithms

• User-created
• Enabling technology
• Etc.

Source: Berkeley School of Information
Big data refers to the use of predictive analytics, user behavior analytics, or other advanced data analytics methods that extract value from data, and seldom to a particular size of data set. "There is little doubt that the quantities of data now available are indeed large, but that’s not the most relevant characteristic of this new data ecosystem.¹" Analysis of data sets can find new correlations to "spot business trends, prevent diseases, combat crime and so on.²"

Machine Learning: a field of computer science that gives computers the ability to learn without being explicitly programmed.

Detailed source data were not available (privacy). Summarized data categorized as:

Table 1: Classification of Physical Activity

<table>
<thead>
<tr>
<th>Device-recorded verified workouts</th>
<th>Light Workouts</th>
<th>Standard Workouts</th>
</tr>
</thead>
<tbody>
<tr>
<td>Steps</td>
<td>5,000-9,999</td>
<td>10,000+</td>
</tr>
<tr>
<td>Calories</td>
<td>100-199</td>
<td>200+</td>
</tr>
<tr>
<td>Time at 60% Maximum Heart Rate</td>
<td>15 minutes</td>
<td>30 minutes</td>
</tr>
</tbody>
</table>

Approximately 300,000 participants over 4 years; continuously reported data, including clinical data available on 8,519 participants between January 1, 2013 and August 31, 2015.
### Table 4: Number of workouts per week

<table>
<thead>
<tr>
<th>Year</th>
<th>Light Workouts</th>
<th>Standard Workouts</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Min</td>
<td>Mean (SD)</td>
</tr>
<tr>
<td>2013</td>
<td>0</td>
<td>0.86 (1.05)</td>
</tr>
<tr>
<td>2014</td>
<td>0</td>
<td>1.27 (1.29)</td>
</tr>
<tr>
<td>2015</td>
<td>0</td>
<td>1.09 (1.04)</td>
</tr>
</tbody>
</table>

Other available measures include BMI, Age, Sex, Smoking status, depression status, no. alcoholic drinks per week, blood pressure and serum cholesterol level.
### Table 6: Predicted 20-month BMI Measure for Two Sample Participants

<table>
<thead>
<tr>
<th>Sample Participant</th>
<th>Baseline BMI Level</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>17</td>
</tr>
<tr>
<td>30-year old Female; 3 std./1 light w/out weekly</td>
<td>17.94 (5.5)</td>
</tr>
<tr>
<td>60-year old Male; 5 std./1 light w/out weekly</td>
<td>17.70 (4.1)</td>
</tr>
</tbody>
</table>
Model 1: BMI

Figure 2: Effect of Exercise Levels on BMI for selected participants

Female - Age 30 - 1 Light Workout

Male - Age 60 - 1 Light Workout
Physical activity even at low levels can have positive impacts on measurable health metrics.

Physical activity levels (light and standard) had the largest impacts on BMI and HDL cholesterol levels, but little to no effect on either blood pressure or LDL cholesterol levels.

A measureable impact on health outcomes requires frequent, intense exercise.
Whoops!

Google Flu example

Why Google Flu Is A Failure

It seemed like such a good idea at the time.

People with the flu (the influenza virus, that is) will probably go online to find out how to treat it, or to search for other information about the flu. So Google decided to track such behavior, hoping it might be able to predict flu outbreaks even farther than traditional health authorities such as the Centers for Disease Control (CDC).

Instead, as the authors of a new article in Science explain, we got “big data hiatus.” David Lazer and colleagues explain that:

"Big data hiccups" is the often implicit assumption that big data are a substitute for, rather than a supplement to, traditional data collection and analysis.

The folks at Google figured that, with all their massive data, they could outsmart anyone.

Symptoms of Influenza

Central

- Headache

Nasopharynx

- Cough

- Runny Nose

FEVER PEAKS

A comparison of three different methods of measuring the proportion of the US population with an influenza-like illness.

Google's algorithms overestimated peak flu levels this year
“My daughter got this in the mail!” he said. “She’s still in high school, and you’re sending her coupons for baby clothes and cribs? Are you trying to encourage her to get pregnant?”

The manager didn’t have any idea what the man was talking about. He looked at the mailer. Sure enough, it was addressed to the man’s daughter and contained advertisements for maternity clothing, nursery furniture and pictures of smiling infants. The manager apologized and then called a few days later to apologize again.
Whoops!

Original Investigation

November 12, 2017

Association of the Hospital Readmissions Reduction Program Implementation With Readmission and Mortality Outcomes in Heart Failure

Ankur Gupta, MD, PhD; Larry A. Allen, MD, MHS; Deepak L. Bhatt, MD, MPH; et al

» Author Affiliations

*JAMA Cardiol.* Published online November 12, 2017. doi:10.1001/jamacardio.2017.4265
RIP Google Health

by John Moore | June 24, 2011

Chilmark Research has not had a very good feeling about Google Health for well over a year now. Back in early May of this year we felt that Google had all but given up and had put Google Health in stasis. Today, Google made it official, Google Health has a little more than six months to live, then it will get the Kevorkian treatment with Larry Page administering the final lethal dose.
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Adj. Assoc. Professor
Dept. of Statistics & Applied Probability
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The Role of Health Actuaries: Pricing

**Pricing**

- How much will be charged for this coverage?
- General considerations
  - What benefits are included in “this coverage”?
  - Who will be offered the coverage?
  - Frequency * Severity
- General terms: Per member per month (PMPM), anti-selection
Pricing projects are becoming more sophisticated, requiring clinical, behavioral economics and predictive analytics expertise.

For example:

You are an actuarial analyst in the pricing area of a large health insurance company. An underwriters calls. One of her clients wants to cover a new benefit – the “smoking cessation patch.” She doesn’t know how much to adjust the client’s per member per month health insurance rate in order to cover this additional benefit.

What factors would you take into account?
The Role of Health Actuaries: Reserving

- How much needs to be put aside to cover our financial obligations?
- General considerations
  - “claims lag”
  - Modeling vs. professional judgment
- General terms: claims triangle
The Role of Health Actuaries: Modeling

General Considerations:
- Model purpose & scope
- Data needs & availability
  - Medical claims data
  - Pharmacy claims data
  - Eligibility data
  - Clinical data
  - Activity data
  - Self-reported data
- Data cleaning, validation, warehousing
- Modeling tools: Excel, Access, R, SAS, etc.
- Modeling (conceptual) vs. Operations (tangible)
The Role of Health Actuaries: Forecasting

Forecasting

What is going to happen next year? In the next three years?

General considerations:

- Trend: price, utilization, intensity
Evaluating Healthcare Intervention Programs

General considerations:

- What is the program?
- What outcomes is it intended to drive?
- Challenges of comparable populations

General Terms: identification & stratification, eligible, targeted, engaged...

Actuaries understand the *risk* (both in terms of cost of the intervention and the population involved) and the impact on premiums.
The Role of Health Actuaries: Predictive Modeling

Predictive Modeling

- Can we better identify members that are more likely to have a specific outcome?
- Why would we want to do this?
- General considerations:
  - Identifying the specific outcome ("dependent variable")
  - Building the model
  - Validating the model
  - Applications of the model
- Two uses of models: risk adjustment and case identification.
We are looking in the wrong place

Despite considerable focus on Care Gaps; studies show that these are not very successful at reducing cost.

Medicare MSSP ACO participants surpassed FFS providers’ quality in 17 or 22 PQRS/ GPRO measures.
- 74% did not receive shared savings payments.

The Association Between Health Care Quality and Cost
A Systematic Review
Peter S. Hussey, PhD; Samuel Wertheimer, MPH; and Aleev Mehrotra, MD, MPH

**Background:** Although there is broad policy consensus that both cost containment and quality improvement are critical, the association between costs and quality is poorly understood.

**Purpose:** To systematically review evidence of the association between health care quality and cost.

**Data Sources:** Electronic literature search of PubMed, EconLit, and EMBASE databases for U.S.-based studies published between 1990 and 2012.

**Study Selection:** Title, abstract, and full-text review to identify relevant studies.

**Data Extraction:** Two reviewers independently abstracted data with differences reconciled by consensus. Studies were categorized by level of analysis, type of quality measure, type of cost measure, and method of addressing confounders.

**Data Synthesis:** Of 61 included studies, 21 (34%) reported a positive or mixed-positive association (higher cost associated with higher quality); 18 (30%) reported a negative or mixed-negative association; and 22 (36%) reported no difference, an imprecise or indeterminate association, or a mixed association. The associations were of low to moderate clinical significance in many studies. Of 9 studies using instrumental variables analysis to address confounding by unobserved patient health status, 7 (78%) reported a positive association, but other characteristics of these studies may have affected their findings.

**Limitations:** Studies used widely heterogeneous methods and measures. The review is limited by the quality of underlying studies.

**Conclusion:** Evidence of the direction of association between health care cost and quality is inconsistent. Most studies have found that the association between cost and quality is small to moderate, regardless of whether the direction is positive or negative. Future studies should focus on what types of spending are most effective in improving quality and what types of spending represent waste.

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For author affiliations, see end of text.
We are looking in the wrong place

Programs focused on reducing admissions have claimed significant outcomes. But the trend in inpatient admissions for chronic conditions has been downward for 15 years, while outpatient trends have been sharply upward.
History of Health Insurance

- UK: Friendly Societies. A group of people contributed to a mutual fund, and receive benefits at a time of need. By the late 1800's there was in the order of 27,000 registered Friendly Societies; the introduction of the National Health Service in 1948 severely reduced membership.

- Germany: Germany has the world's oldest national social health insurance system dating from the Bismarck chancellorship in 1889.

- U.S.: Hospital and medical expense policies were introduced during the first half of the 20th century. During the 1920s, hospitals began offering services to individuals on a pre-paid basis, eventually leading to the development of Blue Cross organizations in the 1930s.

- Early policies covered individuals for either hospital or major medical expenses; (much) later these coverages were integrated in Comprehensive medical insurance. Originally priced on a community-rated basis, more sophisticated rating and underwriting models were developed.
History of Health Insurance

Over time, another significant development was integrated into health insurance: Group Insurance. The first group life policy was issued by the Equitable Life (now AXA Equitable) on the employees of the Pantasote Leather Company, in 1911.

We accept group insurance today as a natural – in the U.S. at least it is a vast business. But in 1911 when the standard life insurance policy required underwriting, the idea of accepting insurance risk on a group of employees was both radical and dangerous. Group insurance required the development of a whole new actuarial theory – how to manage a block of business without underwriting – theory that would prove useful when group health policies grew rapidly in the 1940s.

The first group health insurance policy was written in 1929. Now, the majority of non-Medicare age Americans are covered by group policies.

BUT: a worker from the 1940s would probably not find too much difference in today’s health insurance.
The Scope of the Health Actuarial Practice

Products Include:

- Individual (Exchange) & Group Health (Commercial) Insurance
- Medicare Fee for Service (FFS), Medicare Advantage, Part D
- Medicaid & Managed Medicaid
- Group Life
- Disability (group & individual)
- Long-Term Care

Short-term coverages

Long-term coverages
The Role of Health Actuaries is Varied

- Pricing
- Reserving
- Modeling
- Forecasting
- Evaluating Healthcare products and Intervention Programs
- Predictive Modeling
- Analytics
“...the health actuary of the future at a minimum will need to be part clinician, part behavioral psychologist, part health economist, and part epidemiologist.”

Ian Duncan, FSA MAAA “40-Year-Old Model is No More”

*Contingencies*, Nov/Dec 2014
The Role of Health Actuaries in Change

How can we help change this to......
We are awash in data – how to make sense?

The data volumes are exploding: more data has been created in the past two years than in the entire previous history of the human race.

Data is growing faster than ever before and by the year 2020, about 1.7 megabytes of new information will be created every second for every human being on the planet. Our accumulated digital universe of data will grow from 4.4 zettabytes today to around 44 zettabytes, or 44 trillion gigabytes.

Facebook users send on average 31.25 million messages and view 2.77 million videos every minute.

By 2020, we will have over 6.1 billion smartphone users globally (overtaking basic fixed phone subscriptions). Within five years there will be over 50 billion smart connected devices in the world, all developed to collect, analyze and share data.

Estimates suggest that by better integrating big data, healthcare could save as much as $300 billion a year — equal to reducing costs by $1000 a year for every man, woman, and child.

Cox PH Models of Workers Compensation Data

- Cox PH Model of Data with Imputed Genders
- Cox PH Model of Data without Missing Genders

Probability of Claim Being Open vs. Duration of Claim (in Years)
A word of caution: Prof. Emmanuel Candès of Stanford: “The big data era has created a new scientific paradigm; collect data first, ask questions later….inferences are likely to be false [and] follow-up studies are likely not to be able to reproduce earlier reported findings or discoveries.”