Essays on the Economics of Health Care, Productivity, and Market Structure

HARVARD UNIVERSITY
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DISSERTATION ACCEPTANCE CERTIFICATE

The undersigned, appointed by the Committee for the PhD in Business Economics have examined a dissertation entitled

Essays on the Economics of Health Care, Productivity, and Market Structure

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candidate for the degree of Doctor of Philosophy and hereby certify that it is worthy of acceptance.

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Essays in the Economics of Health Care, Productivity, and Market Structure

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Abstract

The first essay studies how private-equity driven consolidation in health care affects real outcomes. By matching insurance claims data with information on private equity acquisitions of dental clinics, we show that private equity ownership increases both clinic revenue from reimbursements and the volume of procedures clinicians perform, and that these increases overwhelmingly come from the extensive margin. Further, we show heterogeneity in these effects across the types of procedures clinicians perform, with particular effect on X-rays and other diagnostic procedures. The second essay analyzes the relationship between the HITECH Act and very early-stage venture capital activity in the health care information technology industry. We first document increases in entrepreneurial capital in both general health care IT companies and in specifically EHR-related companies. Second, we show that the increase in the proportion of seed-stage funding within health care IT in the years following the HITECH Act is likely not attributable to the Act itself, as IT companies unrelated to health care, as well as health care IT in Europe, both experienced similar shifts in the distribution of venture capital financing. The third essay studies the empirical relationship between the rise of health care information technology and health system consolidation. Motivated by a theoretical model of concentration and technology adoption, we demonstrate that hospital mergers cause significant acceleration in investment in IT capabilities at acquired hospitals. We show that this effect is driven by acquisitions of low-capability hospitals by high-capability systems. Finally, we provide suggestive evidence that a hospital's relative level of IT adoption is predictive of future acquisition activity.

Contents

This dissertation is dedicated to my family and friends.

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1

Private Equity and Dental Practice Consolidation

This paper was co-authored with Angie Acquatella (Harvard University), Rishab Guha (Harvard University and Harvard Business School), Nathan Patrick Palmer (Department of Biomedical Informatics, Harvard Medical School), and Sung Eun Choi (Harvard School of Dental Medicine).

1.1 Introduction

How does investor-driven consolidation affect real outcomes? The rise of private equity in the U.S. has caused a wave of consolidation among middle-market firms across the economic landscape, driven by sophisticated financial investors. Despite substantial policy interest in the consequences of these consolidations, we have relatively little quantitative evidence about how private-equity investors adjust the operations of the companies they acquire. In this project we use granular data on the dental care industry to pursue a detailed study of operational changes at individual providers post-acquisition.

The healthcare industry has been one of the major arenas for private-equity-driven consolidation. Much of this consolidation has involved private equity funds acquiring and rolling up a collection of small owner-operated practices, such as dental clinics or dermatologists' offices[124,134]. Private equity investors have rolled up hundreds of such dental practices since 1990, involving thousands of clinicians and tens or hundreds of thousands of patients. While this mechanism for consolidation is often more subtle than blockbuster mergers or acquisitions, such small deals can have sizable real effects on competition, particularly in segmented industries such as health care.[133]

In this paper, we use the dental care industry as a laboratory for studying the impact that private equity-led consolidation has had on the prices and provision of health care services. After matching insurance claims data from a large, national payer with private-equity acquisitions reported in the financial press, we provide evidence that private equity ownership increases both clinic revenue from reimbursements and the number of procedures clinicians perform. Further, we characterize the types of procedures that private equity ownership tends to increase the most. Finally, we decompose this effect into two components: increases in the number of patients per clinic and increases in the number of procedures per patient, finding that the overall increase in procedure volume is driven by the former, extensive margin effect.

There is growing interest within economics and finance in measuring the effects of private equity investment on portfolio company pricing, operations, and efficiency. For example,[57] study the effect of private equity buyouts on for-profit colleges and find that colleges bought by private equity funds generate higher profits, but also have worse outcomes. However, there has been relatively little research focused on studying the interaction between private equity and health care, even though the health care sector is by many measures the largest recipient of private equity investment. Within the medical literature, there has been some work studying the impact of private equity investment on nursing homes (e.g.,[69,123,66]), but to our knowledge, our study is the first to directly observe changes in prices and quantities of services and to thus illustrate at such a granular level the impacts of private equity investment on operations and management.

Dentistry in particular is a uniquely interesting setting in which to study these phenomena. First, unlike the vast majority of other health care specialties, essentially all dental care in the US is administered at small clinics, rather than at acute care centers or hospitals, ruling out acquisitions by hospital systems that may drive competing effects in otherwise similar medical markets. This allows us to readily isolate the particular effects of private equity ownership on operations. Second, the economic structure of dental markets—in which most procedures are elective and non-emergency and most dental disease is non-communicable and therefore largely free of externalities—analogize dental care more closely than most other medical care to "typical" commodity markets[120]. Relatedly, the landscape of dental insurance differs markedly from the typical health insurance, typically eschewing out-of-pocket limits or catastrophic protection and allowing clinicians to charge at will within "reasonable and customary" limits, rather than stringently-negotiated fee-for-service contracts. As a result, one would expect that any price increases as a result of private-equity driven consolidation to understate the comparable effect in other medical specialties, where professionalized management is also able to negotiate more aggressively with insurers.

The remainder of this paper is organized as follows. To contextualize our findings, Section 1.2 outlines some relevant institutional details of the dental care industry and summarizes relevant literature on the effects of private equity investment on portfolio company operations and on management within health care. Section 1.3 describes our data and methodological approach. Section 1.4 discusses our empirical findings, and Section 1.5 concludes.

1.2 Background

1.2.1 Private Equity and Productivity

Private equity funds refer to professionally managed pools of private capital from private investors known as limited partners. The capital is overseen and deployed by investment professionals employed by a private equity firm and is often used invest in majority or total ownership stakes in companies, both public and private. Over the lifetime of the investment—often five to ten years—private equity managers will often play an active role in the management of the business. Private equity firms gained some notoriety in the 1980s during a wave of leveraged buyouts, transactions financed by large amounts of debt, in addition to equity from limited partners, to make these investments, a practice which continues today. For a more complete treatment of the definition and history of private equity, see[80,118] Investment theses, industry focuses, and post-buyout management practices differ widely across different private equity firms, with relatively little systematic understanding of how this corporate form affects real outcomes.

This paper contributes to the empirical literature studying the impact of private equity investment on real activity, which can often be theoretically ambiguous. A large merged entity may be able to economize on input costs which would allow it to offer lower prices than smaller competitors. Skilled private equity investors may also make firms themselves more efficient through better management and operational practices, thereby improving firm-level productivity.[16] In the dental care industry, this may take the form of improved scheduling or records-keeping technology, group purchasing agreements, or marketing campaigns.[13] finds that industries with greater private equity investment activity have higher growth than the same industry in comparison countries and over time.[79] studies a sample of large management buyouts from the LBO wave of the 1980s, finding that buyouts increase profits through improved incentives for managers. Similarly,[44] study leveraged buyouts from 1980 to 2005, finding that buyouts cause productivity gains at acquired firms by accelerating the exit of lower-producitivity and entry of higher-productivity establishments operated by the firms.[88] analyze investment by innovative firms that are acquired in LBOs, showing that target firms see higher patent citation rates than comparison firms, demonstrating long-run produtivity improvements. Further,[14] study restaurant chains that are acquired by private equity sponsors, finding that chain-operated tend to become cleaner and safer even relative to franchised establishments. The authors additionally find that this effect is particularly pronounced in acquisitions where the acquirer has industry experience, bolstering the hypothesis that private equity managers are offering value-added professional management.

On the other hand, larger practices may use their newfound market power to demand higher prices or to push patients towards more higher margin, but lower value, procedures.[15], studying public hospitals in England, find that greater competition across hospitals results in better hospital performance and management practices.[27,28] finds evidence of softening product market competition following leveraged buyouts of supermarket chains, suggesting scope for both acquired firms and rivals to raise prices. Private equity sponsors may also be more profit-driven than physician-proprietors, who might have non-pecuniary motives to treat underserved communities or improve population health (see Subsection 1.2.3). In this case, changes in ownership may result in decreased provision of care to disadvantaged populations (e.g., Medicaid recipients) or inefficient over- or under-provision of care. Relatedly, private equity takeovers may achieve profitability by breaching implicit contracts with key stakeholders, along the lines of the general mechanism discussed in[117].

[45] highlight the heterogeneity in the effects of private equity buyouts on target firm operations, underscoring the importance of understanding the post-acquisition dynamics of specific types of health care practices and their potential effects on patient care.

1.2.2 Management and Productivity in Health Care

The health care industry, and the provider sector in particular, has experienced massive reorganization over the past several decades. [62] Our study also expands the sizable literature on the operational effects of changes in ownership and management practices within the health care industry.

Much of the research on changes in ownership in health care have analyzed the impacts of hospital mergers on prices and quality of care. Many past studies (e.g.,[39,42]) have focused on the price effects of hospital mergers, generally finding that merged hospitals tend to increase the prices paid by patients and insurers, often by reducing competition to be included in insurers' networks.[22] examine the effect of acquisitions of physician practices by hospital systems, and similarly find that acquisitions tend to result in price increases and that the magnitude of the price increase is correlated with the concomitant increase in market share created by the acquisition.[33] find that mergers of geographically proximate hospitals, but not mergers of distant hospitals, tend to increase prices, and that prices are highly sensitive to both hospital and insurer concentration.[73] hospital mergers in California in the early 1990s, finding ambiguous impacts on several quality metrics, including readmission rates and inpatient mortality.

There has, however, been relatively little focus on the empirical effects of the changes in and increasing consolidation of ownership among independent owner-operated practices, despite their large—and expanding—role in care provision.[124,134] Essentially all dental care, for instance, is provided in a small practice setting, and understanding how changes in market structure affect patients' experience is of first-order importance. While much attention has been paid to the importance of pecuniary incentives for health care providers' behavior (e.g.,[71,72,30,56]), there is substantial empirical and theoretical support for the idea that providers may not perfectly maximize profits. As is the case for most issues in modern health economics research, this idea dates at least to[9], who suggests that the general expectations of physician behavior include a primary concern for patient well-being, an altruistic, reputation- or norms-based motivation separate from purely pecuniary incentives. As such, physicians may depart from profit-maximizing behavior, suggesting that new management may be able to increase profits by effecting operational changes in a number of ways.[82] lends support to this idea, showing that the introduction of cardiac surgeon quality report cards caused increases in surgeon quality but not in demand, demonstrating the importance of non-financial incentives in determining clinician behavior.[38] and[121] note that these expectations around physician behavior may play a role in stunting industry- and firm-level productivity growth by softening the typical role that demand side competition would play in incentivizing entry by high-productivity entrants and the exit of lower-productivity firms.[25] [40] analyze the importance of hospitals' ability to "upcode" patients to higher reimbursement billing codes, finding both that hospitals with greater room to upcode are more likely to experience a change in management and that hospitals that do change management ultimately do upcode more than control hospitals, highlighting the importance of management practice to profitability.

More analogously to our setting,[59] find that dialysis facilities that are acquired by larger chains tend to realign their behavior and practices in accordance with those the acquirer, often with detrimental effects on patient outcomes. The most notable instances the authors cite of this behavior is greater prescription of highly reimbursed drugs and replacing nurses with lower-skill (and lower-cost) technicians. Importantly for our setting, the authors argue that the convergence towards the acquiring firms' strategies writ large, rather than market power alone, drives these changes. The paper closest to ours is[66], in which the authors measure the effects of private equity buyouts of nursing homes. They find that these acquisitions by private equity sponsors, but not those by non-PE corporates, result in lower staffing levels, reduced patient health, and worse aggregate quality metrics.

1.2.3 Dental Care

Several features of the dental care industry meaningfully distinguish it from other markets and from much of the rest of the health care industry in particular that will be important to contextualize our empirical findings below. First, as in medicine, dental practices are beholden to state-level restrictions on "corporate practice of dentistry", which forbid non-dental care professionals from directly operating clinics or making clinical decisions.[26,106]

Second, unlike most medical specialties, nearly all dental care occurs in private single-office solo or group practices unaffiliated with hospitals or other larger health care providers. As of US, approximately 90% of dentists were either sole proprieters or partners in a group practice.[107] This is in stark contrast with other medical specialties which face significant competition from and referral relationships with hospitals and simplifies the understanding of the motivations for acquisition.

Finally, unlike health insurance, which typically has an out-of-pocket maximum above which all marginal expenses are covered by the insurer, dental care insurance typically has an (often relatively low) annual coverage maximum, above which the member is liable for 100% of marginal expenses. A typical dental insurance plan will cover 100% of preventive care, 80% of basic procedures, and

50% of other procedures up to the annual maximum. There will be some variation in copayment, deductible, and annual maximum coverage levels both across plans and across procedures within a plan.[130] This has important implicatiosn for how dentists and dental service organizations manage pricing and billing for members.

1.3 Data and Empirical Strategy

1.3.1 Data Sources

Our primary data source is the set of historical insurance claims data from a large, national private payor between 2012 and 2017. Several features of this data make it ideal for understanding the effects of private equity ownership. The data describes insurance claims at the individual procedure level, including an anonymized identifier for each the patient, a National Provider Identifier (NPI) number for the individual provider performing the work, an additional billing NPI identifying the individual or organization charging for the procedure, and the amount reimbursed by the payor to the provider, as well as a small set of characteristics of patients and providers. Importantly, each procedure has exactly one procedure code, which we match to the Code on Dental Procedures and Nomenclature (CDT) for a verbal description of the procedure, its "procedure group" such as whether the procedure is preventive or restorative in nature. Consequently, we can analyze granular information about clinician behavior–including prices and quantities of individual procedures–before and after an acquisition. Further, the provider-level identifier allows us to track individual clinicians across multiple practice locations over time and to compare how clinician behavior changes under different ownership structures.

To identify whether practices are owned by private equity firms, we supplement the insurance claims data with a dataset of deals involving private equity investment in dental practices. This data, compiled by Preqin, has been aggregated from wire services and other public announcements of private market transactions, and contains information on both the transaction—dates, investors, and transaction values when made public—and on the practice or group being acquired. The identifying information of the practices, including organization and clinic names and physical addresses is sufficient for us to manually match each of the acquired firms to its National Provider Identifier (NPI) using the National Plan and Provider Enumeration System (NPPES) database. If an NPI appears in this list of private equity-associated identifiers, then we label it as "private equity-owned". The numbers of procedures, patients, and providers in our sample are shown in Table 1.1.

Measure	*PE-Affiliated*	*Non-PE-Affiliated*
No. Procedures	783,829	107,016,530
No. Unique Patients	74,245	7,391,832
No. NPIs	4,574	214,081

Table 1.1: Number of Procedures, Unique Patients, and Unique Providers

1.3.2 Aggregation

We aggregate the claims data at the clinician-month level to compute several variables:

- the total number of claims;
- the total reimbursed amount;

- self-biller $\in [0, 1]$, the fraction of claims in a given month that a provider bills to their own NPI;
- PE-biller $\in [0, 1]$, the fraction of claims in a given month that a provider bills to a PE-affiliated NPI.

We repeat this procedure to compute the number of claims and reimbursement amounts at the clinician-month level for several more granular categories of procedures, such as preventive, diagnostic, periodontic, and restorative procedures. This treatment allows us to test whether private equity affiliation has an effect on practice revenue or is associated with a higher or lower propensity to provide certain types of treatments. Additionally, we decompose any changes into the change in the number of patients per provider and the number (or reimbursement amount) per patient.

	# Claims		$ Reimbursed		
Procedure Type	*Mean*	*Std. Dev.*	*Mean*	*Std. Dev.*	*N*
Diagnostic	8.89	14.69	344.71	709.36	4284687
Preventive	5.99	9.85	326.36	486.72	3620063
Restorative	4.27	5.79	945.38	1385.30	2433819
Periodontics	3.97	7.33	409.56	713.97	1056288
Oral & Maxillofacial Surgery	4.38	7.16	641.30	1089.18	696182
Endodontics	1.92	2.16	1035.29	1164.66	390322
Adjunctive General Services	4.22	6.59	289.98	433.28	339815
Orthodontics	2.30	2.92	1542.10	1554.86	175288
Implant Services	2.52	2.35	1751.17	1179.34	107571
Prosthodontics (Removable)	1.83	1.59	845.73	762.41	106403
Prosthodontics (Fixed)	3.70	3.00	1918.46	1346.54	62839
Maxillofacial Prosthetics	2.08	1.38	483.53	453.50	76
All	16.47	26.87	1398.49	2322.02	5061306

Table 1.2: Mean and standard deviation of the number of claims and total reimbursement amounts at the clinic-month level across procedure type. Measures only include providers that bill to the same NPI for the entire month and that billed a positive number of claims in the corresponding specialty.

We also aggregate the procedure data at the patient-provider-date, or *visit*, level. This lets us test whether the likelihood of a a clinician administering a given procedure or category of procedure (e.g., diagnostic) in a given visit changes with private equity ownership. Crucially, this also allows us to follow patients' and providers' interactions over time, in order to analyze whether, for instance, the amount of time between a patients' visits conditional on receiving a diagnostic procedure changes following a private equity buyout. In short, this view offers a highly nuanced view of clinicians' practices that, in conjunction with ownership information, offers a clear window into the effect of private equity ownership on granular practice operations.

1.3.3 Provider-Month-Level Regressions

To estimate the effect of private equity ownership on clinician behavior, we consider the following estimation equation:

$$y_{i,t} = \beta \mathrm{pe}_{i,t} + \alpha_i + \tau_t + \varepsilon_{i,t}$$

In this equation, $\mathrm{pe}_{i,t}$ is a binary variable indicating whether clinician i bills to an NPI matched to a private equity-run dental group in month t. When $\mathrm{pe}_{i,t}$ is equal to 1, we say that clinical i is private-equity affiliated during month t. α_i and τ_t are clinician and time fixed effects, respectively. We estimate the coefficient β for several outcomes of interest, $y_{i,t}$:

- Total number of claims;
- Total reimbursement revenue;
- Number of claims and reimbursement revenue for each category of procedures;
- Number of claims per member;

- Number of unique members seen;
- Number of unique claim codes (i.e., procedures).

where all results are aggregated at the clinical / month level. The results of these regressions are shown in Tables 1.3, 1.4, 1.6, 1.7, and 1.8, respectively.

1.3.4 Visit-Level Regressions

We further estimate several similar regression equations at the visit-level, which captures each unique date, t, on which a patient, j, and provider, i, interacted. For these regressions, we focus on a variety of dependent variables which capture the number of days until j has another visit.

$$\log(\text{Days to next visit})_{i,j,t} = \beta_0 \text{pe}_{i,t} + \beta_1 \text{Diagnostic}_{i,j,t} + \beta_2 \text{pe}_{i,t} \text{Diagnostic}_{i,t} + \varepsilon_{i,j,t}$$

We include a dummy variable indicating whether patient j's visit to dentist i on date t included a diagnostic procedure and that variable's interaction with an indicator for whether dentist i is PE-affiliated. The coefficient of interest, β_2, represents the average percentage change in the number of days until patient j's next visit to a dentist. We estimate this regression with three dependent variables: the number of days until patient j's visit to any dentist, the same dentist (j), or a different dentist. The results of these regressions are shown in Table 1.9

1.4 Results

Our baseline regressions estimate the effect of private-equity acquisition on dollar revenue per month, and the number of claims filed per month at the individual dentist level. In the full sample, we find that PE-affiliation is associated with a 7% increase in total revenue, and an associated 7% increase in the total number of claims: Note that each of these coefficients represents the incre-

	Dependent variable:	
	log($)	log(# Claims)
Billed to PE-affiliated NPI	0.072^{***}	0.074^{***}
	(0.019)	(0.017)
Billed to own NPI	0.030^{***}	-0.026^{***}
	(0.005)	(0.005)
Observations	4,801,782	4,850,196
R^2	0.430	0.533
Dentist fixed-effect	Y	Y
Time fixed-effect	Y	Y

Table 1.3: Regression of revenue and claims on dummies for private equity ownership and self-billing. Standard errors are clustered at the time and individual NPI level.

mental effect on the dependent variable relative to the provider billing to a non-PE-affiliated group practice NPI. This within-clinician identification strategy estimates the average change for dentists who move from working for a non private-equity affiliated practice (including, potentially, their own practice) to working for a private equity affiliated practice.

If we restrict the sample to only observations in which dentists either self-bill or bill to a PE-affiliated NPI, so that our identification is based entirely on dentists who switch between sole-practice to PE-affiliation, the effect sizes increase to a 12% increase in revenue, and a 22% increase in the number of claims. This suggests that the scope for private equity funds to meaningfully affect the operational behavior of dentists is larger for dentists who had previously been solo practitioners, consistent with models in which private-equity acquisition helps targets acquire economies of scale and technical management knowledge.

	Dependent variable:	
	log(Dollar revenue)	log(Number of claims)
Billed to a PE-affiliated NPI	0.125***	0.218***
	(0.036)	(0.033)
Observations	2,523,094	2,548,507
R^2	0.449	0.553
Dentist fixed-effect	Y	Y
Time fixed-effect	Y	Y

Table 1.4: Regression of revenue and claims on a dummy for private equity ownership, with the sample restricted to only dentists who either self-bill or bill to a PE-affiliated NPI. Standard errors are clustered at the time and individual NPI level.

Decomposing these effects into intensive and extensive margins, we find that the increase in volume is driven by the number of unique patients visiting PE-owned clinics rather than the number of procedures being performed for each patient, suggesting that private equity ownership may help dental clinics accelerate their marketing efforts:

In order to further investigate the effect of private equity on dentist behavior, we estimate regressions at the procedure-code level, between procedure groups. For a procedure group g, such as

	Dependent variable:	
	log(Claims per Member)	log(# Members)
PE Biller	-0.029^{***}	0.121^{***}
	(0.008)	(0.015)
Observations	4,969,517	4,969,517
R^2	0.354	0.610
Dentist fixed-effect	Y	Y
Time fixed-effect	Y	Y

Table 1.5: p: 0 *** .01 ** .05 * 0.1. Regression of average claims per member and number of distinct members on a dummy for private equity ownership, with the sample restricted to only dentists who bill to a single NPI in a given month. Standard errors are clustered at the time and individual NPI level.

diagnostic procedures, let c index individual claim codes. Then we estimate

$$\log(y_{c,i,t}) = \alpha_{c,i} + \tau_{c,t} + \beta \mathrm{pe}_{i,t}$$

where y is the code-level dependent variable and α and τ are the analogous fixed effects. We use average price per claim, the average number of claims, the total revenue, and the number of unique members filing a claim as dependent variables.

We find that private equity owners appear to be able to increase both price and quantity for claims within the diagnostic group; this suggests that they are able to expand the efficient frontier for the provision of diagnostic services. This is again consistent with the hypothesis that experienced private equity operators may be able to introduce customer-acquisition techniques that dentists without substantial business training or experience may be unfamiliar with.

Additionally, we find that private-equity acquisition causes reduced price and increased quantity,

Outcome variable	$\hat{\beta}$	t	p	Sample
Total Revenue	0.07	8.31	0.00	full
	0.11	6.67	0.00	restricted
Price per claim	0.04	7.29	0.00	full
	0.04	3.85	0.00	restricted
# of claims	0.03	4.11	0.00	full
	0.07	5.45	0.00	restricted
# of members served	0.03	4.38	0.00	full
	0.06	5.27	0.00	restricted

Table 1.6: Estimated coefficients from a regression of outcome variables on a dummy for private equity ownership for diagnostic claims. The restricted sample contains only dentists who are either self-billing or billing to private-equity-affiliated NPIs

with no significant change in overall revenue, for periodontal (gum disease) treatments. In equilibrium, an increase in quantity without a corresponding increase in revenue is only profitable in the presence of lower marginal costs. Though our data does not permit us to directly observe costs, this provides suggestive evidence that for certain procedure types private equity owners may be able to implement changes to improve efficiency and reduce costs.

We also find that private-equity affiliation increases the number of claim codes that dentists bill within diagnostic, periodontic, and preventive claim groups; in the sample of dentists who move from self-billing to billing to a PE-affiliated NPI, the range of preventive and periodontic codes billed increased by over 20%. In combination with our previous results, this suggests that private equity ownership may increase clinician attractiveness to patients by increasing the services that the clinician can provide.

Finally, we find that the expanded provision of diagnostic care appears to be connected to more

Outcome variable	$\hat{\beta}$	t	p	Sample
Total Revenue	0.01	0.28	0.78	full
	-0.03	-0.85	0.39	restricted
Price per claim	-0.05	-3.33	0.00	full
	-0.10	-3.10	0.00	restricted
# of claims	0.06	3.47	0.00	full
	0.06	2.11	0.03	restricted
# of members served	0.06	5.17	0.00	full
	0.08	3.50	0.00	restricted

Table 1.7: Estimated coefficients from a regression of outcome variables on a dummy for private equity ownership for periodontic claims. The restricted sample contains only dentists who are either self-billing or billing to private-equity-affiliated NPIs

efficient follow-ups: the average time-to-next-visit following an appointment which included diagnostic services is 15% lower for PE-affiliated dentists than for others. This suggests that PE-affiliation may also help clinicians expand care on the extensive margin by enabling them to more quickly and effectively convert diagnostic care into procedures.

1.4.1 Event Study Design

While private equity investors certainly do not choose which dental practices to acquire at random, we provide visual evidence in this section against the hypothesis that acquired providers differ systematically from non-acquired providers in ways that may threaten our identification strategy. In particular, figures 1.1(a) and 1.1(a) plot the estimates of the coefficients of the following regression equation:

$$\log(\text{claims}_{i,t}) = \alpha_i + \tau_t + \sum_{s=-T}^{T} \beta_s 1(t \in s),$$

Procedure group	$\hat{\beta}$	t	p	*Sample*
Preventive	0.06	5.98	0.00	full
	0.22	11.08	0.00	restricted
Periodontics	0.09	5.89	0.00	full
	0.22	7.52	0.00	restricted
Diagnostic	0.05	5.23	0.00	full
	0.14	6.44	0.00	restricted

Table 1.8: Estimated coefficients on a regression of the number of unique claim codes filed in each procedure group on a dummy for private-equity ownership. The restricted sample contains only dentists who are either self-billing or billing to private-equity-affiliated NPIs

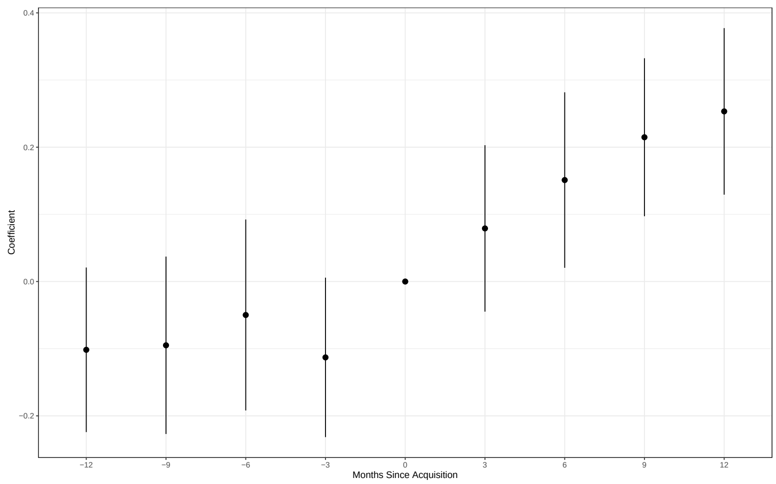
where $s < 0$ indexes the number of months until provider i's next month billing to a PE-affiliated NPI, and $s > 0$ indexes the number of months since i's most recent month billing to its own NPI.

Note that the time $t = 0$ corresponds to between zero and three months since a given provider's most recent month billing to their own NPI. These estimates show that, prior to acquisition, target clinicians do not exhibit a systematic trend in the volume of reimbursements or procedures they perform and that, post-acquisition, claims and reimbursements increase over time.

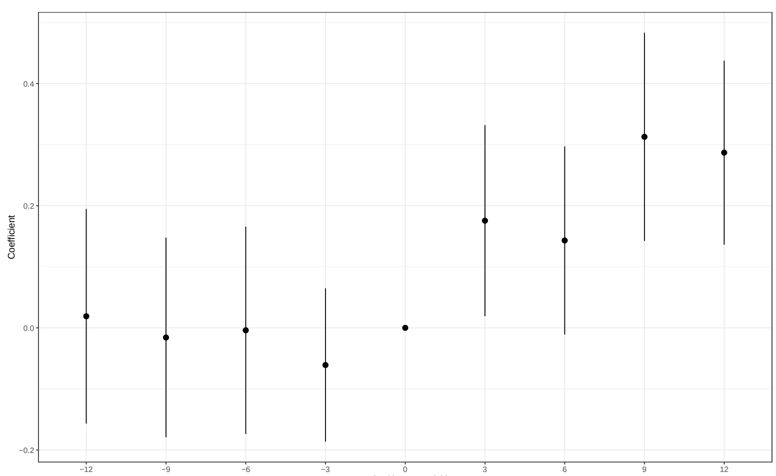
1.5 Conclusion

The overall implications of our results on patient outcomes is unclear. Greater provision of some diagnostic procedures such as X-ray imaging—even within ADA-recommended guidlines—may lead to worse health outcomes over time as the radiation exposure may increase the risks of certain types of cancer with limited marginal diagnostic value.[29,98] .

On the other hand, diagnostic procedures with fewer or more innocuous side effects may im-



(a) # Claims



(b) Allowed Amount

Figure 1.1: Event Study Regression Coefficients

	Dependent variable:		
	log(Days to next dental claim)		
	(1)	(2)	(3)
PE Dummy	0.011	−0.038	−0.037*
	(0.016)	(0.027)	(0.022)
Diagnostic Dummy	0.00004	0.060***	−0.141***
	(0.008)	(0.009)	(0.006)
PE dummy × Diagnostic Dummy	−0.156***	−0.196***	−0.083***
	(0.016)	(0.017)	(0.017)
Sample	Full	Same dentist	Diff dentist
Observations	18,779,592	14,139,681	4,639,911
Adjusted R^2	0.109	0.142	0.138

Table 1.9: Regression of time between claims on a dummy for diagnostic claims interacted with a dummy for PE ownership. The "same dentist" sample includes only patient / claim pairs for which the next observed claim is with the same dentist; the "different dentist" sample includes only patient / claim pairs for which the next observed claim is with a different dentist

prove long-term health by enabling low-cost, high-value interventions before an acute (and expensive) procedure becomes necessary. Further, our empirical findings speak to the association between frequency of patient visits, diagnostic services, and intensity of care, which may lead to inefficient overprovision of health care services—so-called "diagnostic-therapeutic cascades".[37,93] In the dental care setting, we find limited evidence of this phenomenon with respect to private equity ownership: while PE ownership causes reduced follow-up time following a diagnostic procedure, the overall number of procedures performed per patient does not increase on average

In addition, we are currently unable to speak to the cost side of these acquisitions. While some of our results, such as the unchanged total revenue for periodontists following acquisition, suggest that reducing costs is in fact part of the acquirer playbook for increasing profits, our data does not allow us to measure that change quantitatively.

What is clear, however, is that private equity-led rollups of dental practices involves substantial changes to the operations of the businesses: on the whole, the total production, as measured by both total revenue and the raw number of procedures administered, at acquired clinics increases significantly, largely driven by the extensive margin of patients per clinic rather than the intensive margin of procedures per patient. We also provide evidence that the operations of acquired clinics become more efficient: conditional on receiving a diagnostic procedure, a typical patient of a private equity-affiliated dentist will receive their next procedure nearly 20% more quickly than an independent dentist. Connecting these observed operational changes with concrete patient outcomes will be the subject of future work.

2

Entrepreneurship and the HITECH Act

Note: An earlier version of this chapter has been previously published as [91]. *Much, but not all, of the content is very similar or identical to the published version.*

This paper was co-authored with Ariel Dora Stern (Harvard Business School) and William J. Gordon (Harvard Medical School and Partners HealthCare).

2.1 Introduction

In February 2009, as part of the American Reinvestment and Recovery Act—also known as the Obama administration's economic stimulus package—the US Congress passed the Health Information Technology for Economic and Clinical Health (HITECH) Act. The Act authorized tens of billions of dollars in federal subsidies for hospitals and eligibel physicians to adopt certifie electronic health record (EHR) systems. To qualify for subsidy payments, eligible professionals and hospitals were required to certify that they met standards of the Meaningful Use program for EHR systems. Beginning in 2015, nonparticipation in Meaningful Use caused clinicians to incur a reduction in Medicare and Medicaid reimbursements.[19]

Meaningful Use originally comprised three stages, each of which requried meeting increasingly comprehensive EHR adoption standards, as defined by the Centers for Medicare and Medicaid Services and the Office of the National Coordinator for Health IT, to qualify for incentive payments. Meaningful Use Stage 1 set preliminary standards for the electronic recording and reporting of clinical information, requiring eligible physicians to satisfy a set of fifteen core objectives. Stage 2 increased the number of required EHR capabilities and encouraged clinicians to use this information to improve clinical processes. In so doing, Centers for Medicare and Medicaid Services and Office of the National Coordinator for Health IT sought to align the program with the National Quality Strategy.[24]

The government's role in incentivizing private investment and technological innovation has long been a subject of economic importance.[64,68,81] In energy markets in particular, researchers have found that government incentive programs may be effective ways of promoting innovation in new technologies.[46,36,1]

Although the HITECH Act clearly accelerated hospitals' adoption of EHRs, evidence regarding the Act's association with other outcomes has been thin.[53,4] Several researchers have found, at most, a small association with health or quality outcomes after more advanced adoption of health information (IT) capabilities, including EHR technology.[86,6,101] Other researchers have documented meaningful reductions to costs for hospitals in IT-intensive areas beginning several years after EHR implementations and have found that mortality statistics tend to improve after EHR implementations have had time to mature.[51,89] Importantly, some have pointed to the unintended consequences of EHR adoption, such as an increased incidence of clinician burnout associated with the administrative load of EHR adherence and EHRs' difficulty of use.[115,49,61] Improving EHR usability might even improve professional satisfaction and patient health outcomes.[76,119]

To our knowledge, however, there has not been any empirical research on the association between the HITECH Act and innovation in related health care technologies. This is surprising, given that in the health care setting, major policy changes that lead to increased demand for health care products have been shown to increase innovative activities. Notable examples include studies of how pharmaceutical research and development and commercialization activities respond to demand increases created by the passage of Medicare Part D.[18,83]

In this study, we invesigated whether the HITECH Act—which presented a large long-term increase in demand for and use of EHR systems—was associated with an increase in health IT entrepreneurship in the years that followed. In particular, the large-scale digitization of the medical record system was not only a major project in itself, but it would have also created a large trove of digital health data and spurred new clinical workflows upon which other health care IT tools and products could be built. Given the overall ambivalent success of EHR implementations, including some apparent cost and quality benefits at the expense of widespread clinician dissatisfaction, burnout, and usability concerns, understanding how manjor public subsidies for health care IT have shaped investment relative to the broader entrepreneurial landscape will be valuable for guiding future policy and investments in this area.

2.2 Data and Methods

To look for evidence of entrepreneurial finance flowing into the health IT sector, we examined the distribution of venture capital (VC) financing transactions, which typically are investments in young, privately held companies, for health care IT and EHR-related companies before and afer the HITECH Act's passage.[110] We also compared the investment patterns seen with those in the broader universe of VC transactions in the US. We interpreted seed-stage funding—equity investments in companies in the earliest stages of financing—of private companies by VC firms as a proxy for entrepreneurship in the industry, whereby more seed-stage financing is an indicator of greater innovation in the space.

2.2.1 Data

We collected data on VC investments from Capital IQ, a leading data vendor htat aggregates information on private investment transactions from public wire services and surveys of investment firms.

Our data includes the date, funding rund, transaction value (when available), target company's description, and target company's industry for each transaction.

Capital IQ includes a label for each transaction's funding round. We categorized each fundraising round into one of three types: seed, early-stage, and growth (or late). The specifics of the categorization are shown in Table 2.1, below.

Category	Funding Round (from Capital IQ)
Seed	Angel, Accelerator, Crowd-Funding, Pre-Seed, Seed
Early	Pre-Series A, Series A
Growth	Pre-Series B, Series B, Series C, Series D, ..., PIPE
Excluded	Venture, Debt, Bridge

Table 2.1: Funding Round Categorization

To determine whether companies' products were associated with EHRs, we matched the text of company descriptions from Capital IQ to the list of EHR search terms provided by the National Library of Medicine.[127]

2.2.2 Statistical Analysis

We primarily restricted our analysis to transactions that were announced between January 1, 2000, and August 31, 2018, for which the target company was incorporated and headquartered the United States. We also omitted the 31.3% of transactions for which the Capital IQ-recorded funding round was "venture", "bridge", or "debt". We excluded bridge and debt transactions because they are typically not equity investments and do not fit clealry into the fundraising timeline of a typical VC-financed firm (9.5% of transactions). The "venture" label (21.8%) of transactions, on the other hand, describes investments were the specific round is unknown. In robustness tests, we also included venture transactions in teh group of non-seed-stage investments. After applying these inclusion criteria, 70,982 transactions remained. Of these, 1060 transactions involved companies with a primary industry classification of "health care industry software", which we refer to as "health care IT" companies.

Finally, to determine whether companies' products were related to EHRs, we matched the list of EHR keywords from the National Library of Medicine to the text of company descriptions included in the Capital IQ database. If any of the search terms were included in the company description, then we labeled the company as "EHR-related". Of the 1060 health care IT transactions in our data set, we identified 333 as EHR-related.

To analyze whether the composition of the types of funding health care IT companies received changed in the period following the passage of the HITECH Act, we used a difference-in-differences design to test whether the fraction of investment transactions that raised seed-stage funding for US health care IT companies increased more than that of control groups of companies in three US categories: general health care (non-IT), IT (non-health care), and the entire universe of US VC transactions. The non-IT segment of health care companies and the non-health care segment of IT companies, in particular, are natural groups of investments to compare with health care IT investments, because they are likely to draw from the same set of expert investors, in particular those with a sector-specific investment mandate (e.g., IT-focused VC firms or health care-focused VC firms).

We also compared the change for US health care IT companies to that of European health care IT companies—those that would likely be unaffected by the passage of the HITECH Act—over the same time period.

We coded the period from January 1, 2000, through February 17, 2009, as the pre-treatment period, and February 18, 2009, through August 31, 2018, as the treatment period.

The outcome variable in our regressions was a binary variable indicating whether a given investment was seed stage, and the independent variables included whether the investment was in the post-HITECH period, whether the investment was in a health care IT company, an interaction term for these two variables, and a running time variable. In the regression equation, below, the coefficient of interest is β_3, the coefficient on the interaction term:

$$\text{Seed}_{i,t} = \beta_0 + \beta_1 \text{Post-HITECH}_{i,t} + \beta_2 \text{HealthIT}_{i,t} + \beta_3 \text{Post-HITECH}_{\text{i,t}} \cdot \text{HealthIT}_{i,t} + \delta t + \varepsilon_{i,t} \quad (2.1)$$

The model was estimated using ordinary least squares. We used a linear probability model for ease of interpretation of the estimated coefficients.[7,63] In robustness tests, we also implemented a logit specifications.

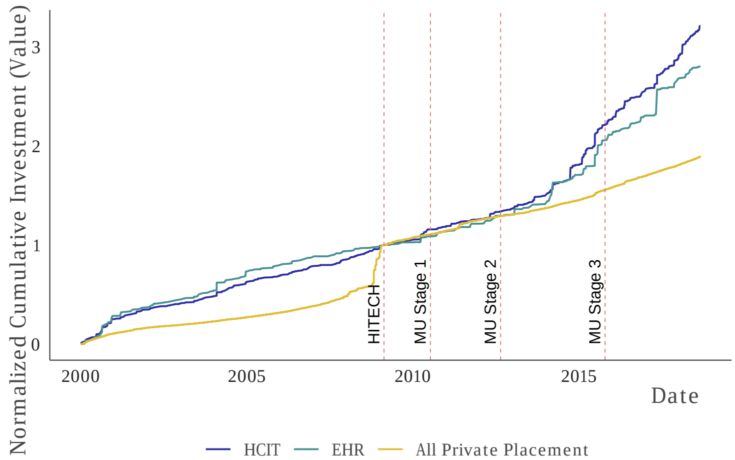
2.3 Results

Table 2.2 shows a breakdown of the number of VC, non-health care IT, health care IT, and EHR-related investments in the US seen both ebfore and after the passage of the HITECH Act. Our final analysis included 70,982 US investments, of which 9425 (13.3%) were seed stage, 10,706 (15.1%) were early stage, and 50,851 (71.6%) were growth stage. Of the seed-stage investments (i.e., those representing the earliest form of invesstment transaction and, thus, likely the youngest entrepreneurial firms), 1046 (11.1%) were in the pre-treatment period and 8379 (88.9%) followed the HITECH Act in the treatment period.

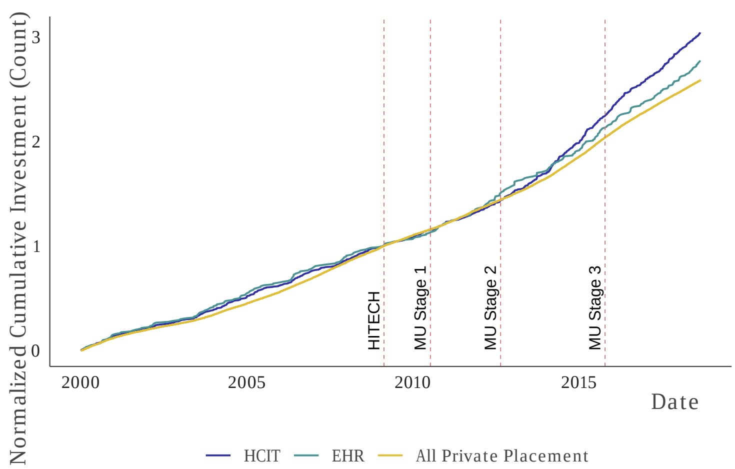
Company Type, Funding Round Group	Transactions, No. (%)	
	Before HITECH	After HITECH
EHR-related		
Seed	3 (2.5)	33 (15.5)
Early	24 (20.0)	29 (13.6)
Late	93 (77.5)	151 (70.9)
Health Care Information Technology		
Seed	10 (2.9)	170 (23.8)
Early	71 (20.6)	112 (15.7)
Late	264 (76.5)	433 (60.6)
All Venture Capital (non-HCIT)		
Seed	1036 (3.8)	8209 (19.2)
Early	4633 (17.1)	5890 (13.8)
Late	21,436 (79.1)	28,718 (67.1)
All Venture Capital		
Seed	1046 (3.8)	8379 (19.2)
Early	4704 (17.1)	6002 (13.8)
Late	21,700 (79.1)	29,151 (67.0)

Table 2.2: US Venture Capital Transactions by Funding Round, Before and After the HITECH Act

Figure 2.1 shows cumulative investment in health care IT, EHR-related companies, and all VC beginning in 2000, normalized on the day the HITECH Act passed. Raw investment figures for health care IT and EHR-related investment are presented in Appendix B.1. Between January 1, 2000, and the passage of the HITECH Act, only $2.7 billion was invested in health care IT companies, compared with $6.2 billion between the Act and August 31, 2018. Furthermore, compared with the broader universe of VC investment, the number of investments in health care IT companies increased at a faster rate (12.4% vs 10.5% annualized), whereas the pace of investment in EHR-related companies stayed steady. Weighted by the dollar value of transactions, however, investment in both health care IT companies and those we identify as EHR-related increased at a rate much faster (13.0% and 11.4%, respectively) than VC as a whole (6.9%).



(a) Transaction Value



(b) Number of Transactions

Figure 2.1: Investments in Health Care Information Technology (HCIT), Electronic Health Record (EHR) Technology, and All Other Private Placements Before and After Passage of the Health Information Technology for Economic and Clinical Health (HITECH) Act

Figure 2.2 shows graphically the distribution of funding rounds for EHR-related, health care IT, and all VC transactions in our sample before and after the HITECH Act. In all three categories, the proportion of seed stage investments increased in the post-HITECH period. This shift, shown as an increase in the size of the darkest blue region in the figure, is most pronounced among the broader category of health care IT, and appears somewhat attenuated for the subset of companies we identify as EHR-related.

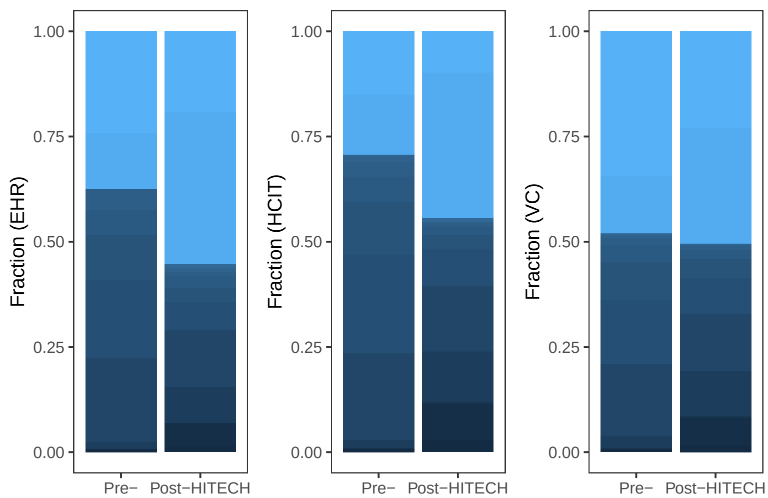


Figure 2.2: Distribution of funding rounds, pre- and post-HITECH Act, for EHR-related, health care IT, and all companies receiving venture funding

Table 2.3 shows the results of the difference-in-differences regression described in Equation 2.1, extending the comparison shown the figure. After controlling for a positive linear time trend, health care IT companies saw an additional 5.1% and 13.6% probability of transactions being seed stage compared with the entire sample of VC transactions and with non-IT health care VC transactions, respectively. In the comparison with non-health IT, however, health care IT had essentially zero increased probability of a transaction being seed-stage, suggesting that the trajectory of seed stage investment in health care IT companies was similar to that of non-health care IT investments, both before and after the HITECH Act.

	Dependent variable:		
	Seed-stage		
Comparison group:	All VC	Health care (non-IT)	IT (non-health care)
Post-HITECH	0.095^{***}	0.030^{***}	0.169^{***}
	(0.005)	(0.009)	(0.010)
HCIT	−0.007	−0.008	−0.015
	(0.018)	(0.015)	(0.019)
t	0.006^{***}	0.004^{***}	0.005^{***}
	(0.0005)	(0.001)	(0.001)
Post-HITECH × HCIT	0.051^{**}	0.136^{***}	−0.008
	(0.022)	(0.019)	(0.024)
Constant	0.010^{***}	0.018^{***}	0.025^{***}
	(0.003)	(0.005)	(0.005)
Observations	70,982	15,580	26,153
R^2	0.052	0.030	0.083

Table 2.3: Difference-in-differences estimates comparing the fraction of venture capital funding allocated to seed-stage companies in health care IT to other industries. p: 0 *** 0.01 ** 0.05 * 0.01 · 1

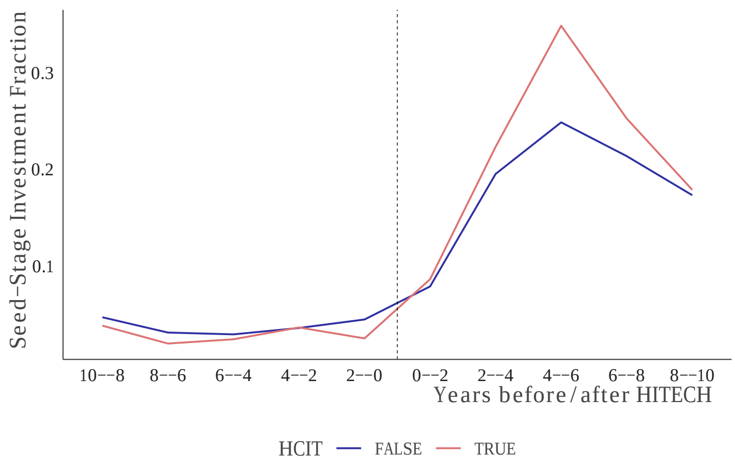
Finally, Table 2.4 displays hte results of the difference-in-differences regression comparing US health care IT with that of European companies, which would be exposed to similar secular changes in underlying technologies—e.g., cloud computing, advances in machine learning—but would not be affected by the HITECH Act.

	Dependent variable: Seed-stage
Post-HITECH	0.192^{***}
	(0.039)
US	0.001
	(0.036)
Post-HITECH · US	−0.026
	(0.043)
Constant	0.027
	(0.033)
Observations	2,076
R^2	0.049

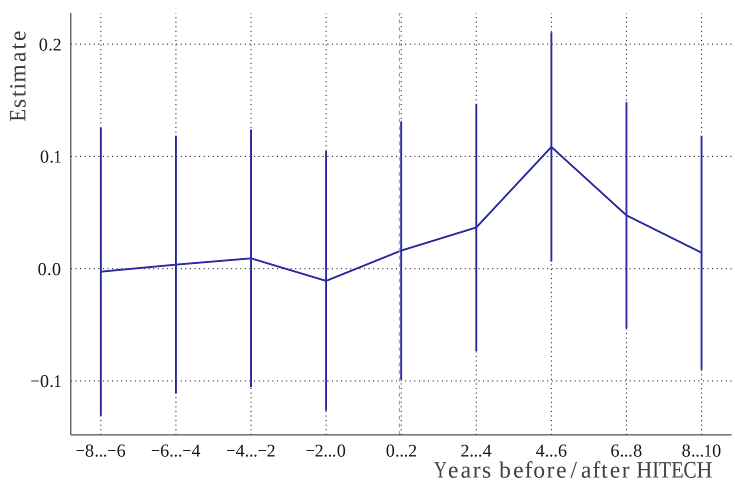
Table 2.4: Difference-in-differences estimates, US vs. Europe, pre- and post-HITECH health care IT. p: 0 *** 0.01 ** 0.05 * 0.1 $^{\cdot}$

2.3.1 Parallel Trends

The identifying assumption of the difference-in-differences design is that the outcome variable for the treatment and control groups would have evolved in parallel in the counterfactual absence of the treatment. Although this assumption is not directly testable, we provide visual evidence supporting the validity of this assumption in Figure 2.3 below. Subfigure 2.3(a) plots the fraction of investments that were seed-stage for health care IT and the rest of the VC universe in two-year intervals around the date the HITECH Act passed. Visually, the parallel trends assumption appears to hold: before the HITECH Act, the fraction of investments that were seed stage within health care IT and the rest of VC moved in tandem, slightly decoupling in the years following the Act. This comparison is made more explicitly in Subfigure 2.3(b), which plots the interaction-term coefficients from an event study regression of the whether transactions were seed-stage investments on dummy variables for two-year intervals around the Act's passage and those variables interacted with whether the target company is in the health care IT industry.



(a) Seed-stage Fraction of Investments, Health Care IT and All VC



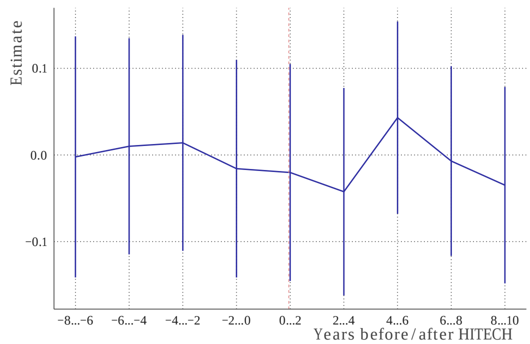
(b) Event-Study Coefficients

Figure 2.3: Assessing the parallel trends assumption, comparing health care IT to the universe of venture capital investments

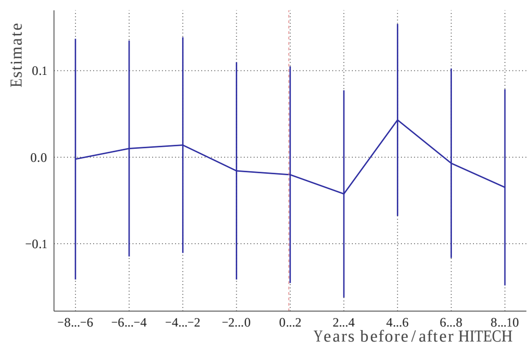
By the same token, the fraction of funding going to seed stage companies within US health care IT, US non-health care IT, and European health care IT moved in lockstep both before and after the Act (Figure 2.4). This difference, though, jumps in the years following the Act relative to non-IT health care (Subfigure 2.4(a)), while any difference between health care IT and non-health care IT or between US health care IT and European health care IT is undetectable (Subfigure 2.4(b), Subfigure 2.4(c)).

2.4 Discussion

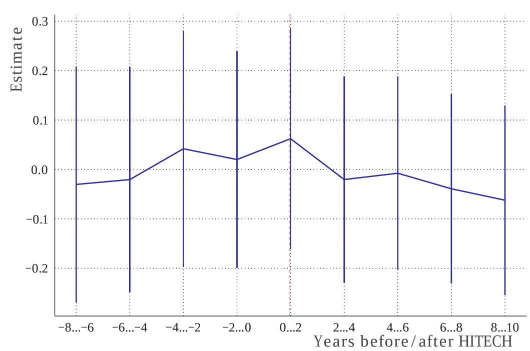
In this study, we analyzed the association of a large federal incentive program for EHR adoption with subsequent indicators of entrepreneurship in health care IT. We found that, in the years after the program's enactment, investments in health care IT and EHR-related companies increased at a rate much faster (13.0% and 11.4%, respectively) than VC as a whole (6.9%). In addition, the share of VC investments in seed-stage companies increased by 5.1% compared with trends in the broader VC investment landscape, suggesting that entrepreneurial activity in this sector became more attractive after the HITECH Act. To put the magnitudes of this association in perspective, for the near-decade leading up to the HITECH Act, fewer than 3% of health care IT transactions involved seed-stage financing. Furthermore, our results suggest that investment and entrepreneurship trends in the health care IT industry operated more similarly to those seen throughout the IT sector than those seen in health care investing more broadly. A decade after the HITECH Act, these results are important not only for understanding the full scope of the outcomes associated with the HITECH Act, but also



(a) Comparing HCIT with non-IT Health Care



(b) Comparing HCIT with non-health care IT



(c) Comparing US HCIT with European HCIT

Figure 2.4: Assessing the parallel trends assumption, comparing health care IT to US non-IT health care, US non-health care IT, and European health care IT

for understanding how public policies may stimulate innovation writ large.

As seen in Figure 2.1 and Figure B.1, there was a notable increase in overall VC funding around the time of the HITECH Act. We hypothesize that this sharp, 1-time increase in the pace of private placements is associated with the contemporaneous economic recession and recovery as investors reached for yield through riskier investment strategies. However, a formal analysis is beyond the scope of this article.

Our analysis does not imply that the HITECH Act or its subsequent implementation per se caused a shift in the type of health care IT companies that receive VC financing, nor can we claim a particular mechanism by which this may have occurred; several explanations are plausible. For example, a shift in unobserved investor demand for seed-stage health care IT investments may have been coincident with, or an input into, the Obama administration's desire to upgrade nationwide health care infrastructure; ostensibly unrelated, contemporaneous changes in the IT landscape (eg, the advent of cloud computing) may have induced greater opportunity for innovation in IT broadly (including health care IT); or, by accelerating the adoption of EHR systems, the HITECH Act may have, as a second-order consequence, created the opportunity for would-be entrepreneurs in the health care IT industry to build business models that rely on EHRs for data, processes, and/or customers.

Entrepreneurship, marked by the formation and funding of early-stage companies, has long been recognized as an important input into or proxy for innovation.[114,113,10] By spurring adoption of EHRs and digitization of clinician workflows (ie, automated collection of clinical data, clinical decision support capabilities, computerized order entry, and other software-driven tools) the HITECH

Act represented a substantial opportunity for demand-pull innovation in health care IT, in which greater market-wide demand for EHR capabilities in the US spurred research and innovation in the industry.

The latter explanation of the experience of the post-HITECH VC industry suggests that the HITECH Act may have been associated with the development of new technologies and, as a result, greater prospective productivity in the health care industry.

As EHR systems become more pervasive and functional, stimulated by the HITECH Act, new products can be built on top of those capabilities. Moreover, our results imply an important role for government incentive programs in promoting entrepreneurship around follow-on technologies in general, dovetailing with prior literature on the government's capacity to use grants and other financial incentives to promote innovation.[17]

Critically, our results exist in the larger context of EHR implementation and usage realities in the US. Electronic health records have numerous benefits: they have been shown to have a positive association with certain costs, outcomes, and some measures of quality.[8,116,101,51,89] Furthermore, EHRs enabled tremendous clinical research opportunities and fostered better population and public health management.[35,84] Yet EHRs have also been problematic and are associated with increased costs, poor usability, intense clinician dissatisfaction, and other unintended consequences.[99,100,31,61] Our results—specifically, that VC investments in EHR-related and health IT companies increased after the HITECH Act, but that those investments may have happened even in the absence of the Act—may be disappointing vis-a-vis many of the challenges associated with contemporary EHRs and the ability of government incentive programs to align funding and needs. That the funding was skewed towards very young companies also suggests a nascent industry that may still take time to mature.

In 2018, the Meaningful Use program was renamed Promoting Interoperability, and the focus of the incentive program shifted towards interoperability and improving patient accesss to health data. The industry has been slow to advance towards those goals even as EHR adoption has accelerated, and, as a result, they have become a focal point of US policy efforts.[75,23]

This study has several limitations. First, our study focused on VC investment; we are unable to address other funding streams that existing companies could have used to invest in EHR or other technologies without such external financing, such as a publicly traded company or a privately held company that invested in research and development. It is possible, for instance, that although our results do not show a marked increase in outside investment in VC-financed companies developing EHRs, existing companies have been able to finance these projects internally. In addition, we were unable to assess the outcomes for the companies that received funding (e.g., how many hospital customers they had or how many health care clinicians used their products).

3

Health Care IT and Hospital Consolidation

3.1 Introduction

Investment and innovation in health care information technology (IT) has been a defining trend of recent years. In the years since the passage of the HITECH Act, an incentive program for hospitals and other qualified provider organizations to implement electronic medical record (EMR) systems, over 90% of hospitals have adopted an EMR system that meets the standards set out by the Obama administration for Meaningful Use.[4]

As technological adoption at hospitals has expanded, capabilities and workflows have improved markedly, with important implications for care, cost, and quality with respect to patient outcomes.[6,52] Electronic medical records are now critical components of many hospitals' operations, serving not only as repositories for clinical information, but also as intra-hospital referral systems, billing or revenue management hubs, and clinical decision support for providers. The breadth of data collected and analyzed within the EMR ecosystem and the provider-side capabilities that they enable continues to grow.[21] Although provider dissatisfaction and burnout related to EMR use remains a challenge to the industry, ongoing improvements in electronic medical record systems' capabilities and integration with provider workflows suggest that they will continue to grow in importance.[5,122,125,92]

Alongside advancements in IT capabilities, recent decades have seen rampant provider market consolidation. The consequences of this consolidation—its effects on prices, productivity, and welfare—are of intense policy and academic focus. see, e.g.,[12,33,32] Small individual and group practices are increasingly being acquired by chains and by hospitals, representing tens of billions of dollars of transaction value annually, with significant effects on practice operations.[65] Large health systems, too, are merging with or acquiring other hospitals: nearly 1000 hospital acquisitions took place between 2008 and 2014, and this trend appears to be accelerating.[33]

The welfare implications stemming from this concentration are theoretically ambiguous. On the one hand, standard models of oligopolistic competition suggests that greater consolidation should result in higher prices in the product market. This theoretical prediction is borne out in the empirical literature.[43,41,39] On the other hand, merger proponents argue that consolidation allows for improved economies of scale in production and greater management efficiency, both of which can reduce cost.[32,50]

There is substantial anecdotal evidence that the rise of IT and provider market consolidation are related phenomena. Hospital CEOs highlight the centrality of EMR systems—large, durable, high fixed-cost investments—in driving consolidation decisions, citing the importance of the greater referral network and ease of health information portability within a larger, consolidated system in improving hospital and system productivity.[55] As an example (emphasis added):

> Wetzel County Hospital signed a letter of intent to merge with WVU Health … While Wetzel County Hospital will also gain more specialist physicians, patients will have a wider physician reach thanks to WVU Health's Epic EHR.
>
> "Really, the most important piece of the puzzle though is the [Epic EHR]," said David Hess, MD, CEO of Wetzel County Hospital … "They will have Epic and be completely connected to every physician, every other healthcare entity in the system, which is a big plus."[55]

In this paper, we seek to use granular data on hospital IT capabilities and merger activity understand the empirical relationship between IT adoption and consolidation via acquisition. We test the hypothesis, motivated by a theoretical model of technological adoption and market structure, that more productive firms—those more likely to adopt information and communication technologies—are more likely to expand via acquisition, and whether IT adoption leads to further industry concentration. Further, we analyze whether hospitals' levels of IT adoption are useful predictors of acquisition behavior.

We find that, relative to controls, acquired hospitals tend to increase their rate of adoption of IT capabilities significantly more rapidly post-acquisition. This increase begins soon after acquisition and continues in the years following acquisition. We also find that this effect is driven by low-capability target hospitals and high-capability acquiring systems. Further, we find that having a low level of established IT capability relative to peers is a significant predictor of whether a hospital will be acquired. Conversely, high-capability hospital systems are significantly more likely to acquire other hospitals.

The remainder of this paper is organized as follows. To help contextualize our results, Section 3.2 offers an overview of relevant literature and industry detail. Then, we outline the theoretical model of entry, technology adoption, and concentration described in[77] and discuss how it can be applied to the hospital sector in Section 3.3. Section 3.4 describes the datasets we use for our analysis, including a description of how we merge the datasets for tractable analysis. Section 3.5 then explains the empirical methodology we use to investigate these questions, and Section 3.6 describes our results. Finally, Section 3.7 discusses the importance of these results and concludes.

3.2 Background

This paper sits at the intersection of two disparate bodies of literature. First, this paper contributes to the large and growing body of research dedicated to understanding the complex relationship between innovation in information technology and outcomes in the health care sector. While much of this literature, particularly in the context of health services research, focuses on clinical outcomes directly, our contribution is to introduce an important and understudied mechanism connecting technology and hospital behavior: market structure.

Second, while a substantial amount of research has been conducted on mergers and consolidation in the health care provider sector, this paper empirically draws out a novel mechanism driving consolidation—high fixed cost IT installations—that is poised to increase in importance over the coming years. Moreover, this paper describes a mechanism for potential efficiency gains from consolidation that has, to our knowledge, been largely unstudied.

3.2.1 Information technology in health care

The Health Information Technology for Economic and Clinical Health (HITECH) Act was passed in 2009 as part of the American Recovery and Reinvestment Act, a package of economic stimulus measures enacted by the Obama administration in response to the 2008 recession. The HITECH Act provided a series of incentive payments for hospitals to adopt electronic medical record systems (EMRs) at varying levels of capability and use and to encourage interoperability—the portability of clinical and other patient information across disparate sites of care, irrespective of EMR vendor. EMRs promise to be consolidated repositories of patient characteristics, diagnoses, imagings, treatment plans, and other relevant clinical information, as well as the ability to systematize clinician workflows such as drug prescriptions, referrals, and care team coordination. EMRs broadly also provide the promise for more advanced functionality as patient data collection and analytical capabilities improve. An illustrative schematic of an EMR is shown in Figure 3.1.

The implementation of the HITECH Act coincided with the rise of widely available cloud computing and storage capabilities that promised to revolutionize the use of information technology in health care, ranging from more efficient billing operations for providers to advanced predictive

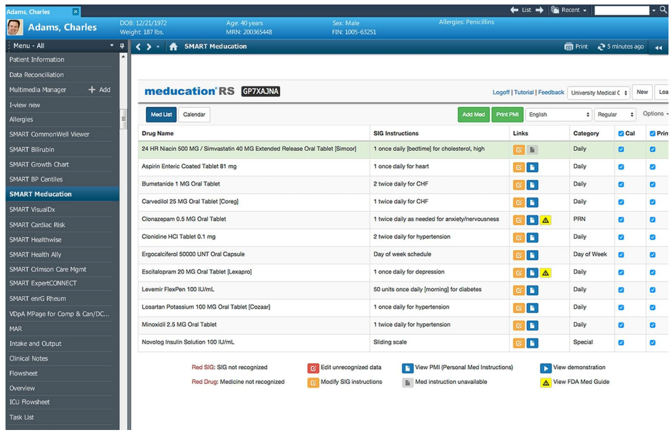


Figure 3.1: An illustration of an EMR showing a patient's medication list, dose instructions, and demographic information[20]

analytics to support diagnosis and treatment.

The incentive payments from the HITECH Act, which totaled in the tens of billions of dollars, played an important role in driving the widespread adoption of EMR systems.[54,4] These installations and maintenance have become significant parts of hospitals' cost structures, accounting for up to a third of hospitals' capital investment annually.[2]

By the end of 2014, the final year of the data on hospital IT capabilities used in this paper, a significant majority had met the criteria to for incentive payments under the first stage of Meaningful Use—the set of IT capabilities such as computerized order entry, digitized image storage, and basic documentation that consitutes a"basic EMR"—but adoption of more advanced capabilities remained (and, for many hospitals, continue to be) a challenge.[2] For a more detailed summary of the rollout of the HITECH Act and the Meaningful Use program, see[92].

The downstream consequences of these implementations and other technological innovations on hospital operations, health care delivery, and physician workflows, and patient outcomes have been studied in depth. EMRs, in principle, can offer a multitude of productivity or efficiency improvements for patients and provider organizations.[11] For example, by systematizing communication and clinical decision support, EMRs can potentially reduce medication errors, such as administering drugs a patient is allergic to or at an incorrect dosage. EMRs can help providers track and manage patient comorbidities and coordinate care across multiple physicians or sites of care. More bloodlessly, EMRs can streamline billing and collection operations by offering a structured way of capturing relevant patient data and automating charges to payors.

A substantial amount of empirical research has been conducted analyzing these purported benefits. While the state of the art in EMR and related technologies is constantly changing, this research has generally found that EMR installations result in modest improvements to hospital costs and patient outcomes, particularly several years after implementation, suggesting a potentially important mechanism for efficiency gains from the increased EMR adoption that we find mergers can effect.

Our paper, however, is, to our knowledge, the first to document an empirical connection between the rise of EMRs as a cornerstone technology in health care delivery and changes in market structure, a topic of intense policy interest and debate.[32,105,126] Understanding how changes in market structure (e.g., via consolidation) affect EMR adoption is of first order importance in analyzing the dynamic welfare effects of these mergers.

Empirically, hospitals' costs tend to increase in the first several years following adoption of large EMR installations but decrease thereafter.[52]

Partners HealthCare's experience provides one striking example: the multi-site installation of the Epic EMR in 2015 reportedly cost $1.2 billion, in addition to the costs of training and maintenance.

It also caused significant turmoil among providers who were required to adapt to unfamiliar methods of recording patient data, overwhelmed by a fire hose of notifications, and forced to reduce the number of patient visits at some of the Massachusetts's system's hospitals.[103]

These results point to a cost-side dynamic central to our paper's intuitive results: the adoption of large-scale, advanced EMR capabilities by hospital systems is accompanied by high fixed costs, manifesting both as the sticker price of installation but also costly changes to operations, overhead, and other business processes as hospital employees adjust to new processes and workflows. Over the longer-term, however, productivity improvements dominate the fixed costs, lowering costs overall.

The empirical literature on the effects of EMR adoption on clinical outcomes and hospital profits is more mixed. Some relatively early work estimating structural productivity parameters find only mild value-added gains from incremental investment in IT-related capital.[87]

EMRs appear to improve providers' ability to quickly and accurately bill payers for services.[58] [6] analyzes the effect of EMR systems on selected clinical and administrative outcomes for hospitals using Medicare claims data from 1998-2005. The author finds no evidence of cost-savings from health IT installations, but modest increases in billed charges, consistent with explanations of the value proposition of early EMR systems: systematized billing operations or "revenue cycle management." In addition, the author finds little evidence of substantial clinical benefits, including reduced mortality or readmission rates.

By contrast,[97] use a similar methodological approach to measuring the clinical benefits of health care IT using a slightly more recent sample of Medicare discharge data from 2002-2007, finding clear mortality benefits for complex patients who require cross-specialty or coordinated care and only modest effects for routine cases. Other research has documented improvements in patient safety and various clinical quality measures at hospitals and ambulatory surgical centers.[96,95,60] EMR installations also appear to result in better patient safety as measured by adverse drug events, medication errors, and other complications[108,78] and a reduction in neonatal deaths.[102]. [90], too, find improved mortality outcomes at hospitals that adopt EMRs beginning several years after installation, dovetailing with the[52] finding that the productivity benefits of EMR systems take some time to accrue.

Our paper suggests an understudied mechanism by which the rise of information technology in health care provision is affecting the health care industry: its relationship to equilibrium market structure. Balancing the efficiency implications of particular mergers or acquisitions will require weighing the clinical and administrative benefits caused by any resulting increased investment in IT adoption. Converseley, crafting pro-competitive policy necessitates an understanding of the factors driving consolidation, including IT.

3.2.2 Consolidation in the services economy

From a broader perspective, the US economy of the past several decades has been characterized by twin secular trends: a steady shift towards services—such as health care provision—over over the past several decades, and increasing concentration among top firms in those industries.[48,77] Our paper documents one underlying mechanism and consequence for this shift in the hospital industry: information technology. The productivity and welfare implications of these changes writ large are profound.

[34] document the recent empirical history of economy-wide market structure shifts—notably, increases in concentration—and investment. The authors describe a secular shift towards (inefficient) concentration and the entrenchment of larger incumbents. As a consequence, they find, the economy has suffered from lower investment and productivity growth and higher prices.

This accords with the picture painted by [47], who explain recent stagnation in productivity growth and rising concentration by arguing that the rising importance of intangible investments—e.g., software or other information technology—shifts basic cost structure of firms towards fixed costs. Similar to the [77] model, such intangible investments reduce firms' marginal costs while increasing fixed costs, which advantages firms with lower adoption costs who can then deter entry by higher-cost firms. [47] The direct effect of consolidation on productivity, however, remains an open question. [112]

[94] provide empirical support for the [77] model of technology-driven consolidation in the cement industry. The authors study the relationship between competition and adoption of a cost-reducing technology in the cement industry, finding a positive relationship between adoption and the degree of cost-savings. Analogizing this finding to the health care industry suggests that one would expect a similar relationship to obtain between adoption of advanced hospital IT capabilities and efficiency or productivity. By a similar token, [131] constructs a calibrated model of oligopolistic competition in which firms make a productivity-enhancing investment decision. This in turn drives down competition by deterring entrants and spurs concentration by high-productivity firms.

Analyzing consolidation in the health care provider sector in particular has produced a rich body of literature. Much of this work has focused on the price effects of hospital mergers, generally finding that consolidation results in higher prices.[39,43,41,33] [12] studied the effect of mergers on standard quality metrics, finding modest declines in quality at acquired hospitals.

Relatively little attention, however, has been paid to the relationship between the growth in the technological capabilities available to hospitals and their merger and acquisition behavior. The jumping-off point for this paper is a theoretical model of technology-driven concentration in services industries offered by[77]—outlined in Section 3.3—and the observation that advances in information and communication technologies (ICT) offers the capacity to dramatically scale the quality and provision of health care services.

[77] document several headline empirical facts about changes in market structure over the past several decades. From 1977 to 2013, average industry concentration, as measured by the employment share of the top decile of firms, has increased, but with substantial heterogeneity across industries. As (this measure of) concentration increases, industry employment and the number of establishments per firm—the number of locations or local markets served by each firm—tend to increase. Within industries, increases in concentration are largely due to extensive margin growth by top firms, rather than organic growth.

[77] then offer a model of firm size, technological change, and market entry that describes the relationship between innovation and the secular trends in the authors document in the economy. The model has the immediate testable empirical implication that the most productive firms—those that can and do invest in ICT—should also be those that are most able to expand into new markets. In the health care industry context, we expect this to show up empirically as greater integration of

health systems: hospital acquisitions. This paper focuses on exploring this hypothesis.

Exploring the relationship between these two accelerating trends is only likely to grow in importance. As hospital consolidation proceeds, understanding the implications on not just price, but productivity and efficiency, is of first-order importance. Conversely, as the productivity implications of innovation in health care information technology grow in importance, it will become crucial for researchers and policy- and decisionmakers to bear in mind how investment in technology is intertwined with broader questions of market structure.

3.3 Model

The motivating theoretical model for this paper is that proposed by[77], who note the rising importance of information technology in health care provision, as well as prevalent merger activity in the health care provider industry. In this section, we describe the basic structure of the model, omitting much of the technical detail, and elaborate on the appropriateness of using the model to understand key dynamics in the hospital sector.

In summary, the model describes the entry behavior across heterogeneous markets or locations of firms with heterogeneous productivity. When firms are able to make investments in a technology that raises their fixed cost of operation but also increases productivity (or reduces marginal cost), the most productive firms will choose to invest most intensively in the technology and consequently expand further into more markets. Mapping this behavior to empirical behavior, this expansion can take the form of either building new facilities or, more simply, acquisition.

This dynamic drives increasing concentration, driven by growth of high-productivity firms. It also predicts

3.3.1 A model of hospital entry and concentration

Suppose hospital i performs services j in location n out of a continuum of locations with total mass N.*

Each hospital pays two types of fixed costs. First, a hospital system pays F_j to perform service j at all. This may be interpreted as the legal or bureaucratic costs associated with incorporating a hospital system, as well as some basic operating or back office functions. Second, the system must pay a location-specific fixed cost $f_n w_n$ to operate in location n. This cost may be interpreted as the cost of building a facility or buying an existing facility, scaled in magnitude by the local wage.

Each hospital has a productivity parameter A_{ij} that is shared across locations. At each location, hospital i hires L_{ijn} units of labor. Location-specific revenue, then, is simply $R_{ijn} = p_{jn} A_{ij} L_{ijn}$, where p_{jn} is the local price of service j.

Hospital i then chooses the set of markets in which to operate, $\mathbb{N}_{ij}$, and labor in each market to maximize total profit:

$$\Pi_{ij} = \max_{\mathbb{N}_{ij}, L_{ijn}} \int_{\mathbb{N}_{ij}} \left[p_{jn} A_{ij} L_{ijn} - L_{ijn} w_n - f_n w_n \right] dn - F_j \tag{3.1}$$

Suppose demand exhibits constant elasticity of substitution with parameter $\sigma > 1$, and that hospi-

*Please note that this setup is attributable to[77]. All errors in interpretation or explanation are mine.

tals are monopolistic competitors. This allows us to express local prices as a function of productivity, labor, and the elasticity of substitution across varieties: $p_{jn} = E_n(A_{ij}L_{ijn})^{-1/}$, where E_n is local expenditure determined in equilibrium.

Solving for the profit-maximizing level of local employment for hospital i, conditional on producing j in market n yields $L_{ijn} = A_{ij}^{\quad -1}\left[\frac{\quad -1}{\quad}\frac{E_n}{w_n}\right]$.

Hospital i will choose to enter market n if profits in that market, inclusive of location-specific fixed costs, are positive. Rewriting this inequality shows that i will enter if productivity is above a location-specific threshold α_n given as:

$$A_{ij} > \left(\frac{\sigma}{(\sigma-1)^{\quad -1}}\frac{f_n}{\frac{E_n}{w_n}}\right)^{1/(\quad -1)} \equiv \alpha_n \sim \Gamma(\alpha)$$

For convenience, we say that α is distributed according to some cumulative distribution function $\Gamma(\cdot)$, but leave the functional form unspecified.

Note that this threshold is increasing in the fixed cost of entry and the local wage but decreasing in local expenditure.

Finally, hospital i will choose to produce j if total profits (Equation 3.1) are positive:

$$\begin{aligned}
\Pi_{ij} &= \int_{n|A_{ij}> \quad n} \left[p_{jn}A_{ij}L_{ijn} - L_{ijn}w_n - f_n w_n\right] dn - F_j \\
&= \int_{n|A_{ij}> \quad n} \left[w_n A_{ij}^{\quad -1}\frac{(\sigma-1)^{\quad -1}}{\sigma}\left(\frac{E}{w}\right) \quad - f_n w_n\right] dn - F_j \\
&= \int_0^{A_{ij}} f\cdot\left(\left(\frac{A_{ij}}{\alpha}\right)^{\quad -1} - 1\right) d\Gamma(\alpha) > 0,
\end{aligned}$$

where the last equality follows from an assumption that $f_n = f$ for all n.

3.3.2 A new technology

Now, suppose hospitals can choose to adopt a technology (such as an advanced EHR system) that increases both productivity A_{ij} by a factor of $h > 1$ and the fixed cost F_j by $h \quad , \eta > 0$.[†]

Hospital i will adopt this technology if the increased profits in existing markets plus the profits from new market is greater than the incremental fixed costs:

$$(h \quad - 1)\frac{F_j}{f} < \int_0^{A_{ij}} \left(\frac{A_{ij}}{\alpha}\right)^{\quad -1} (h^{\quad -1} - 1)\, d\Gamma(\alpha) + \int_{A_{ij}}^{hA_{ij}} \left(\left(\frac{hA_{ij}}{\alpha}\right)^{\quad -1} - 1\right) d\Gamma(\alpha) \qquad (3.2)$$

Differentiating the right-hand side with respect to productivity A_{ij} shows that the benefits of adopting the technology increase in productivity. Therefore, there is a productivity threshold above which high productivity hospitals will adopt the technology and expand into more markets.

Generalizing to the case where hospitals can choose a *level* of technology $h \geq 1$ to adopt, with the productivity and cost implications as before, we can differentiate the right-hand side of the above inequality again with respect to h to show that hospitals' choices of h are increasing in A_{ij}.

3.3.3 Model implications

The model outlined above has several testable empirical implications. First, the model predicts that acquired hospitals are likely to exhibit greater year-over-year increases in the level of technological

[†]This setup is still attributable to [77]. All errors are my own.

capabilities. In particular, the mechanics of the model suggest that acquiring hospital systems, as they acquire to expand into new markets, will share technological capabilities with target hospitals that those hospitals would not have invested in otherwise. Second, the model implies that this effect should be driven by high-capability systems acquiring lower-capability hospitals. Finally, we expect to see that hospitals with greater levels of technological adoption *ex ante* are more likely to acquire rival hospitals and hospitals in other markets and that, conversely, low-capability hospitals are more likely to be acquired.

We devote the rest of this paper to empirically testing these predictions.

3.4 Data

Our data primarily comes from three sources. The main dataset we use for our analysis comes from the Healthcare Information Management and Systems Society (HIMSS). This dataset comprises granular data on electronic medical recordkeeping and other IT capabilities at a large sample of US hospitals. It contains the largest, most comprehensive sample of its kind[85] and is commonly used in the health economics and IT literature (e.g.,[6,54]).

HIMSS further defines a proprietary scoring model for hospital EMR adoption (the EMR Adoption Model, or EMRAM), which grades hospitals on a 0 to 7 scale based on which capabilities hospitals have implemented that indicates the scope of their EMR functionality. A table enumerating the specific criteria for each grade can be found in Appendix C.1. While HIMSS does not make hospitals' EMRAM scores directly available, we use these listed criteria along with the hospital-level capabilities information to compute each hospital's EMRAM score in each year. Table 3.1 lists the number of hospitals in the HIMSS survey and the average and standard deviation EMRAM score in each year of the sample.

Year	N	Avg. EMR score	SD EMR score
2008	5166	2.91	1.99
2009	5236	3.45	1.99
2010	5282	3.78	2.00
2011	5338	4.11	2.02
2012	5463	4.46	2.03
2013	5465	4.95	1.92
2014	5473	5.54	1.66
2015	5472	5.92	1.38
Total	42895	4.41	2.12

Table 3.1: EMR adoption scores over time

Notably, the average score improves steadily over time, while the spread in the scores increases somewhat in the early years of EMR adoption, and declines as more hospitals EMR systems come online. Figure 3.2 displays the distribution of EMRAM scores in each year of the HIMSS survey, starkly demonstrating the steady increase in capabilities over time.

For some of our analyses, we label each hospital and hospital system in each year as high- or low-capability based on their EMRAM stage in that year. A hospital is categorized as high-capability if its EMRAM stage is greater than 4. A hospital system is is categorzied as high-capability if the highest stage of its constituent hospitals is greater than 4.

To determine whether a hospital is being acquired by a high-capability system, we use the EMRAM stages of all hospitals in the system *excluding* the target hospital. This threshold was chosen

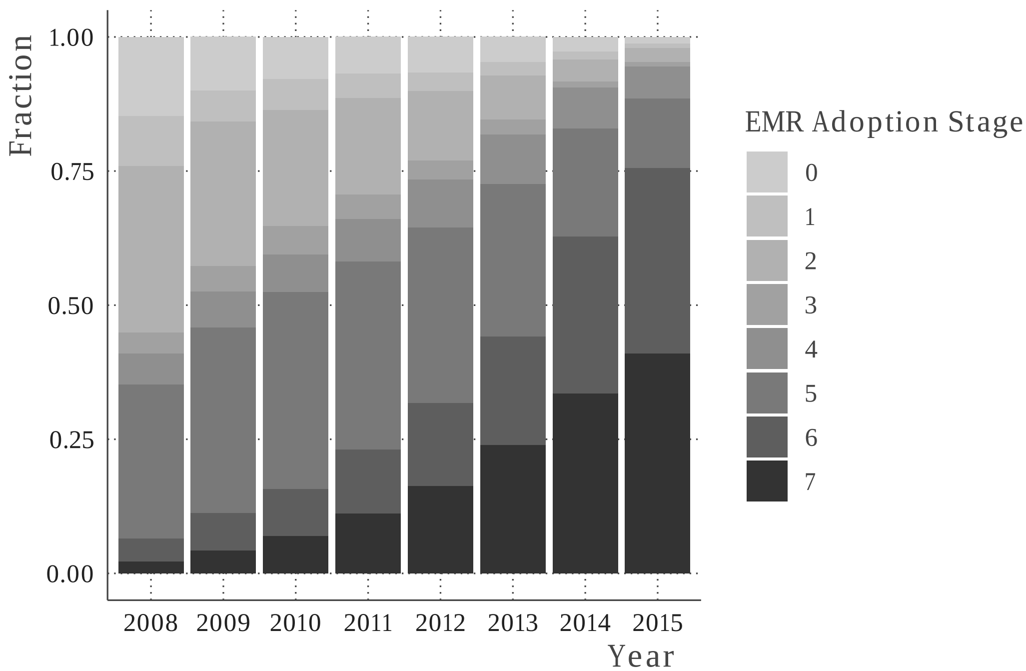


Figure 3.2: EMR adoption scores over time

to approximate at the level of functionality that would allow a hospital to certify that its EHR installation met the conditions of Meaningful Use I to receive HITECH Act incentive payments. Moreover, this approximates a level of functionality that would allow a casual observer to recognize a modern EHR system, with physicians documenting clinical and other patient information using structured templates, electronic order submission with basic clinical decision support, basic back office functionality, etc. All results using this feature are qualitatively robust to changing the threshold up and down by one level.

This dataset is, to our knowledge, the most comprehensive enumeration of hospitals' granular IT capabilities. The completeness and response rate is much higher, for instance, than the AHA's IT

Supplement. In addition, the aggregation of capabilities into a single "score" is a key component of our analysis.

Second, we incorporate historical data on hospital mergers and acquisitions. This data was compiled by[33], and the authors have made this data freely available. The data includes all hospital mergers and acquisitions between 2001 and 2014 and is the most complete source of hospital acquisition information available. Table 3.2 shows the number of target and acquiring hospitals over time. Following the lead of Cooper et al., we use the following terminology: a *target* hospital is a hospital that gets acquired in a given year, while an *acquiring* hospital is one that belongs to a system acquiring a target. The rightmost column in Table 3.2 displays the number of hospitals in the HIMSS sample for the corresponding year.

Year	# Targets	# Acquirers	N
2008	78	664	5166
2009	79	567	5236
2010	86	717	5282
2011	102	721	5338
2012	98	721	5463
2013	279	757	5465
2014	184	780	5473

Table 3.2: Number of target and acquiring hospitals over time

Table 3.3 shows the number of mergers in our sample that have high- or low-capability targets and acquirers. Note that the total number of mergers shown in this table differs slightly from the total number of mergers in Table 3.2 as it only includes those mergers for which the HIMSS sample contains data on both the target and acquirer.

	Acquiring System Capabilities	
	Low	High
High-capability Target	19	41
Low-capability Target	561	245

Table 3.3: Acquisitions with high- and low-capability targets and acquirers

While a majority of mergers are between two low-capability hospitals or systems, approximately a third are a high-capability system acquiring a low-capability target. Our theoretical prediction is that the effect of interest in this paper—an increase in IT investment at a hospital following acquisition—to primarily obtain in this latter category of mergers, as sophisticated hospital systems share technological or technology-enabled processes and systems with acquired hospitals. Crucially, however, we might *also* expect it to show up in some of the mergers between lower-capability hospitals, as the combined entity is able to capture greater economies of scale.

Finally, we use data from the American Hospital Association's (AHA's) annual survey of hospitals. This survey offers a census of US hospitals and includes data on each hospital's name, location, and other identifying information. It also includes some hospital characteristics, such as the number of full-time equivalent employees (FTEs) and the number of beds.

Since the historical mergers and acquisitions data uses AHA identifiers to uniquely identify hospitals, we use (combinations of) each hospital's name, address, zip code, and Medicare number when available to match EMR adoption scores from the HIMSS dataset to a "best guess" AHA ID using the AHA survey. This in turn allows us to determine whether or when a given hospital in the HIMSS sample was involved in a merger. This procedure returns a match for just over 95% of observations in the HIMSS dataset.

As mentioned above, the HIMSS dataset is not a complete census of US hospitals each year. As Table 3.4 shows, the HIMSS dataset contains 80-90% of all hospitals in each year. The missing hospitals are smaller than average as measured by number of full-time equivalent employees and the number of beds. Further, the HIMSS data contains just over 96% of acquired hospitals.

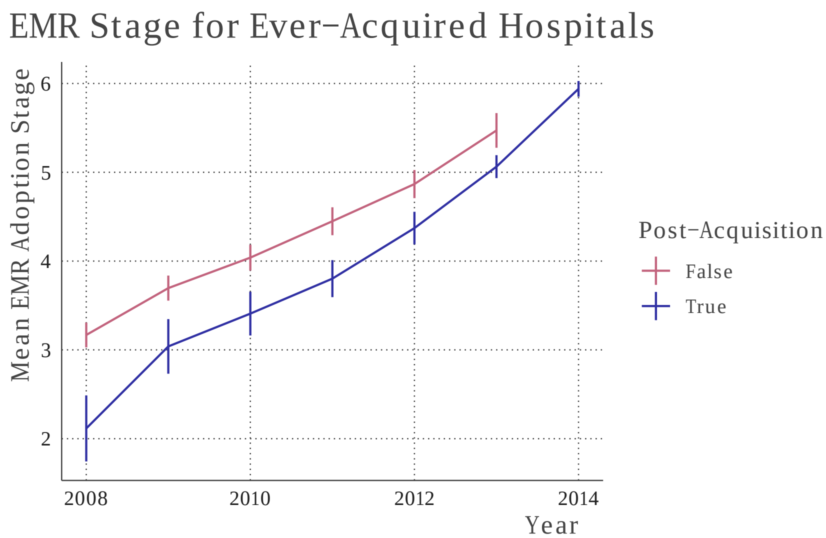
	Not in HIMSS			*All Hospitals*		
Year	Avg. FTE	Avg. Beds	N	Avg. FTE	Avg. Beds	N
2008	549	137	1214	821	154	6349
2009	590	138	1127	838	154	6269
2010	588	138	1118	842	154	6268
2011	558	131	1114	846	152	6253
2012	568	131	1118	856	151	6241
2013	627	131	1137	876	151	6230
2014	623	128	1133	877	150	6174

Table 3.4: Comparison of hospitals missing from the HIMSS sample to all hospitals

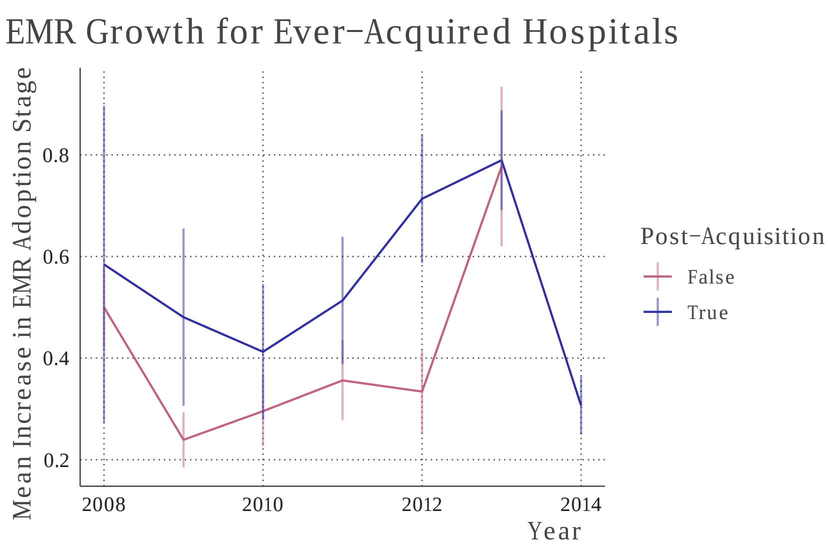
The model motivating our empirical exercise implies that we should expect to see low-capability hospitals acquired by high-capability hospitals and systems and then rapidly digitize. This type of merger represents approximately a third of the mergers in our sample (see Table 3.3). Figures 3.3(a) and 3.3(b), below, depict graphically the annual average EMR adoption stage and growth for those hospitals in the sample that are ever acquired conditional on whether each hospital has already been acquired.[‡] These graphs suggest some of our intuitive results: acquired hospitals tend to have somewhat lower EMR capability than non-acquired counterparts, but exhibit greater growth following

[‡]Note that the 'False' group has no members in 2014 as every hospital that has been acquired in the sample has been acquired by 2014.

acquisition. We describe how we quantify these comparisons in the following section.



(a) Stage



(b) Growth

3.5 Methods

In this section, we describe the empirical methodology we use to assess the relationships between acquisition activity and IT capabilities.

We begin by assessing three related questions: Does acquisition affect a hospital's EMR adoption? Is any effect a one-time level shift, or does the change in investment persist post-acquisition? Does a hospital's level of EMR adoption predict future acquisition activity, either the propensity to acquire or be acquired?

Our basic empirical strategy is a two-way fixed effects estimator—a generalized difference-in-differences—using hospital and time period fixed effects. This identification strategy has been extensively used in similar settings, including to estimate various operational and clinical effects of hospital mergers.[109,12] To estimate the partial effect of acquisition on EMR capabilities, then, we consider the following estimation equations:

$$\mathrm{EMR}_{i,t+\Delta t} - \mathrm{EMR}_{i,t} = 1\{\mathrm{Target}_{i,t}\} + \alpha_{s,t}$$

$$\mathrm{EMR}_{i,t+\Delta t} - \mathrm{EMR}_{i,t} = 1\{\mathrm{Target}_{i,t}\} + \alpha_i + \alpha_t$$

The right-hand variables are an indicator equal to 1 if hospital i is acquired in year t and state-year or hospital and year fixed effects, respectively. Hospital fixed effects control for time-invariant hospital-level differences that may be correlated with IT investment, while yearly fixed effects controls for secular changes in the level of investment that are common across hospitals. Similarly, state-year-level fixed effects restricts our identifying variation to that within each state-year combination.

The left-hand variable is equal to the growth in the EMR adoption stage of hospital i from year t to year $t + \Delta t$, where $\Delta t = 1$. We use this variable as a measure of hospital i's investment in IT capabilities from year to year.

These estimates, along with a number of alternate specifications and robustness checks, provide evidence that hospital acquisition leads to greater investment in IT capabilities as measured by the EMR adoption score.

The primary robustness check we perform is to estimate a propensity score-reweighting estimator based on that described in [104] and [111].[§] To control for potential selection in hospital acquisitions, we construct a propensity score for acquisition. To construct the score, we use the fitted values from a logistic regression of acquisition on measures of hospital size and indicators for nearby rival hospitals based on [39].

The estimand, then, is:

$$\hat{\text{ATE}} = \frac{1}{N}\sum_{i=1}^{N} \frac{Y_i D_i}{p(X_i)} - \frac{Y_i(1 - D_i)}{1 - p(X_i)}$$

where Y_i is the outcome variable (1-year change in EMR capabilities), D_i is a binary variable equal to 1 if the corresponding hospital was acquired in the corresponding year, and $p(X_i)$ is the propensity score (fitted probability of acquisition) based on characteristics X_i.

We compute standard errors for this estimator using a standard boostrap resampling procedure. We randomly sample N draws from our dataset, where N equals the size of the dataset, compute

[§]See also [67] for more detail on this clas of estimator.

the propensity score-reweighting estimator as described above, and record the estimated value of the coefficient of interest. We then use the standard deviation of the distribution of the estimated coefficient to form confidence intervals and perform significance tests.

Further, to assess whether this change in investment behavior persists, we estimate the same regression equations as above but setting $\Delta t = 2$. In addition, we estimate similar regressions, but using whether hospital i has *ever* been acquired as our independent variable, forming a more standard difference-in-differences design. We also show the standard corresponding event-study plots as a visual indication that the identifying assumption of the difference-in-differences design—that the outcomes for the treatment and control groups would exhibit parallel trends in the (counterfactual) absence of the treatment—holds.

Finally, we assess whether the *level* of EMR adoption or IT capabilities is predictive of near-term acquisition (whether a hospital will be a target or an acquirer). To do this, we regress whether a hospital is a target (acquirer) on lags of its EMR adoption score, effectively creating a linear model for the probability of acquisition (acquiring another hospital).

$$1\{\text{Target}_{i,t}\} = \text{EMR}_{i,t-\Delta t} + \alpha_{s,t}$$

$$1\{\text{Target}_{i,t}\} = \text{EMR}_{i,t-\Delta t} + \alpha_i + \alpha_t$$

We perform a similar fixed effects estimation for a logit model of acquisition, as well. A negative coefficient on the independent variable in these specifications suggests that lower-adoption hospitals are, on average, more likely to be acquired.

3.6 Results

In this section, we describe and comment briefly on the findings of our empirical analysis.

3.6.1 Effect of acquisition on EMR adoption

Table 3.5 shows the results of a regression of the one-year increase in EMR adoption scores, a proxy for IT investment, on whether a hospital was acquired in a given year. The estimated coefficients are positive and significant: post-merger, hospitals tend to increase their rate of adoption of IT capabilities substantially more quickly than comparison hospitals and more quickly than they do in non-acquisition years.

	Dependent variable:	
	1-Year EMR Stage Increase	
Target	0.141^{**}	0.137^{*}
	(0.063)	(0.063)
# FTE	-0.00002^{***}	
	(0.00000)	
State-Year FEs	Y	–
Hospital and Year FEs	–	Y
Observations	33,386	37,112
R^2	0.032	0.109

Table 3.5: p: 0 *** 0.1 ** 0.05 * 0.1. Regression of a hospital's increase in EMR capabilities over the following year on whether the hospital was acquired in a given year.

The specification shown in the first column includes state-year fixed effects, while the specification shown in the second column includes hospital- and year-level fixed effects. The latter specification shows an additional increase of 0.137 "points" in the EMRAM scoring system in the year immediately following a hospital's acquisition.

To control for potential selection in which hospitals are acquired and when, we employ a propensity-score reweighting strategy as described by[104] and[111] and bootstrap resampling to obtain standard errors. The results of this procedure are shown in table 3.6. The point estimates are nearly identical to the two-way fixed effects strategy above, with somewhat greater statistical significance.

	1-Year EMR Stage Increase
Target	0.146***
	(0.049)

Table 3.6: *p*: 0 *** 0.01 ** 0.05 * 0.1. Propensity score-reweighting estimate of the effect of acquisition on 1-year increase in EMR stage. Standard errors computed using bootstrap resampling

To test the intuition implied by our earlier theoretical framework (see Section 3.3) that this effect would be driven by high-capability hospital systems acquiring low-capability hospitals, we perform two sets of regressions.

First, we regress one-year EMR stage increase on acquisition status, an indicator for whether the hospital is a low-EMR adoption hospital (defined here as having an EMRAM score of 4 our less[¶]), and their interaction, as well as the same fixed effects structure as in our specifications above. The results of these regressions are displayed in Table 3.7 and show that, as our theoretical intuition would suggest, the jump in investment is driven by low-capability targets.

[¶]This threshold was chosen as this score roughly corresponds to the original Stage 1 Meaningful Use standards laid out by the Office of the National Coordinator for Health IT, created in the wake of the HITECH Act. The exact capabilities used to construct the scores are shown in Appendix C.1. The results are qualitatively robust to using a threshold of 3 or 5.

	Dependent variable:	
	1-Year EMR Stage Increase	
Target	−0.005	−0.101***
	(0.039)	(0.024)
Low-adoption	0.745***	1.749***
	(0.027)	(0.190)
Target × Low-adoption	0.343***	0.400*
	(0.126)	(0.193)
# FTE	0.00002***	
	(0.00000)	
State-Year FEs	Y	–
Hospital and Year FEs	–	Y
Observations	36,035	37,112
R^2	0.133	0.280

Table 3.7: p: 0 *** 0.01 ** 0.05 * 0.1. Regression of a hospital's increase in EMR capabilities over the following year on whether the hospital was acquired in a given year and had EMRAM score < 5.

Similarly, we regress the one-year increase in EMRAM score on indicators for acquisition, whether the acquiring system is a high-capability system—defined as whether the maximum EMRAM score of the hospitals in the acquiring system are greater than or equal to 5—and their interaction. These results are displayed in 3.8. Those hospitals acquired by high-capability acquirers experience a one-year increase in their EMR adoption model score that is approximately 0.7 points greater than they would have otherwise.

Taken together, these results suggest that the observed increases in investment in information technology by hospitals is driven by high-capability acquirers sharing or transferring technological capabilities to acquired hospitals.

Table 3.9 shows the estimated coefficients for a similar regression using the two-year increase in

	Dependent variable:	
	1-Year EMR Stage Increase	
Target	−0.268	−0.538**
	(0.166)	(0.166)
High-adoption	−0.229***	−0.274***
	(0.051)	(0.066)
Target × High-adoption	0.425**	0.737***
	(0.184)	(0.171)
# FTE	−0.00003***	
	(0.00000)	
State-Year FEs	Y	–
Hospital and Year FEs	–	Y
Observations	22,856	23,931
R^2	0.061	0.142

Table 3.8: p: 0 *** 0.01 ** 0.05 * 0.1. Regression of a hospital's increase in EMR capabilities over the following year on whether the hospital was acquired in a given year and belonged to a system in which the maximum EMRAM score of all other hospitals was > 4.

EMR capabilities as the dependent variable and reveals a similar pattern.

	Dependent variable:	
	2-Year EMR Stage Increase	
Target	0.288^{***}	0.255^{**}
	(0.070)	(0.083)
# FTE	-0.00004^{***}	
	(0.00001)	
State-Year FEs	Y	–
Hospital and Year FEs	–	Y
Observations	29,630	31,445
R^2	0.039	0.224

Table 3.9: *p*: 0 *** 0.1 ** 0.05 * 0.1. Regression of a hospital's increase in EMR capabilities over the following two years on whether the hospital was acquired in a given year.

Table 3.10 shows that this pattern holds when controlling for the EMR adoption stage of the hospital in year *t*.:

	Dependent variable:	
	ΔEMR_1	ΔEMR_2
Target	0.102^{*}	0.186^{***}
	(0.056)	(0.058)
# FTE	0.00004^{***}	
	(0.00001)	
State-Year FEs	Y	Y
EMR Stage FEs	Y	Y
Observations	33,386	31,445
R^2	0.167	0.275

Table 3.10: *p*: 0 *** 0.01 ** 0.05 * 0.1. Regression of a hospital's increase in EMR capabilities over the following one and two years, respectively, on whether the hospital was acquired in a given year, with state-year and EMR adoption level fixed effects.

When the independent variable is whether a hospital has *ever* been acquired, creating a more traditional difference-in-differences design, we find that acquired hospitals adopt additional IT capabilities significantly more rapidly than control hospitals, as shown in table 3.11:

	Dependent variable:		
	1-Year EMR Stage Increase		
Post-Acquisition	0.127^{***}	0.192^{*}	0.110^{***}
	(0.034)	(0.089)	(0.030)
# FTE	-0.00002^{***}	-	0.00004^{***}
	(0.00000)		(0.00001)
State-Year FEs	Y	-	Y
EMR-Stage FE	-	-	Y
Hospital and Year FEs	-	Y	-
Observations	33,386	37,112	33,386
R^2	0.033	0.109	0.168

Table 3.11: p: 0 *** 0.01 ** 0.05 * 0.1. Regressions of a hospital's yearly increase in EMR capabilities on whether the hospital has ever been acquired.

To test whether the parallel trends assumption holds in this setting, we show the standard event study plot in Figure 3.3 below. While the hospital-level fixed effects control for time-invariant heterogeneity that may covary with the outcome variable, we may still worry that systematic trends pre-acquisition would pose a threat to identification. Visually, the parallel trends assumption appears to hold.

In addition, we show the results of ordered logit and probit regressions of the level of a hospital's year $t + 1$ EMR adoption stage on acquisition in year t in Appendix C.3.

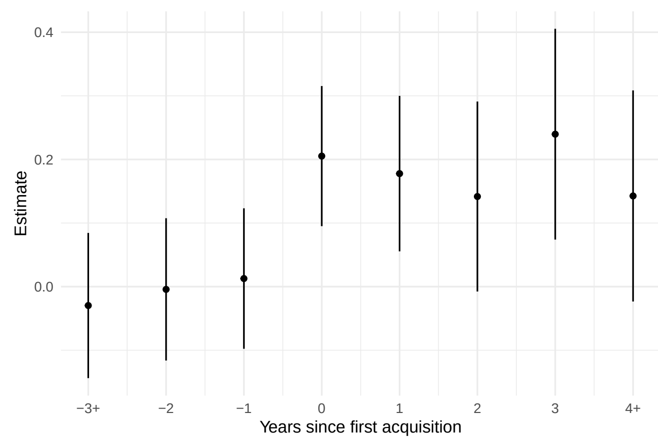


Figure 3.3: Coefficients from regression of one-year EMRAM stage increase on dummies for years relative to acquisition. Standard errors clustered at the year and hospital level.

3.6.2 Is EMR adoption predictive of acquisition behavior

In this subsection, we show whether the *level* of EMR adoption, as measured by EMRAM stage, is predictive of whether a hospital will be acquired and whether a hospital system will acquire another hospital by regression binary variables indicating acquisition (target or acquirer) on lags of hospitals' EMR capabilities.

Tables 3.12 and 3.13 show the estimated coefficients in a linear probability model of whether a hospital is acquired on the level of its EMR adoption. Our preferred specification, that with hospital and year fixed effects, both show a negative, albeit not statistically significant, relationship, suggesting that, on average, less-advanced hospitals are more likely to be acquired. The marginal EMR adoption stage in year t reduces the probability of acquisition in year $t+1$ or $t+2$ by $20-30$ basis points. To put these estimated magnitudes in perspective, recall that, as shown in Table 3.2, the unconditional probability of acquisition in a given year is between 2% and 4%.

	Dependent variable:	
	Target	
Lagged EMR Stage	−0.0001	−0.003
	(0.001)	(0.001)
State-Year FEs	Y	–
Hospital and Year FEs	–	Y
Observations	31,701	31,701
R^2	0.029	0.177

Table 3.12: p: 0 *** 0.01 ** 0.05 * 0.1. Regression of hospital acquisition on the level of the hospital's EMR capability in the previous year.

	Dependent variable:	
	Target in year t or $t-1$	
Twice-lagged EMR Stage	−0.0001	−0.002
	(0.001)	(0.002)
State-Year FEs	Y	–
Hospital and Year FEs	–	Y
Observations	26,086	26,086
R^2	0.026	0.213

Table 3.13: p: 0 *** 0.01 ** 0.05 * 0.1. Regression of hospital acquisition on the level of the hospital's EMR capability two years prior.

Similarly, Table C.5 in Appendix C.5 shows the estimates using a fixed-effects logit specification.

Finally, below we show the regression coefficients estimating the relationship between whether a hospital will be an acquirer on its level of EMR adoption. The first three columns of Table 3.14 show that additional EMR adoption is strongly positively associated with the hospital's system making an acquisition in the same year (column 1), the following year (columns 2), and two years (column 3), as one would intuitively expect.

	Dependent variable:			
	Acquirer			
EMR Stage	0.102***			−0.002
	(0.009)			(0.022)
Lagged EMR Stage		0.101***		−0.023
		(0.010)		(0.029)
Twice-Lagged EMR Stage			0.132***	0.152***
			(0.011)	(0.021)
# FTE	0.00003***	0.00001	0.00000	0.00000
	(0.00001)	(0.00001)	(0.00001)	(0.00001)
State-Year FEs	Y	Y	Y	Y
Observations	33,613	28,920	23,619	23,619
R^2	0.004	0.004	0.007	0.007

Table 3.14: p: 0 *** 0.01 ** 0.05 * 0.1. Logistic regression of whether a hospital is part of an acquiring system on the level of the hospital's EMR capability.

3.7 Conclusion

This paper tests several empirical predictions motivated by the theoretical model of information technology-driven consolidation by[77] in the context of the hospital industry. First, we show that acquired hospitals accelerate their investment in EHR capabilities. This takes place both immediately, in the year following acquisition, and on an ongoing basis.

Second, we show that this effect is driven by high-capability acquiring systems and low-capability targets, where the distinction between high- and low-capability is defined as in Section 3.4. This type of acquisition comprises just under a third of all acquisition in our sample (see Table 3.3). While we cannot speak to this particular mechanism directly,[74] test whether merging hospitals with non-interoperable EMR systems consolidate technological operations by eliminating redundant EMR vendors. The authors show that in about a third of cases, the acquired hospital changes EMR vendor to that used by the plurality of the acquiring system hospitals. This decomposition suggests that the acceleration of investment in EHR capability is a result of a transfer of technological capabilities and processes from the sophisticated acquiring hospital system to the relatively unsophisticated target.

Finally, we show that the level of a hospital's EMR capabilities is predictive of the hospital's propensity to acquire or be acquired: high-capability hospitals are significantly more likely to make an acquisition in the near future, and low-capability hospitals are, on average, modestly more likely to be acquired.

These results suggest that the economics of information technology play an important role in the way economists, policymakers, and decisionmakers in the health care industry should think about consolidation and market structure. Hospital merger proponents often cite efficiency improvements and economies of scale that merged hospital systems enable that smaller systems or standalone hospitals cannot obtain. e.g.,[32] Often, skeptical regulators, competitors, and researchers are more skeptical, pointing to the history of merged entities using newfound market power to increase prices.[33,43]

While comparing the magnitudes of the welfare consequences of subsequent price increases and productivity improvements stemming from better, more capable IT utilization is beyond the scope of this paper, our results suggest that those making the case for mergers, particularly for acquisitions of smaller, less advanced hospitals by larger, more sophisticated ones, Improved technological capabilities offers the potential for improved patient care[102,90]; more efficient communication across disparate sites of care and management of complex cases[97]; or lower costs for hospitals[52]. As such, the mechanism described in this paper suggests that hospital mergers can have welfare-improving benefits.

Further, our results have important implications for productivity and efficiency in the health care industry, particularly in the context of increasing consolidation, a topic with considerable topical policy relevance. Despite the advances in EHR-based products and provider workflows, significant provider dissatisfaction and the so-called "productivity paradox" remains a challenge to the health care technology industry.[5,129] Our results suggest that some of this may be attributable to the high-fixed cost nature of these technologies that prevent some hospitals from fully investing in them. This lens suggests that industry-wide productivity growth may naturally accelerate as higher-productivity hospitals acquire lower-productivity hospitals and spread capabilities and best practices.

By driving IT adoption at lower-resource hospitals, too, consolidation has hte potential to help close the "digital divide" in the advanced use of EMRs that has emerged in recent years in health care.[3] By expanding the use of advanced IT tools and any concomitant clinical or productivity benefits to target hospitals, mergers may contribute to the expansion of higher-quality health care to smaller or otherwise lower-productivity hospitals.

Our results are unable to speak to a number of important questions. First, we analyze data on the installed capacity at a survey of hospitals, but are unable to observe anything related to hospital-level utilization of EMR systems. Hospitals with identical technological capabilities on paper may differ markedly in the way those technologies are used in practice by providers. Second, as mentioned previously, while our results suggest a potentially significant efficiency-enhancing rationale for mergers—accelerated productivity growth at low-capability acquired hospitals—we do not attempt to quantify these benefits or compare them to the any efficiency losses that obtain as a result of greater market power by the merged entity. These topics promise to be fruitful topics for future research.

A

Private Equity and Dental Practice Consolidation

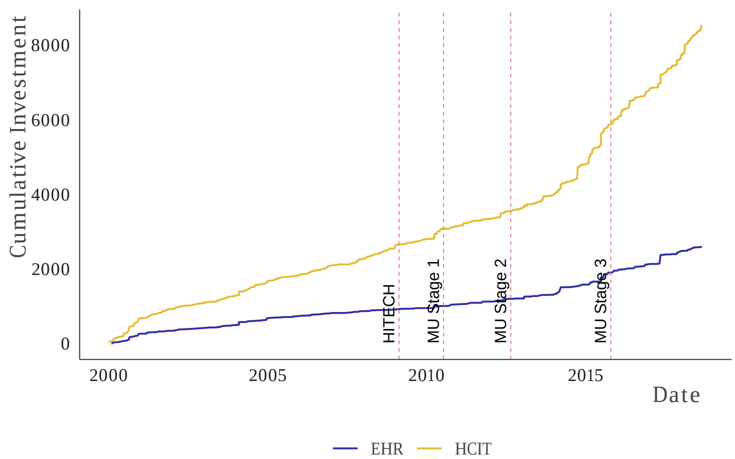
A.1 Sample Procedures by Category

Group	*Sample Procedure*	*Group*	*Sample Procedure*
Adjunctive General Services	Enamel Microabrasion Missed Appointment Cancelled Appointment Regional Block Anesthesia Occlusal Guard Adjustment	Orthodontics	Fixed Appliance Therapy Removable Appliance Therapy Repair Of Orthodontic Appliance Re-Cement Or Re-Bond Fixed Retainer Periodic Orthodontic Treatment Visit
Diagnostic	Sialography Viral Culture Diagnostic Casts Pulp Vitality Tests Electron Microscopy	Periodontics	Periodontal Maintenance Apically Positioned Flap Gingival Irrigation - Per Quadrant Pedicle Soft Tissue Graft Procedure Provisional Splinting - Intracoronal
Endodontics	Apicoectomy - Anterior Root Amputation - Per Root Endodontic Endosseous Implant Retrograde Filling - Per Root Apicoectomy - Molar (First Root)	Preventive	Prophylaxis - Adult Prophylaxis - Child Sealant - Per Tooth Oral Hygiene Instructions Sealant Repair - Per Tooth
Implant Services	Interim Abutment Provisional Implant Crown Implant Removal, By Report Second Stage Implant Surgery Repair Implant Abutment, By Report	Prosthodontics (Removable)	Complete Denture - Maxillary Complete Denture - Mandibular Immediate Denture - Maxillary Immediate Denture - Mandibular Tissue Conditioning, Maxillary
Maxillofacial Prosthetics	Feeding Aid Surgical Stent Surgical Splint Nasal Prosthesis Radiation Shield	Prosthodontics, Fixed	Connector Bar Stress Breaker Pontic - Titanium Precision Attachment Retainer Crown - Titanium
Oral & Maxillofacial Surgery	Myotomy Arthrotomy Synovectomy Arthroplasty Condylectomy	Restorative	Coping Post Removal Crown - Titanium Protective Restoration Gold Foil - One Surface

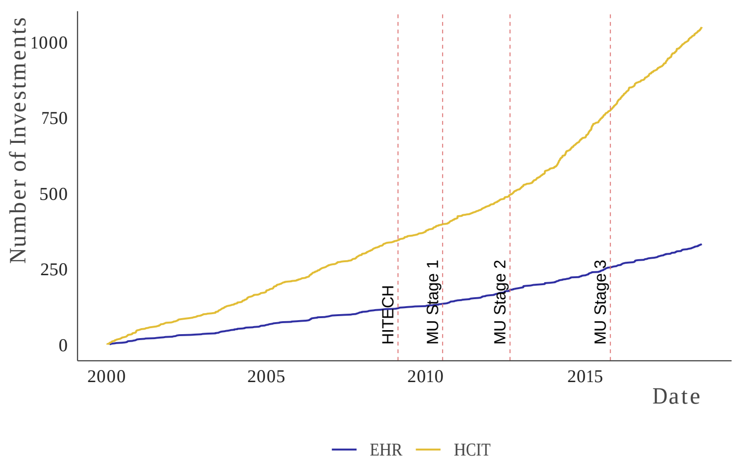
B

Entrepreneurship and the HITECH Act

B.1 Raw Investment



(a) Transaction Value



(b) Number of Transactions

Figure B.1: Investments in Health Care Information Technology (HCIT), Electronic Health Record (EHR) Technology, and All Other Private Placements Before and After Passage of the Health Information Technology for Economic and Clinical Health (HITECH) Act

C

Health Care IT and Hospital Consolidation

C.1 EMRAM Stages

Stage 7	Complete EMR; External HIE; Data Analytics, Governance, Disaster Recovery, Privacy And Security
Stage 6	Technology Enabled Medication, Blood Products, And Human Milk Administration; Risk Reporting; Full CDS
Stage 5	Physician Documentation Using Structured Templates; Intrusion/Device Protection
Stage 4	CPOE With CDS; Nursing And Allied Health Documentation; Basic Business Continuity
Stage 3	Nursing And Allied Health Documentation; EMAR; Role-Based Security
Stage 2	CDR; Internal Interoperability; Basic Security
Stage 1	Ancillaries: Laboratory, Pharmacy, And Radiology/Cardiology Information Systems; PACS; Digital Non-DICOM Image Management
Stage 0	All Three Ancillaries Not Installed

Source: https://www.himssanalytics.org/emram

C.2 Additional controls

In this section, we show the results of our baseline regression specification with some additional control variables. Table C.1 includes the local county-level unemployment rate in the corresponding year to address potential endogeneity concerns. Both merger decisions and IT investment may be driven by local economic conditions. The estimated coefficient of interest remains qualitatively similar, although the precision of the estimates is reduced substantially.

	Dependent variable:	
	1-Year EMR Stage Increase	
Target	0.105^{*}	0.118
	(0.063)	(0.063)
# FTE	-0.00003^{***}	
	(0.00000)	
Unemployment Rate	0.004	-0.004
	(0.004)	(0.008)
Hospital FEs	–	Y
Year FEs	–	Y
State-Year FEs	Y	–
Observations	34,912	34,912
R^2	0.032	0.102

Table C.1: p: 0 *** 0.1 ** 0.05 * 0.1. Regression of a hospital's increase in EMR capabilities over the following year on whether the hospital was acquired in a given year.

Management quality is another potential source of omitted variable bias. Past researchers have noted both the importance and difficulty of controlling for managerial practices when estimating the relationship between mergers and hospital-level outcomes.[109,12] Table C.2 adds hospital system-level fixed effects to our baseline specifications to control for hospital system-level management quality. Upon acquisition, a hospital's system affiliation immediately switches to that of the acquiring hospital.

This is an imperfect way of controlling for management quality: managerial practices are unlikely to be perfectly time-invariant at the system level, and the fixed effect is probably not uncorrelated with investment conditional on management quality. As such, the loss of precision in our estimates is expected, and the sign remains positive.

	Dependent variable:	
	1-Year EMR Stage Increase	
Target	0.079	0.059
	(0.085)	(0.052)
# FTE		-0.00002^{***}
		(0.00000)
Hospital FEs	Y	–
Year FEs	Y	–
System FEs	Y	Y
State-Year FEs	–	Y
Observations	30,370	30,311
R^2	0.106	0.091

Table C.2: p: 0 *** 0.1 ** 0.05 * 0.1. Regression of a hospital's increase in EMR capabilities over the following year on whether the hospital was acquired in a given year, including fixed effects as indicated.

Moreover, it is not clear that the correct estimand partials out the effect of system-wide managerial practices on IT investment. To the extent that the change in IT investment can be attributed to the merger, whether that increase occurs through the channel of improved managerial quality is largely immaterial.

C.3 Ordered Categorical Regressions

Model:	Logit	Probit
Target	0.5249***	0.2903***
	(0.06099)	(0.03552)

Table C.3: p: 0 *** 0.01 ** 0.05 * 0.1. Ordered logit and probit regressions of year $t+1$ EMR stage on whether a hospital was acquired in year t. Estimated "cut points" are not shown.

Model:	Logit	Probit
Target	0.4205***	0.2521***
	(0.06324)	(0.03754)

Table C.4: p: 0 *** 0.01 ** 0.05 * 0.1. Ordered logit and probit regressions of a hospital's binned EMR stage ([0,4], [5,6], [7]) in year $t+1$ on whether a hospital was acquired in year t. Estimated "cut points" are not shown.

C.4 EMRAM Over Time by Group

In the graph below (Figure C.1), we depict the evolution of the mean EMR adoption stage over our sample window for four (not mutually exclusive) groups of hospitals: those that are ever acquisition targets during our sample, those that ever ever acquirers, those that are neither targets or acquirers, and all hospitals.

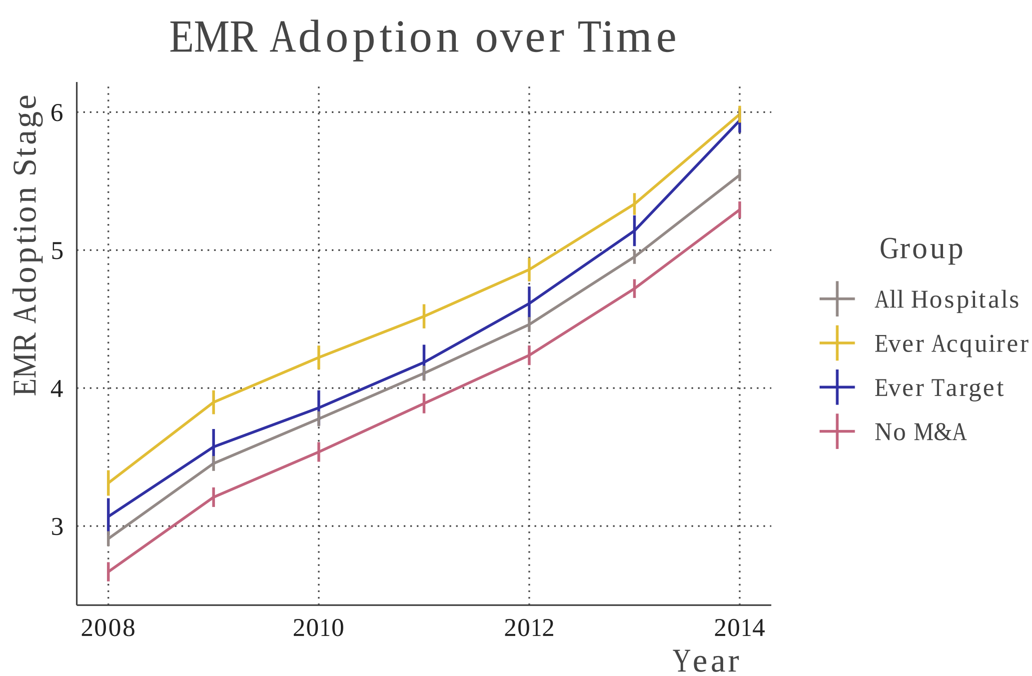


Figure C.1: EMR adoption scores over time for hospitals that, in our sample, are ever targeted, acquirers, and neither targeted nor acquired, as well as all hospitals

Those hospitals in the acquisition group have significantly higher mean levels of EMR adoption in each year than the full sample of hospitals. Hospitals that are ever targeted begin the sample much closer in mean level to the full sample of hospitals but converge towards the acquisition group in mean capabilities.

A similar annual depiction of hospitals' change in EMR adoption stage is depicted below in Figure C.2.

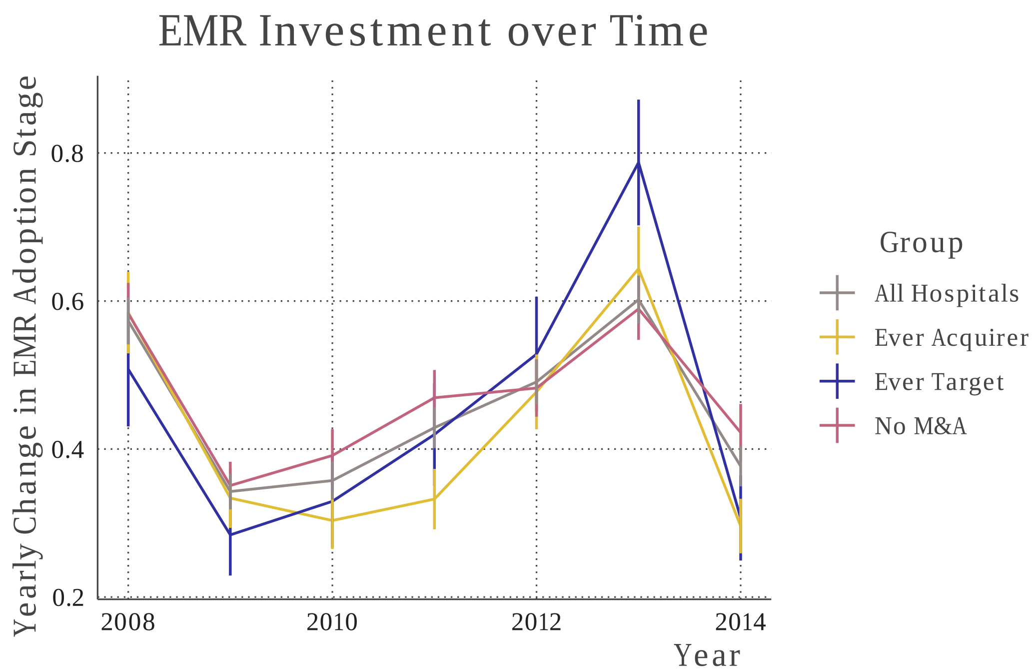


Figure C.2: Yearly change in EMR adoption scores over time for hospitals that, in our sample, are ever targeted, acquirers, and neither targeted nor acquired, as well as all hospitals

Note that these figures do not show *when* any given hospital acquires or is acquired.

C.5 Two-way Fixed Effects Logit Model Results

Table C.5 below shows the results of a logit model estimating the relationship between acquisition and lagged EMR stage. Using both state-year and hospital and year fixed effects, the estimated coefficient is negative but imprecise.

	Dependent variable:	
	Target	
Lagged EMR Stage	−0.002	−-0.09*
	(0.02)	(0.04)
State-Year FEs	Y	–
Hospital and Year FEs	–	Y

Table C.5: p: 0 *** 0.01 ** 0.05 * 0.1. Regression of hospital acquisition on the level of the hospital's EMR capability in the previous year.

Table C.6 shows the results of similar regressions, with outcome variable whether hospital i is part of an acquiring system in year t. As above, the magnitudes lack a clear interpretation, but the estimated coefficients of interest in both regression specifications are positive, as expected.

	Dependent variable:	
	Acquirer	
Lagged EMR Stage	0.074***	0.001
	0.01	0.01
State-Year FEs	Y	–
Hospital and Year FEs	–	Y

Table C.6: p: 0 *** 0.01 ** 0.05 * 0.1. Regression of whether a hospital acquires on the level of the hospital's EMR capability in the previous year.

C.6 Other Notes

All regression output tables are created using the `stargazer` library.[70] Figures created using the `fira theme` for `ggplot2`.[128,132]

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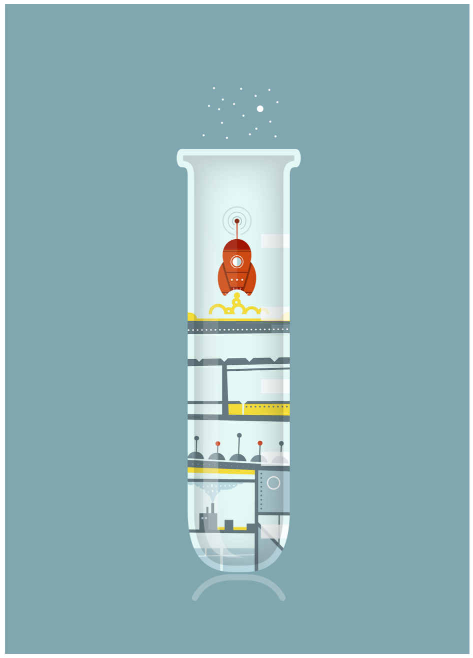

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