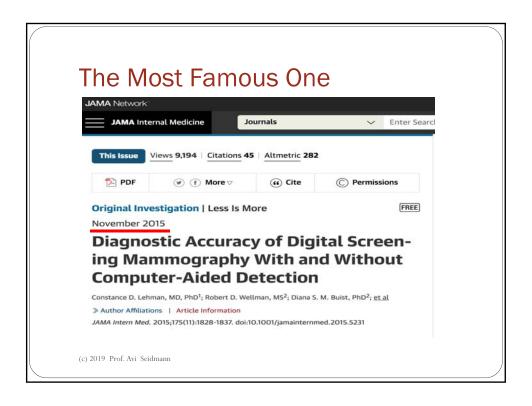
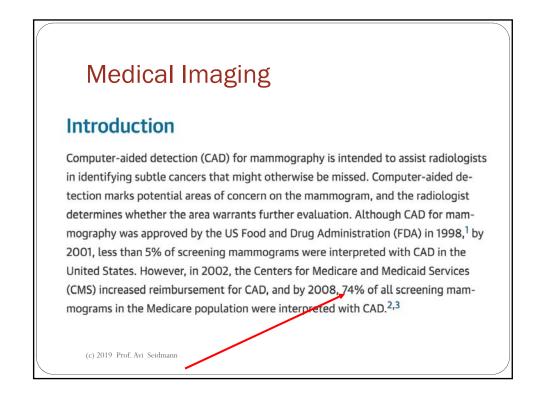


The Role of Medical Informatics

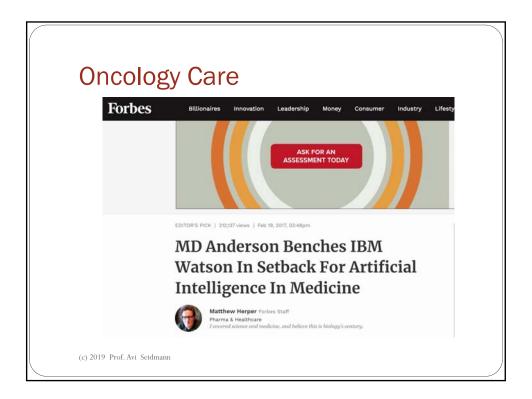
Big Data and AI





Medical Imaging

Conclusions and Relevance Computer-aided detection does not improve diagnostic accuracy of mammography. These results suggest that insurers pay more for CAD with no established benefit to women.



Rise of Al-as-a-medical-device

 The FDA is fast-tracking approvals of artificial intelligence

software for clinical imaging & diagnostics.

- In April 2018, the FDA approved AI software that screens patients for diabetic retinopathy without the need for a second opinion from an expert.
- It was given a "breakthrough device designation" to expedite the process of bringing the product to market.
- The software, IDx-DR, was able to correctly identify patients with "more than mild diabetic retinopathy" 87.4% of the time, and identify those who did not have it 89.5% of the time.

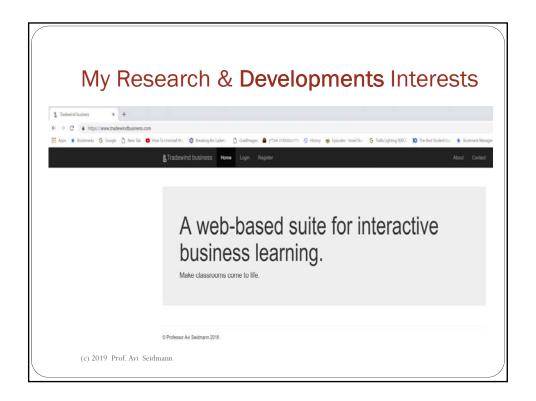
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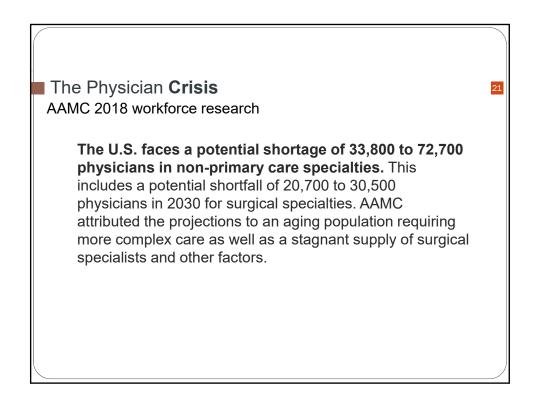
Apple disrupts clinical trials

- Since 2015, Apple has launched two open-source frameworks — ResearchKit and CareKit — to help clinical trials recruit patients and monitor their health remotely.
- The frameworks allow researchers and developers to create medical apps to monitor people's daily lives.
- In January 2018, Apple announced that iPhone users will now have access to all their electronic health records from participating institutions on their iPhone's Health app
- The App is Called "Health Records."

Our Telemedicine Research Sample

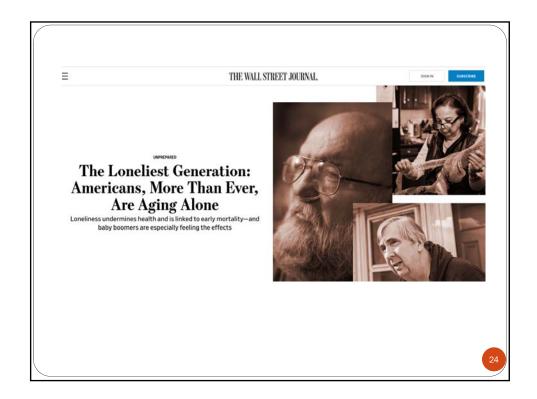
- "Randomized, controlled trial of "virtual housecalls" for Parkinson disease" (with Dorsey et al),
 - JAMA Neurology (2013)
- "Telemedicine in leading US neurology departments" (with George, et al)
 - The Neurohospitalist (2012)
- "The competitive impact of telemedicine mode of treatment for chronic conditions" (with Rajan and Dorsey)
 - Journal of Management Information Systems (2013)
- "Telemedicine for patients suffering from Migraine" (with Freidman and Rajan), HICSS (2019)
- "Service Systems with Heterogeneous Customers: Investigating the Effect of Telemedicine on Chronic Care" (with Tezcan and Rajan),
 - Management Science (2018)















Our Talk Today

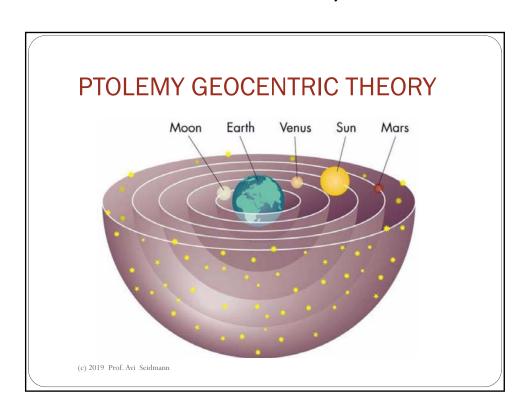


- Lessons from Galileo Galilei
 - Observations can be misleading...
- 1. Information Hang-overs in Healthcare Service Systems
 - The value of systematic (end to end) process flow analytics
- 2. Does Technology Substitute for Nurses?
 - The data and economics of process flow automation
- 3. The Operational Effects of Telemedicine on Chronic Care
 - MDs and Patients as players in complex Non-Atomic Games
- Overall Data & Analytics Insights from it all
 - Why Medical Schools start teaching Medical Informatics

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What you know about,
 You See

Goethe (1851)







Four Quick Lessons to Recall

- Galileo Galilei, like Kepler, was a mathematician. He combined his newly Observed Data with Math Modelling.
- 2. Galileo complained to Kepler that some of the philosophers who opposed his discoveries had **refused even to look through his telescope**.
- 3. When the truth contradicts what WE believe, WE tend to abandon the truth.
- 4. WE tend to refuse to consider <u>evidence</u>—if what they might discover contradicts what WE believe.



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Analyzing the Differential Impact of Radiology Information Systems Across Radiology Modalities

Atanu Lahiri, MS, Abraham Seidmann, PhD

Purpose: The aim of this study was to assess the impact of redesigning a medical imaging workflow using a commercial radiology information system (RIS), particularly the impact of implementing a disciplined collection of background clinical information all along the clinical service chain.

Materials and Methods: The impact of the RIS on the total report turnaround time and on its various components, such as the radiologist interpretation, transcription, and radiologist review turnaround times, was empirically investigated. Advanced statistical tools were used, including lognormal survival functions and x-tests, to compare and analyze the pre-RIS and post-RIS operational performance of a regional network of outpatient clinics.

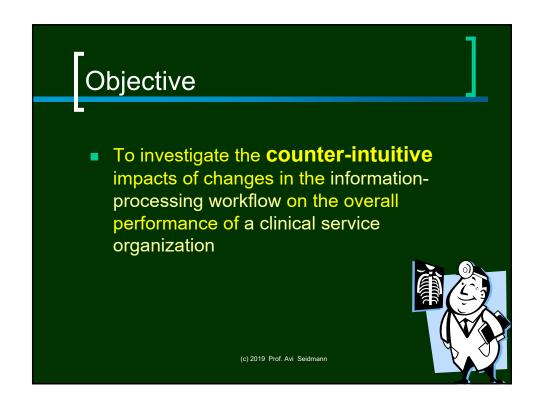
Results: The RIS installation did not produce uniform benefits for all modalities. There was no statistically significant impact on report turnaround times for magnetic resonance imaging. On the other hand, turnaround times for mammographic studies declined significantly.

Conclusion: Although the additional time needed to navigate through the RIS screens might have (unexpectedly) increased the radiologists' interpretation cycle times, the overall benefits of the RIS outweighed this negative effect in this study. Before the RIS installation some clinical background information was not available to the radiologists at the time of interpretation. As a part of the RIS implementation the radiology practice introduced several disciplined data collection procedures to make such information readily available downstream. These procedures significantly reduced the percentage of mammographic studies that had to be put on hold, increasing radiologists' overall performance and income. The effectiveness of any RIS solution, therefore, significantly depends on systemwide analyses of all relevant performance metrics and also on the creative implementation of new clinical and administrative workflows.

Key Words: Radiology information system, economic impact, workflow redesign, report turnaround, radiologist productivity, medical information systems

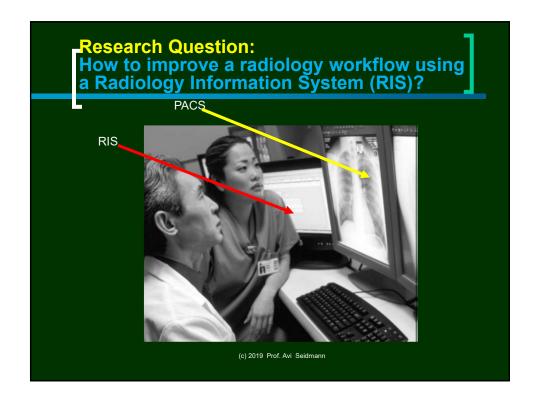
J Am Coll Radiol 2009;6:705-714. Copyright © 2009 American College of Radiology

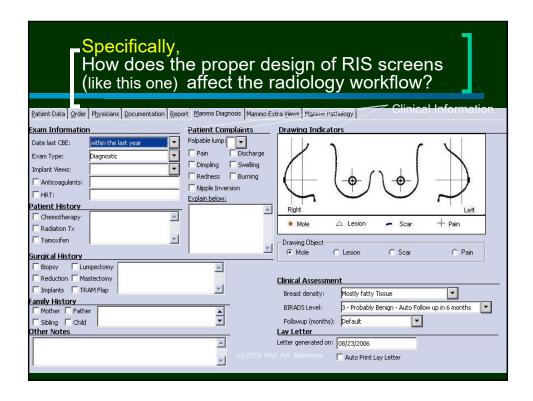


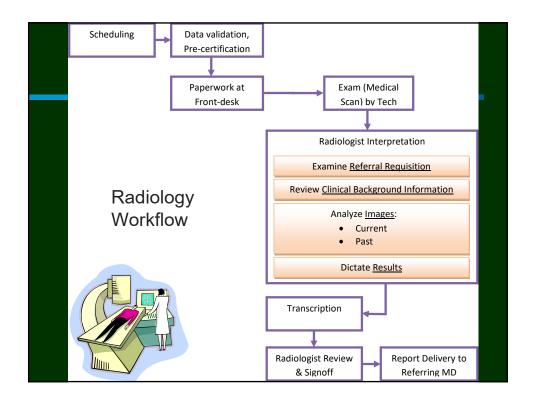


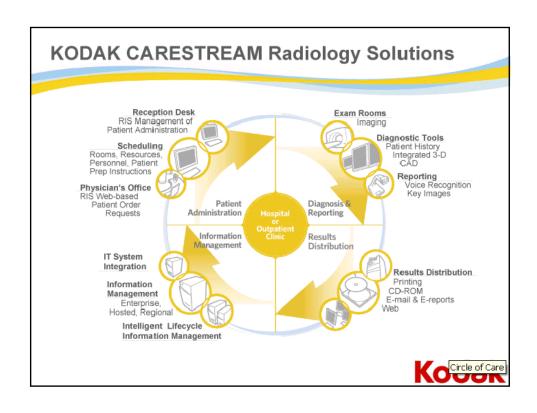
Information *Hang-overs* in Healthcare Service Systems

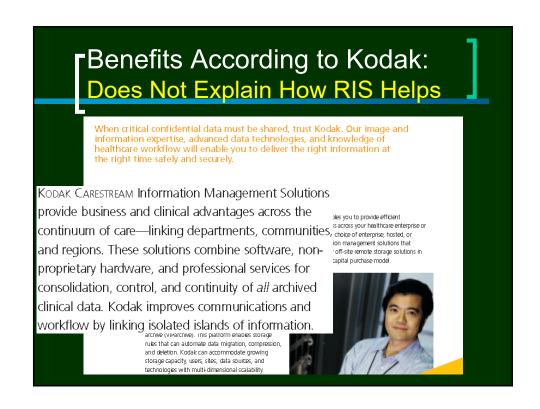
- At Yale, Holt et al. (2007), find that nearly 23% of 1,800 surgeries were delayed because of missing information, putting patients at severe risk!
- "Day-of-surgery delays caused by missing information remain relatively common despite pre-anesthesia evaluation..."
- Holt, N. F., D. G. Silverman, R. Prasad, J. Dziura, K. J. Ruskin, 2007. Pre-anesthesia clinics, information management, and pregning grown delays: results of a survey of practicing anesthesiologists. Anesthesia and Analgesia 104(3) 615-618.

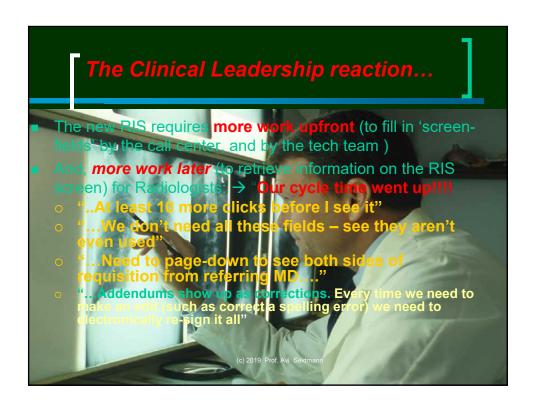




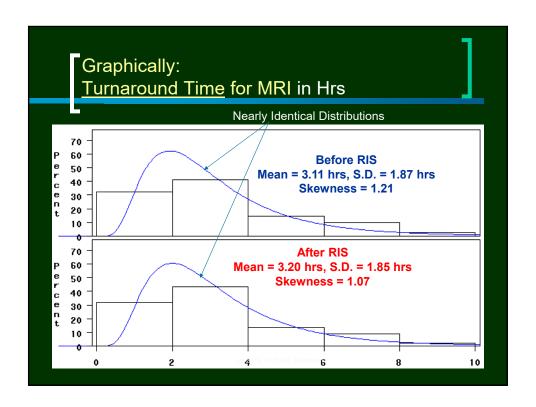


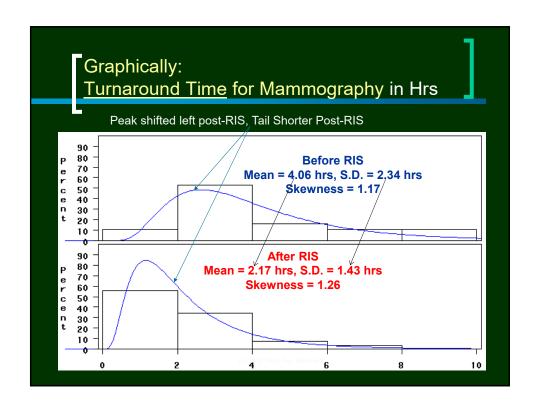


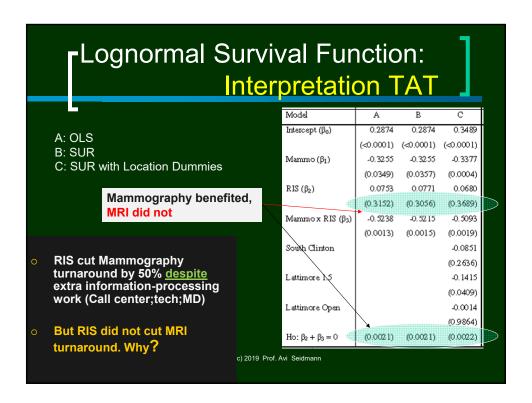


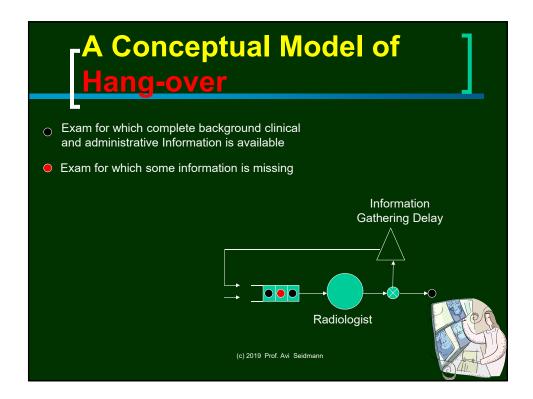


Performance Measure		Pre-RIS Post-RIS						
Significant Adverse Impact on Scheduling	Mean		SD		Mean		SD	
Scheduling-Call Length (existing patients) in Minutes	2.4	19	1.5	32	2.7	73*	1.2	.3
Scheduling-Call Length (new patients) in Minutes	3.1	0	1.1	18	4.4	14*	1.5	9
Scheduling-Call Abandonment Rate	2.22	2%	1.23	3%	3.59	9%*	1.69)%
Significant but Non-uniform	Mammo	graphy	M	RI	Mammo	ography	MF	₹I
Positive Impact on MDs	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Interpretation TAT in Hours	1.58	1.84	1.62	1.06	0.76*	0.60	1.67	0.98
Transcription TAT in Hours	0.44	0.42	0.54	0.36	0.36	0.37	0.50	0.57
Review TAT in Hours	2.04	1.05	0.95	1.41	1.06*	1.24	1.03	1.35
RTAT (sum of the 3 TATs above) in Hours	4.06	2.34	3.11	1.87	2.17*	1.43	3.20	1.85

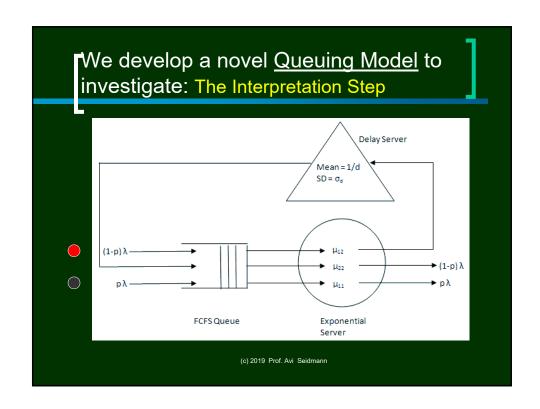








What is this 'Missing' Data about?
Radiologist-speak
"Missing patient full name, DB error at PACS"
"Call back diagnostic"
"Additional views are present, need to discuss with tech why they took those additional views"
"Missing previous study"
"Explain surgical scars shown"
"No referral MD notes on swelling"
"Spoke with patient"
"Wrong prior mammography films presented"



Model Characteristics

- Feedback Queue is NOT product-form:
 - Fixed (Deterministic) Feedback: 2 rounds of Service for hang-over exams, 1 round for the rest
 - Delayed Feedback: Information-gathering delay
 - Multiple Classes of Customers:
 - > Some require additional info, Some don't
 - Service times of exponential server:
 - Depends on Class and the Round of Service

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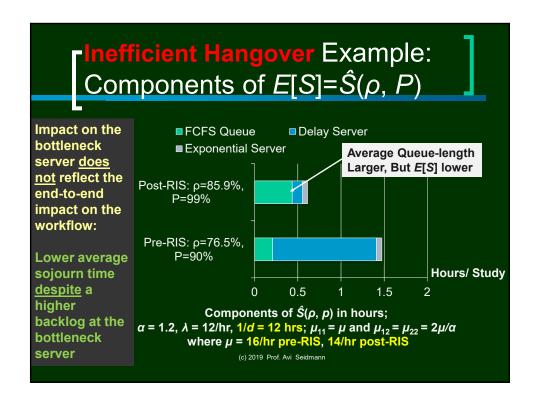
Theorem 1: Analytical Solution: Expected Sojourn Times

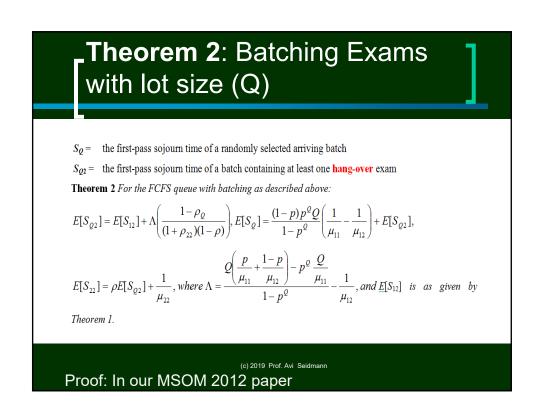
 First moments, i.e., Expected Sojourn Times, can be obtained using Operational Analysis (Denning and Buzen 1978)

$$\begin{split} E[S_{11}] &= \frac{\frac{1}{\mu_{12}} + \rho_{11}(\frac{1}{\mu_{11}} - \frac{1}{\mu_{12}}) + \frac{\rho_{22}}{\mu_{22}}}{(1 + \rho_{22})(1 - \rho)} + (\frac{1}{\mu_{11}} - \frac{1}{\mu_{12}}) \\ E[S_{12}] &= \frac{\frac{1}{\mu_{12}} + \rho_{11}(\frac{1}{\mu_{11}} - \frac{1}{\mu_{12}}) + \frac{\rho_{22}}{\mu_{22}}}{(1 + \rho_{22})(1 - \rho)} \\ E[S_{22}] &= \rho \frac{\frac{1}{\mu_{12}} + \rho_{11}(\frac{1}{\mu_{11}} - \frac{1}{\mu_{12}}) + \frac{\rho_{22}}{\mu_{22}}}{(1 + \rho_{22})(1 - \rho)} + \frac{1}{\mu_{22}} \end{split}$$

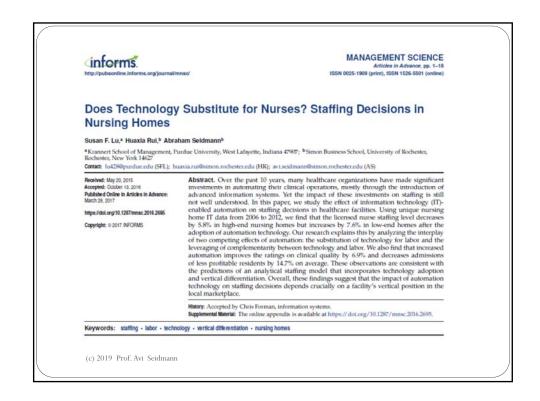
And, the mean so journ time, E[S], equals:

$$(p+(1-p)(1+\rho))^{\frac{1}{\mu_{12}}+\rho_{11}(\frac{1}{\mu_{11}}-\frac{1}{\mu_{12}})+\frac{\rho_{22}}{\mu_{22}}}+p(\frac{1}{\mu_{11}}-\frac{1}{\mu_{12}})+(1-p)(\frac{1}{\mu_{22}}+\frac{1}{d})$$



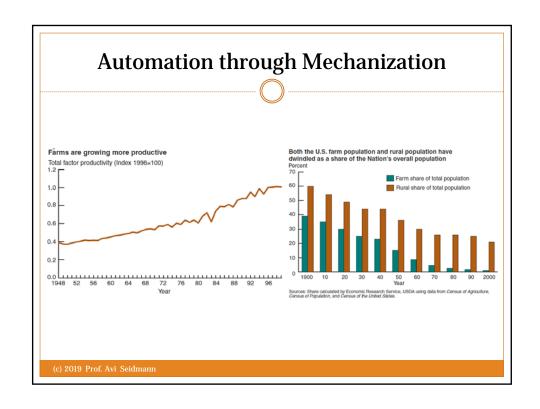






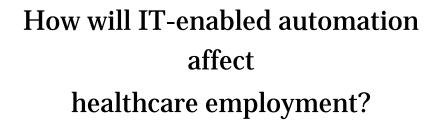








Research Question



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Nursing Homes in the United States

- A nursing home is a place for people who do not need to be in a hospital but can no longer be cared for at home.
- Due to the aging of the baby boomer generation, approximately \$ 111 billion was spent on nursing home care in the United States in 2011.
- Unique features compared to hospitals:
 - Relatively simple structure of labor provision
 - Relatively homogeneous services: chronic care

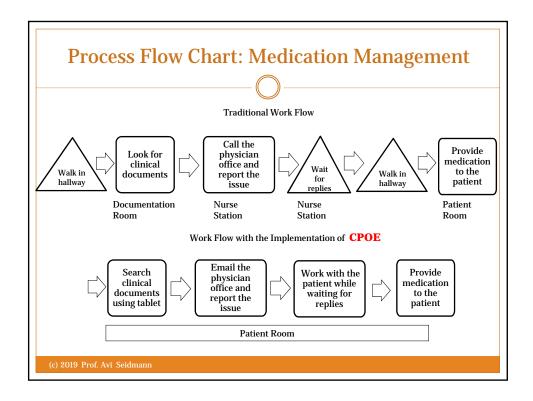
Quality Mix

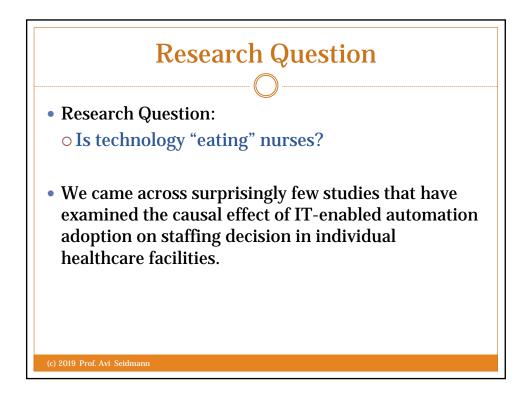
- Patient types
 - Short-term care patients (post-acute care)
 - Long-term care patients (chronic care)
- Payer Types: Quality Mix
 - About 60% of patients are Medicaid (daily rate \$140)
 - 20% are Medicare patients for post-acute care (daily rate \$500)
 - o 20% are private-paying patients (daily rate \$300-400)
 - The whole industry chases lucrative patients as a new trend.

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Vertical Differentiation

- The entire nursing home industry is competitive.
- The quality of care in a nursing home is mainly determined by the nurses on a daily basis.
 - Five star ratings
 - Manor Care
 - Kindred
 - Staffing (positively associated with star ratings)
 - **▼** The dispersion of staffing-to-resident ratio is between 1 percentile and 99 percentile is 4.59 HPRD.
 - ➤ The state minimum staffing standards provide an exogenous lower bound for the staffing level in each individual market.







• A nursing home's staffing problem:

Vertical Position

$$\max_{S} V(s) = R(q, \theta) - w * s$$
Revenue (\$)/Pt Quality Level

Parameterization:

Care Quality
$$Q(r,k) = rk, \qquad R(q,\theta) = 1 - \theta e^{-A\theta q}. \quad \{\partial R/\partial q > 0, \ \partial^2 R/\partial q^2 < 0\}$$
Staff-to-patient ratio Technology Level
$$0 < \underline{\theta} < \overline{\theta} < \sqrt{\frac{we^2}{Ak}}.$$

$$0 < \underline{\theta} < \overline{\theta} < \sqrt{\frac{we^2}{Ak}}$$

Model Analysis

Lemma:

The optimal staffing level s^* , the optimal quality level q^* , and the resulting average revenue per patient for a nursing home with vertical

position
$$\theta$$
 are given below:

$$s^* = \frac{1}{Ak\theta} \ln \frac{Ak\theta^2}{w}, \qquad q^* = \frac{1}{A\theta} \ln \frac{Ak\theta^2}{w}, \qquad R(q^*, \theta) = 1 - \frac{w}{Ak\theta}.$$

Proposition 1:

The optimal staffing level s^* , the optimal quality level q^* , and the average revenue per patient $R(q^*, \theta)$ are increasing in θ .

Model Analysis



Proposition 2:

The optimal quality level q^* and the average revenue per patient $R(q^*, \theta)$ are increasing in the automation level k.

Proposition 3:

An increase in automation level leads to <u>an increase</u> of a nursing home's staffing level (S) if the vertical position: $\theta < \sqrt{\frac{we}{Ak}}$, but it leads to <u>a decrease</u> of a nursing home's staffing level (S) if the vertical position: $\theta > \sqrt{\frac{we}{Ak}}$.

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Hypotheses



- Hypothesis 1: An increase in automation level leads to an increase in the quality level of a nursing home.
- Hypothesis 2: An increase in automation level leads to a decrease in staff-to-patient ratio for a nursing home with a high vertical position.
- **Hypothesis 3**: An increase in automation level leads to an *increase* in staff-to-patient ratio for a nursing home with a low vertical position.

Hunting for Reliable Data



Data Sources

- □ The Online Survey Certificate and Reporting Database (OSCAR) from 2006 to 2012
- □ The Health Information Systems Society (**HIMSS**) from 2005 to 2011

□ Key Variables:

- Process Quality: the number of patient complaints
- Staff-to-Patient Ratio: staff hours per patient day (HPRD) for licensed nurses (LNs)
- Vertical Position

Econometric Models



• Average Effect:

$$S_{it} = \alpha_0 + \alpha_1 I T_{i,t-1} * Post_{t-1} + \alpha_2 X_{it} + \alpha_3 Z_{ct}$$

$$+ \alpha_4 State_s * Year_t + \alpha_i + \alpha_t + \varepsilon_{it}$$
(1)

• Heterogeneous Effect:

$$S_{it} = \beta_0 + \beta_1 IT_{i,t-1} * Post_{t-1} + \beta_2 IT_{i,t-1} * Post_{t-1} * Position_i + \beta_3 X_{it} + \beta_4 Z_{ct} + \beta_5 State_s * Year_t + \beta_i + \beta_t + \varepsilon_{it}$$
(2)

(2)

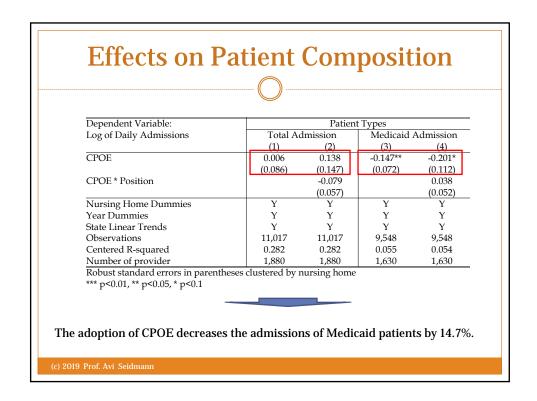
- Endogeneity Issues
 - The adoption of CPOE is not randomly assigned.

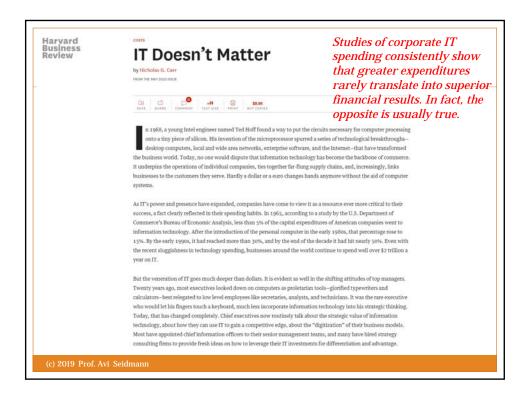
Instrumental Variable (IV)

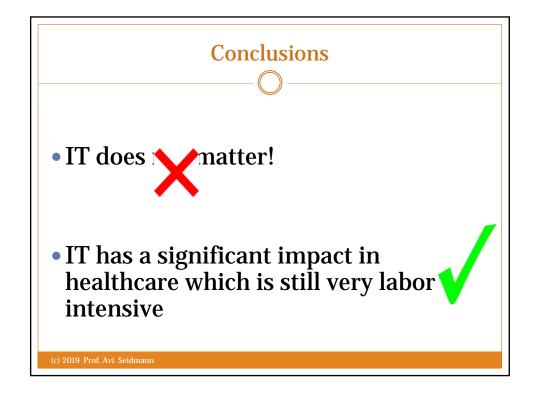
- We construct an instrumental variable, *hospital_CPOE*, describing the yearly hospital CPOE adoption rates in the local market where we define a county as a market.
 - Exclusion criteria
 - o Inclusion criteria
 - ➤ First stage: 0.552 (p-value < 0.001)
 - **×** Weak IV problem:
 - The Kleibergen-Paap rk Wald F statistics is 622.17, allowing us to easily reject the null hypothesis.
- Alternative IV
 - We divided the number of non-affiliated hospitals that adopted CPOE by the total number of non-affiliated hospitals in the local market in a given year.

Dependent Variable:	Baseline						
Consumer Complaints		Total Complaints					
on Process Quality	OLS	First Stage	2SLS				
	(1)	(2)	(3)				
CPOE	0.000		0.012				
	(0.014)		(0.027)				
IV: Hospital_CPOE		0.552***					
		(0.022)					
Nursing Home Dummies	Y	Y	Y				
Year Dummies	Y	Y	Y				
Individual State Linear Trends	Y	Y	Y				
Weak Identification Test	Kleibergen-Paap	Kleibergen-Paap rk Wald F statistic: 622.17***					
Observations	12313	12313	12250				
Within R-squared	0.06	0.272	0.06				
Number of provider	2119	2119	2056				
Robust standard errors in parentheses clustered	by nursing home						
*** p<0.01, ** p<0.05, * p<0.1		_					

	()				
Dependent Variable:	I	icensed Nurse	Registered Nurses			
Hours per patient Day	Minimum LNs			Minimum RNs		
	OLS	2SLS	2SLS	2SLS	2SLS	
	(1)	(2)	(3)	(4)	(5)	
CPOE	0.106***	0.282***	0.145***	0.154***	0.073**	
	(0.036)	(0.062)	(0.046)	(0.040)	(0.029)	
CPOE * Position	-0.065**	-0.172***		-0.145***		
	(0.029)	(0.042)		(0.044)		
CPOE * High End			-0.255***		-0.109**	
			(0.071)		(0.047)	
Nursing Home Dummies	Y	Y	Y	Y	Y	
Year Dummies	Y	Y	Y	Y	Y	
State Linear Trends	Y	Y	Y	Y	Y	
F test: CPOE+CPOE* High End			-0.110**		-0.036*	
Observations	12,313	12,250	12,250	12,250	12,250	
Within R-squared	0.046	0.040	0.041	0.057	0.058	
Number of provider	2,119	2,056	2,056	2,056	2,056	
Robust standard errors in parentheses clustered by *** p<0.01, ** p<0.05, * p<0.1				g decision		







Key Findings



IT-enabled automation: CPOE

- No effect on staffing on the industry average, BUT....
- Data Analytics supports the Economic Model's Predictions:
- **CPOE Implementation**
 - o **reduces** staffing by 5.8% in high-end nursing homes, (**Substitute**) but
 - **increases** staffing by 7.6% in low-end nursing homes (**Complement**).
- Results in a 14.7% significant **decrease** in the admissions of Medicaid patients, the least profitable type patients.

ONLINE FIRST

CLINICAL TRIALS

SECTION EDITOR: IRA SHOULSON, MD

Randomized Controlled Clinical Trial of "Virtual House Calls" for Parkinson Disease

E. Ray Dorsey, MD, MBA; Vinayak Venkataraman, BS; Matthew J. Grana, BA; Michael T. Bull, BS; Benjamin P. George, MPH; Cynthia M. Boyd, MD, MPH; Christopher A. Beck, PhD; Balaraman Rajan, MBA, MS; Abraham Seidmann, PhD; Kevin M. Biglan, MD, MPH

Importance: The burden of neurological disorders is increasing, but access to care is limited. Providing specialty care to patients via telemedicine could help alleviate this growing problem.

Objective: To evaluate the feasibility, effectiveness, and economic benefits of using web-based videoconferencing (telemedicine) to provide specialty care to patients with Parkinson disease in their homes.

Design: A 7-month, 2-center, randomized controlled clinical trial.

Setting: Patients' homes and outpatient clinics at 2 aca-

Participants: Twenty patients with Parkinson disease with Internet access at home.

Intervention: Care from a specialist delivered remotely at home or in person in the clinic.

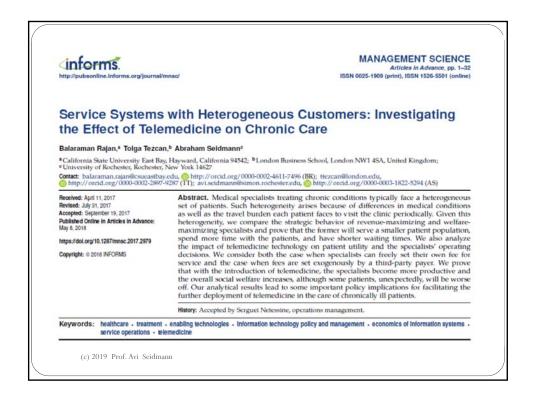
Main Outcome Measures: The primary outcome wariable was feasibility, as measured by the percentage of telemedicine visits completed as scheduled. Secondary outcome measures included clinical benefit, as (c) 2049/PPI-08 Pln 38-iBWAParkinson Disease Questionnaire, and economic value, as measured by time and

Results: Twenty participants enrolled in the study and were randomly assigned to telemedicine (n=9) or in-person care (n=11). Of the 27 scheduled telemedicine visits, 25 (93%) were completed, and of the 33 scheduled in-person visits, 30 (91%) were completed (P=99). In this small study, the change in quality of life did not differ for those randomly assigned to telemedicine compared with those randomly assigned to in-person care (4.0-point improvement vs 6.4-point improvement; P=.61). Compared with in-person visits, each telemedicine visit saved participants, on average, 100 miles of travel and 3 hours of time. 100 miles of travel and 3 hours of time

Conclusion and Relevance: Using web-based video-Conclusion and Refevence: Using web-based video-conferencing to provide specialty care at home is fea-sible, provides value to patients, and may offer similar clinical benefit to that of in-person care. Larger studies are needed to determine whether the clinical benefits are indeed comparable to those of in-person care and whether the results observed are generalizable.

Trial Registration: clinicaltrials.gov Identifier:

JAMA Neurol. Published online March 11, 2013. doi:10.1001/jamaneurol.2013.123



Symptom	Medication	
Movement	Carbidopa-levodopa (Sinemet [®])	
	Carbidopa-levodopa	
	Amantadine (Symmetrel*)	
	Entacapone (Comtan*)	
	Pramipexole (Mirapex*)	

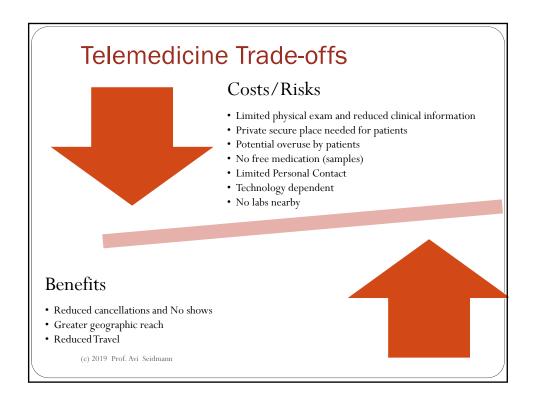
Comments from the patients (Pro TM)

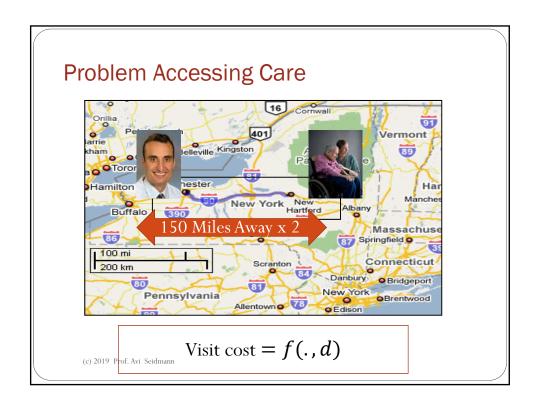
- "I spend more time in the car than with the Dr."
- "I would hope that telemedicine would provide more access to a doctor for those who were unable to see their doctor in person. I would like more access to best health care."
- "No travel to downtown, no toll fees, and no long walk from the parking garage to the office."
- "little interruption to normal schedule"
- "I don't have to take off the entire day, drive 120 miles, fight the traffic, the horrible parking situation, eating out expensive."

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On the other hand (Negative)...

- "I would not like to put any communication barriers between myself and my doctor, including a camera or distance."
- "I do not get a real patient visit where the doctor reviews all my systems to see if I am getting better, the worse, or the same. Trying to provide good patient care over the Internet is superficial,"
- "I think the doctor listens more carefully when I have an
 office visit, and I feel like I am able to better communicate
 my personal medical issues to the doctor."
- "It may seem less personal."
- "I would miss shaking hands with my doctor."







Pilot telemedicine program for ophthalmology helps to increase interventions for preventing vision loss

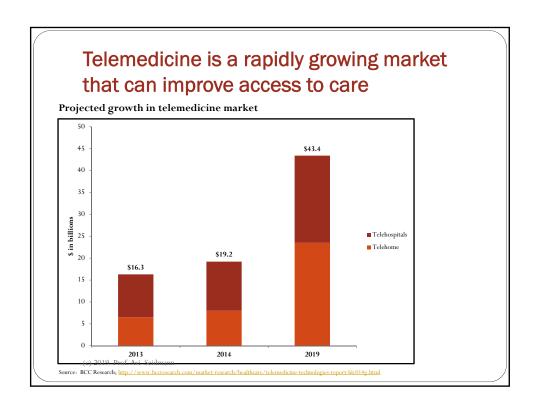
Telemedicine-based diabetic retinopathy detection at URMC



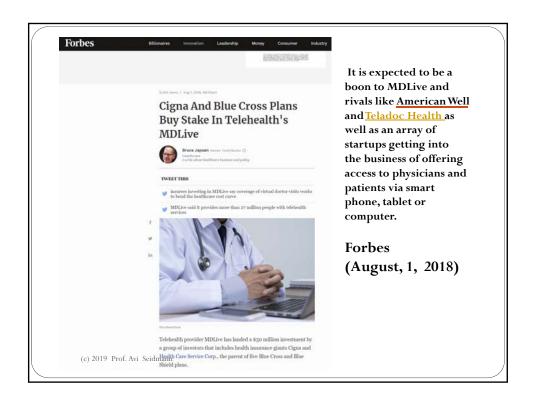
Rajeev Ramchandran, MD URMC Ophthalmologist

- In 2013, Flaum Eye Institute received a \$600,000 grant from the Greater Rochester Health Foundation in support of Rochester Area Tele-I-Care
- •Tele-I-Care program links the Flaum Eye Institute, RGHS Department of Ophthalmology, and primary care physicians to identify people with diabetes who are at risk of vision loss

Source: Rajan B, Seidmann A, Ramchandran R. Teleophthalmology for Diabetic Patients: Saving Vision through IT. hicss, 4239-43. 2014 47th Hawaii International Conference on System Sciences.
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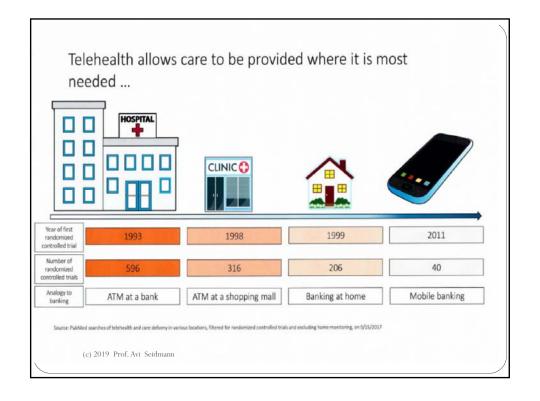


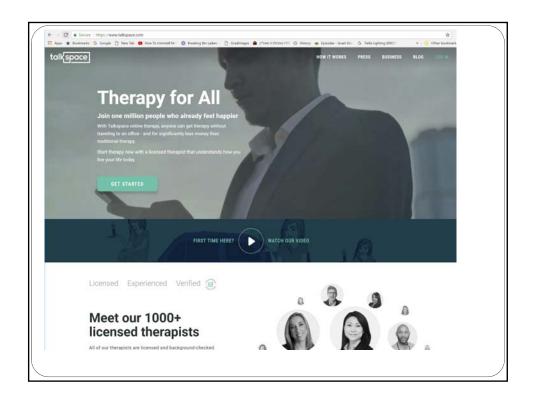


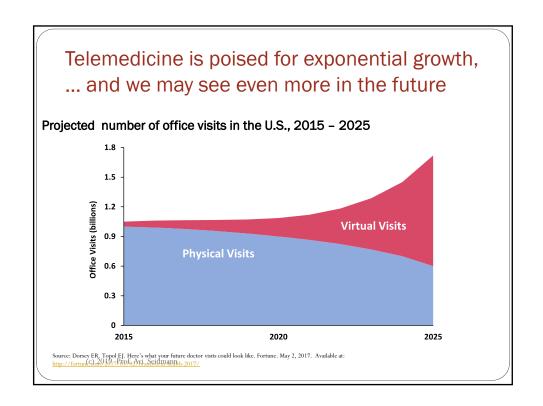


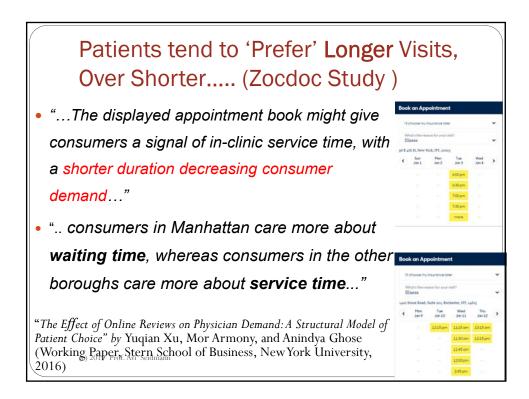


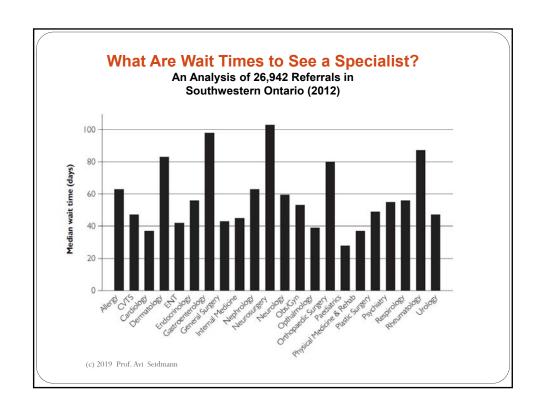


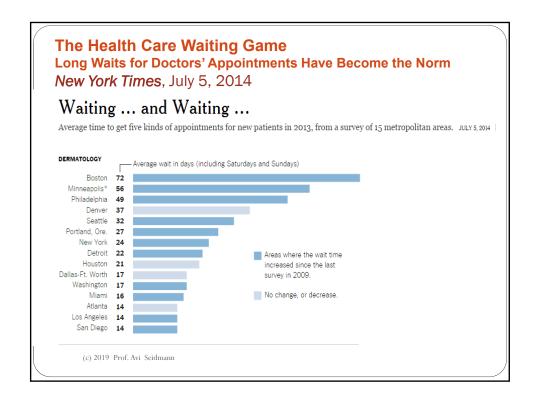


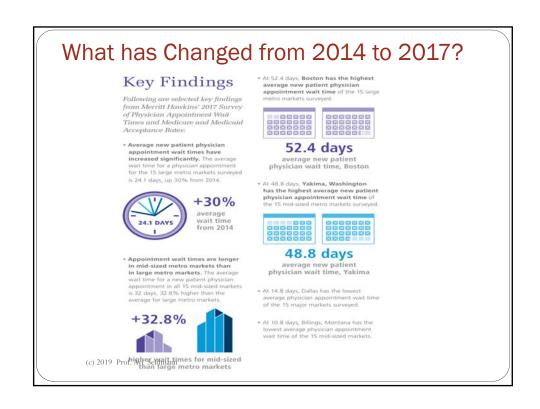












What has Changed from 2014 to 2017?

FAMILY MEDICINE

City	Total Responses	Shortest Time to Appt.	Longest Time to Appt.	Average Time to Appt.	Accept Medicaid? YES (%)
Boston, 2017	18	3 days	365 days	109 days	78
Boston, 2014	20	12 days	152 days	66 days	65
Boston, 2009	17	6 days	365 days	63 days	53
Los Angeles, 2017	20	1 day	365 days	42 days	45
Los Angeles, 2014	19	1 day	126 days	20 days	53
Los Angeles, 2009	20	1 day	365 days	59 days	30
Portland, 2017	20	1 day	240 days	39 days	55
Portland, 2014	20	3 days	45 days	13 days	60
Portland, 2009	19	3 days	16 days	8 days	79
Miami, 2017	20	3 days	180 days	28 days	40
Miami, 2014	16	1 day	56 days	12 days	56
Miami, 2009	15	1 day	25 days	7 days	40
Atlanta, 2017	20	1 day	169 days	27 days	35
Atlanta, 2014	20	1 day	112 days	24 days	40
Atlanta p2009	Seidmann 18	3 days	21 days	9 days	67

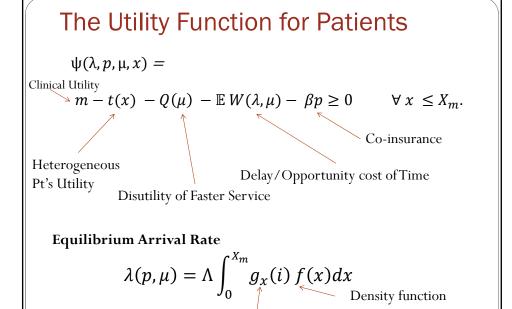
Motivation

- **Patients** have some expectations when they come to see the specialist.
 - Expect to spend "quality" time with the specialist.
 - All patients are "different" (Distance, morbidity condition...)
 - Perceive **more time with the specialist** as providing higher quality
 - Expect to get an appointment within minimal waiting time.
- **Specialists (MDs)** have a finite capacity for treating patients.
 - Expects to be paid **a fair fee** per office visit
 - Address the broad spectrum of **heterogeneous** population
 - Need to **balance** long-term patient expectations with short-term revenue generation.
- Each patient walking into the clinic generates **a negative externality** for the other patients.

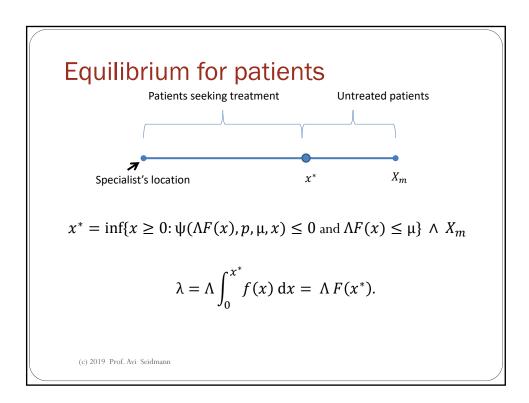
Our Research Questions today

- How to identify and measure the operational impacts of telemedicine?
- Why should a "busy" specialist offer telemedicine?
- What is the impact of patients heterogeneity on the optimal operation policy of the specialist?
- Who wins and who loses from using telemedicine technology for Chronic Care Delivery?
 - Medical Outcomes
 - Economics
 - Operations

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1 if chooses to seek treatment



The Physician Optimization Objective

Revenue Maximization Objective:

$$R(p,\mu) = \begin{cases} p \, \lambda(p,\mu), & \text{if } p \ge 0 \text{ and } \mu > \lambda(p,\mu) \\ 0, & \text{otherwise.} \end{cases}$$
$$R^* = \max_{p,\mu \ge 0} R(p,\mu).$$

Social Welfare Maximization objective:

$$V(\lambda) = \Lambda \int_0^{X_m} m - t(x) \ g_x(i) \ f(x) dx.$$

$$U(\lambda, \mu) = \begin{cases} V(\lambda) + \lambda(-Q(\mu) - \mathbb{E} \ W(\lambda, \mu)), & \text{if } \mu > \lambda, \\ 0, & \text{otherwise.} \end{cases}$$

$$U(\lambda, \mu) = \begin{cases} V(\lambda) + \lambda(-Q(\mu) - \mathbb{E} \ W(\lambda, \mu)), & \text{if } \mu > \lambda, \\ 0, & \text{otherwise.} \end{cases}$$

Solution to Revenue Maximization: Proof approach

Theorem: Equivalent Specialist Revenue

function
$$\tilde{R}(\lambda,\mu) = \begin{cases} p(\lambda,\mu) \lambda, & if \lambda \in [0,\Lambda] \ and \ \mu > \lambda \\ 0, & otherwise. \end{cases}$$

$$\max_{p,\mu\geq 0} R(p,\mu) = \max_{\lambda,\mu\geq 0} \tilde{R}(\lambda,\mu).$$

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Solving the Optimization Problem

The Specialist's Revenue Maximization Objective

Problem 1=
$$R(p, \mu)$$
 =

$$\begin{cases} p \lambda(p, \mu), & \text{if } p \ge 0 \text{ and } \mu > \lambda(p, \mu) \\ 0, & \text{otherwise.} \end{cases}$$

$$R^* = \max_{p,\mu \ge 0} R(p,\mu).$$

Problem 2 =

$$\tilde{R}(\lambda,\mu) = \begin{cases} p(\lambda,\mu) \ \lambda, & if \lambda \in [0,\Lambda] \ and \ \mu > \lambda \\ 0, & otherwise. \end{cases}$$

$$\max_{p,\mu\geq 0}R(p,\mu)=\max_{\lambda,\mu\geq 0}\widetilde{R}(\lambda,\mu).$$

Established Bounds on the Service Rate

Let
$$\kappa = \Lambda F \left(t^{-1} \left(m - Q \left(\frac{c}{M_v} \right) \right) \right)$$

Lemma 2: If
$$\mu \geq Q^{-1}(M_v)$$
 or if $\mu \leq \lambda + \frac{c}{M_v}$, then $\tilde{R}(\lambda, \mu) = 0$ for any $\mu \geq 0$ and $\lambda \in [0, \Lambda]$. Also if $\lambda \geq \kappa$, then $\tilde{R}(\lambda, \mu) = 0$ for any $\mu \geq 0$.

$$R^* = \sup_{\lambda \ge 0, \, \lambda + \frac{C}{M_v} \le \mu \le Q^{-1}(M_v)} \tilde{R}(\lambda, \mu).$$

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Results: Optimal Service Rate

Let $\gamma(\lambda)$ be given by $\left\{\mu: Q'(\mu) - \frac{c}{(\mu - \lambda)^2} = 0 \text{ and } \mu > \lambda\right\}$.

i. Lemma 4: If there exists μ such that $p(\lambda, \mu) > 0$, then

$$\max_{\mu \geq 0} \tilde{R}(p(\lambda, \mu), \mu) = \tilde{R}\left(p(\lambda, \gamma(\lambda)), \gamma(\lambda)\right)$$

$$\max_{\mu \ge 0} U(\lambda, \mu) = U(\lambda, \gamma(\lambda))$$

ii. **Lemma 5**: $\gamma(\lambda)$ is a well-defined continuous function for any finite constant:

$$M>0 \text{ and } 0<\gamma'(\lambda)=\tfrac{2c}{2c+(\gamma(\lambda)-\lambda)^3Q''\left(\gamma(\lambda)\right)}\leq 1.$$

Optimal Arrival Rate (Patients Load)

$$V'(\lambda) + \lambda V''(\lambda) - Q\left(\gamma(\lambda)\right) - \frac{c}{\gamma(\lambda) - \lambda} - \frac{c\lambda}{(\gamma(\lambda) - \lambda)^2} = 0$$

Proposition 1. Consider two travel burden functions t_1 and t_2 such that $t_1(x) = a$ and $t_2(x) = t(x) + a$ for some constant $a \ge 0$, for all $x \ge 0$. The following results hold:

(i)
$$\lambda_1^* \geq \lambda_2^*$$
,

(ii) If in addition
$$\lambda_1^* > 0$$
 and $\lambda_2^* > 0$, then $\mu_1^* \ge \mu_2^*$.

As the "*distance*" cost per mile <u>increases</u> the optimal service rate of the specialist <u>decreases</u>:

- Specialists will treat fewer patients, as per (i)
- Specialists will tend to compensate for the traveling burden by spending more time with the patient, as per (ii)

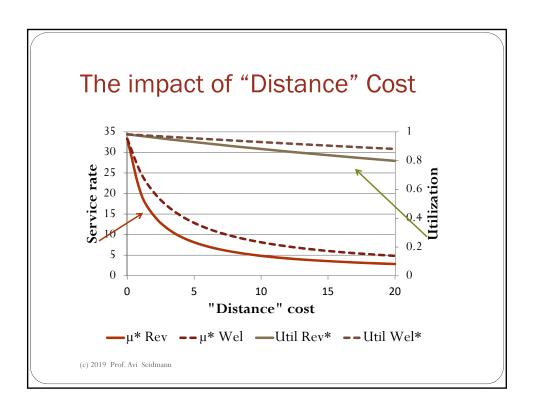
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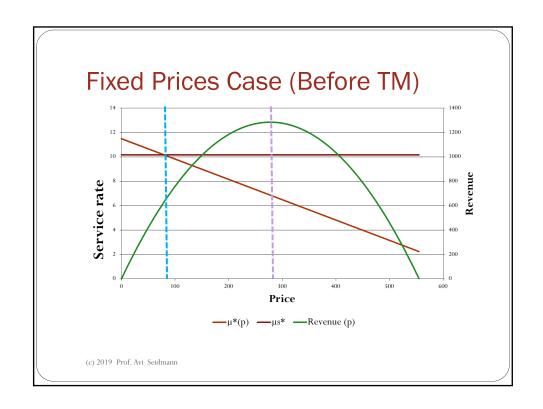
Analytical Results

- I. Given an arrival rate, the **optimal service rate** (for the specialist) will be non-decreasing with the arrival rate, $0 < \gamma'(\lambda) \le 1$.
- II. **Proposition 2:** A specialist trying to maximize revenue generation rate will operate slower and see fewer patients as compared to a specialist trying to maximize social welfare.

$$\mu_R^* < \mu_S^*$$
 and $\lambda_R^* < \lambda_S^*$

- II. As the "distance" cost per mile <u>increases</u> the optimal service rate of the specialist <u>decreases</u>:
 - The optimal decisions of the revenue maximizer and the welfare maximizer diverge.

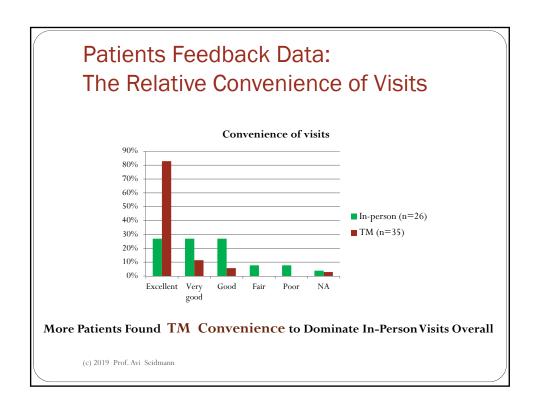


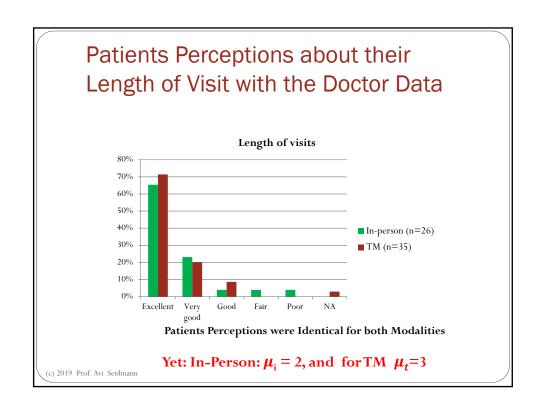


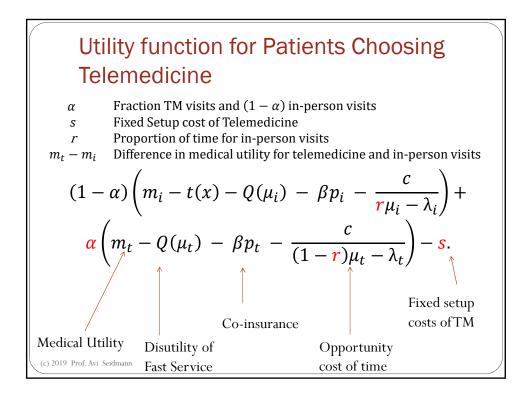


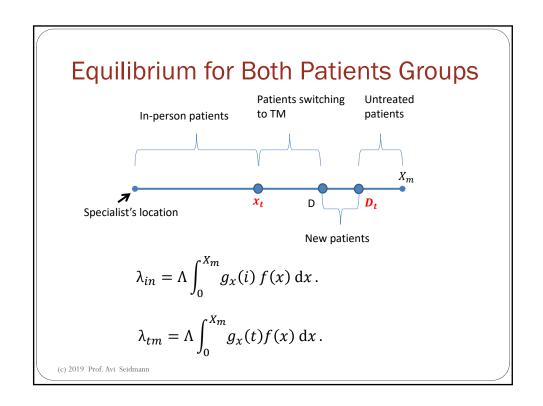
What does Telemedicine change?

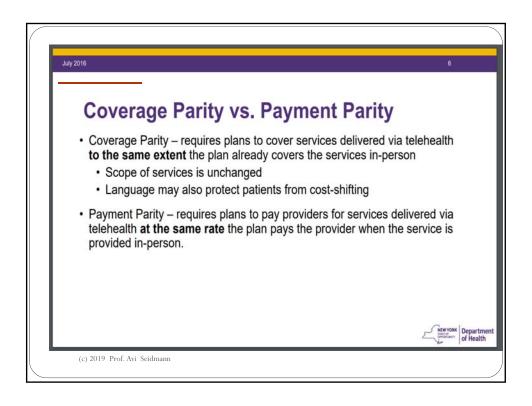
- Telemedicine "almost" removes the distance factor from the equation.
 - The distance "cost" reduces but is not removed altogether.
- Patients may bear an initial fixed set-up cost (\$ S) if they opt for telemedicine.
- ullet Out-of-pocket costs for the patient per visit (\$ $oldsymbol{eta} p_t$)
- Patients, based on their utility may choose to (i) opt out of treatment or (ii) choose treatment in person or (iii) choose treatment through telemedicine















The Clinical/OM/ECON Impact of TM for Chronic Care - Key (Analytical & Empirical) Conclusions Impact on Patients: Impact on Specialists:

- (+) Better/same overall care quality.
- (+) Total Patients' welfare increases.
- (+) The price per visit goes down.
- (-) Increased waiting times for appointments.
- (-) The expected face-to-face times get shorter.
- (+/-)Yet, not all patients share the same TM benefits:
 - $\bullet\,\,$ Patients nearby will suffer from reduced utility.
 - Patients located "farther away" benefit relatively more.
 - The 'Demographic Impact' issue

- (+) Visit length gets shorter.
- (+) MD Utilization increases.
- (+) Treats more patients
- MD Capacity Increases.
- (-) Price per visit will go down.
 - Optimal to partially subsidize the Patients' technology setup costs.
- (+)Yet, the overall revenue will increase.
- (+/+) In the long run:
 - Gain market power
 - Reduce clinical office costs
 - Partition the visits:
 - Interventional do F2F
 - Pre/Follow-ups with TM

Important Applications Data-Intensive Medical Research

- I. **Diagnosis support research** from common conditions to complex diseases typically build upon comparative AI/Stat studies with similar persons
- II. Consumer-directed diagnostic testing from fertility at-home to blood or saliva samples mailed testing
- III. Image analytics for radiological diagnostics aim to support early detection, treatment planning and disease monitoring in oncology, cardiology and other areas.

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Important Applications Data-Intensive Medical Research

- IV. **Price transparency** aimed at allowing patients a more personalized view into their treatment options.
- V. Provider search and ratings should allow patients to read reviews of potential providers in hopes of making informed care decisions.
- III. Physicians' staffing, appointments and scheduling including wait times at urgent care clinics, allowing users to book appointments, most within (two hours), manage the timing of specialty procedures and deal with last minute Patient or MD cancellations of an appointment.

Our Talk Today



- Lessons from Galileo Galilei
 - Observations can be misleading...
- 1. Information Hang-overs in Healthcare Service Systems
 - The value of systematic (end to end) process flow analytics
- 2. Does Technology Substitute for Nurses?
 - The data and economics of process flow automation
- 3. The Operational Effects of Telemedicine on Chronic Care
 - MDs and Patients as players in complex Non-Atomic Games
- Overall Data & Analytics Insights from it all
 - Why Medical Schools start teaching Medical Informatics

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Overall.....

- Data will tell us what did happen
- Models can tell us what an 'alternative future' may look like, and explain the data we see
- Ideally, use both in your research to calibrate and to verify
- In Physics: To get a Nobel, each new theory (Model) requires experimental validation (Data)

