

Does Private Equity Hurt or Improve Healthcare Value? New

Evidence and Mechanisms

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Online Appendix

Appendix A
Table A1: Relevant Survey Questions from AHA IT Supplement

Section 1: Intra-hospital IT		
<i>Does your hospital currently have a computerized system which allows for:</i>		
1. Electronic Clinical Documentation	2. Results viewing	3. Computerized Provider Order Entry
a. Physician notes	a. Laboratory tests	a. Laboratory tests
b. Nursing notes	b. Radiology tests	b. Radiology tests
c. Problem lists	c. Radiology images	c. Medications
d. Medication lists	d. Diagnostic test results (e.g. EKG report, Echo report)	d. Consultation requests
e. Discharge summaries	e. Diagnostic test images (e.g. EKG tracing)	e. Nursing orders
f. Advanced directives (e.g. DNR)	f. Consultant reports	
4. Decision support	5. Other functionalities	
a. Clinical guidelines (e.g. Beta blockers post-MI, ASA in CAD)	a. Bar coding or Radio Frequency (RFID) for supply chain management	
b. Clinical reminders (e.g. pneumovax)	b. Telehealth	
c. Drug allergy alerts	c. Remote patient monitoring	
d. Drug-drug interaction alerts		
e. Drug-Lab interaction alerts		
f. Drug dosing support (e.g. renal dose guidance)		
Section 2: Health Information Sharing		
<i>Which of the following patient data does your hospital electronically exchange/share with one or more of the provider types listed below?</i>		
Ancillary Information Sharing:		
1. Patient demographics	2. Laboratory results	3. Radiology reports
a. With Hospitals inside of your System	a. With Hospitals inside of your System	a. With Hospitals inside of your System
b. With Hospitals Outside of your system	b. With Hospitals Outside of your system	b. With Hospitals Outside of your system
c. With Ambulatory Providers inside of your system	c. With Ambulatory Providers inside of your system	c. With Ambulatory Providers inside of your system
d. With Ambulatory Providers outside of your system	d. With Ambulatory Providers outside of your system	d. With Ambulatory Providers outside of your system
Clinical Information Sharing:		
4. Medication history	5. Clinical / Summary care record in any format	
a. With Hospitals inside of your System	a. With Hospitals inside of your System	
b. With Hospitals Outside of your system	b. With Hospitals Outside of your system	
c. With Ambulatory Providers inside of your system	c. With Ambulatory Providers inside of your system	
d. With Ambulatory Providers outside of your system	d. With Ambulatory Providers outside of your system	
Section 3: Patient-Facing Digital Health Access		
<i>Are patients treated in your hospital able to do the following:</i>		
a. View their health/medical information online	b. Download information from their health/medical record	c. Electronically transmit (send) transmission of care/referral summaries to a third party
d. Request an amendment to change or update their health/medical record	e. Request refills for prescriptions online	f. Schedule appointments online
g. Pay bills online	h. Submit patient-generated data (e.g. blood, glucose, weight)	i. Secure messaging with providers

Appendix B: Double Machine Learning (DML) Estimation

To address potential identification concerns in our DID model (i.e., selection bias in treatment assignment), we employ a DML approach which provides a flexible framework to control for covariates that may affect both treatment selection and outcomes (Chernozhukov et al. 2018). Following Xu et al. (2024), we adopt a three-step DML procedure to estimate the effect of PE ownership on care value.

$$\begin{aligned} \text{Step 1: } \text{Care Value}_{it} &= g_0(\mathbf{Z}_{it}) + \varphi_i + \tau_t + \epsilon_{it} & (b1) \\ \text{Step 2: } \text{PE_ownership}_i * \text{Post}_{it} &= m_0(\mathbf{Z}_{it}) + \varphi_i + \tau_t + \mu_{it} & (b2) \\ \text{Step 3: } (\text{Care Value}_{it} - \widehat{\text{Care Value}}_{it}) &= \delta \times \mu_{it} + \gamma_{it} & (b3) \end{aligned}$$

where Care Value_{it} represents the key dependent variable in our main analyses, and φ_i and τ_t are the hospital and time dummies, respectively. ϵ_{it} is the error term in step 1 which represents the portion of the outcome that is unexplained by the control variables and fixed effects. μ_{it} is the residual in step 2, representing the unexplained portion of the treatment (i.e., PE ownership) assignment. δ is the key parameter of interest in step 3, which represents the causal effect of PE ownership on care value.

The DML approach follows a three-step procedure. In step 1, we model the outcome variable (i.e., care value) as a function of $\mathbf{Z}_{it}$ and hospital and year dummies. Vector $\mathbf{Z}_{it}$ represents a set of variables including the controls in our DID model and variables affecting the PE market (PE M&A secondary sale, and IPO), which may influence a PE firm's decision to invest in the local hospital market. Specifically, to measure PE market characteristics, we include the deal volume and deal value of PE exit with mergers and acquisitions, secondary sales, and initial public offerings (IPOs) that occurred within the same Core-Based Statistical Area (CBSA) over the past two years.¹ In step 2, we model the $\text{PE_ownership}_i * \text{Post}_{it}$ term using the same variables as in step 1. The functions $g_0(\cdot)$ and $m_0(\cdot)$ in equations (b1) and (b2) are estimated using machine learning. In our DML analysis, we use gradient boosted tree, a non-parametric model, for both $g_0(\cdot)$ and $m_0(\cdot)$.

The key intuition behind this three-step DML process is that PE ownership may be correlated with observable characteristics of hospitals and their local PE markets. Simply regressing the outcome on the treatment variable without isolating these confounding factors would introduce selection bias in

¹ The CBSA-level PE exist information is collected from the PE Exist database of SDC Platinum.

the estimated effect of PE ownership. By separately modeling and removing the explainable components of both the outcome and treatment assignment (steps 1 and 2) and then regressing the residualized outcome on the residualized treatment indicator in step 3, DML yields a more robust estimate of the treatment effect. This procedure effectively "doubles" the use of machine learning to isolate the causal impact of PE ownership on hospital care value.

Table B1: DML Estimation of PE Impact on Care Value

	(1)
Dependent variable	Care Value
Post×PE_Ownership	-0.026*** (0.009)
Observations	5,073

Notes: Robust standard errors are given in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Appendix C: Additional Empirical Results

Figure C1: Parallel Trend Plot

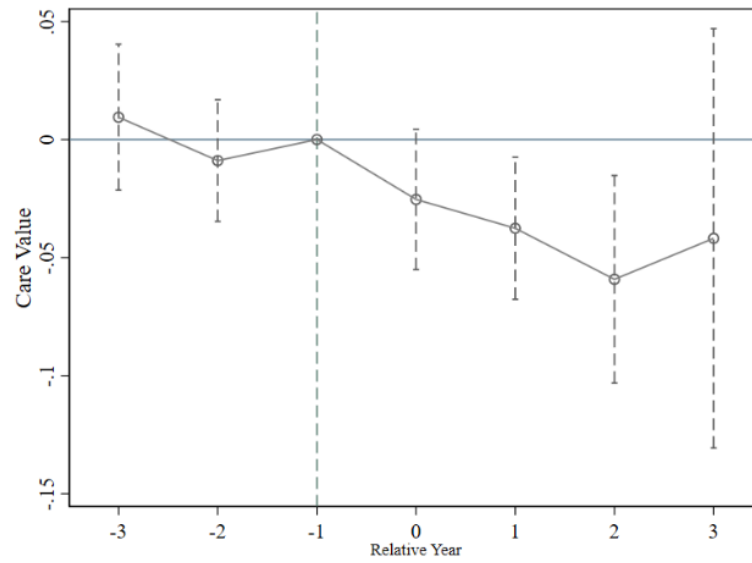


Figure C2: Results of Placebo Test

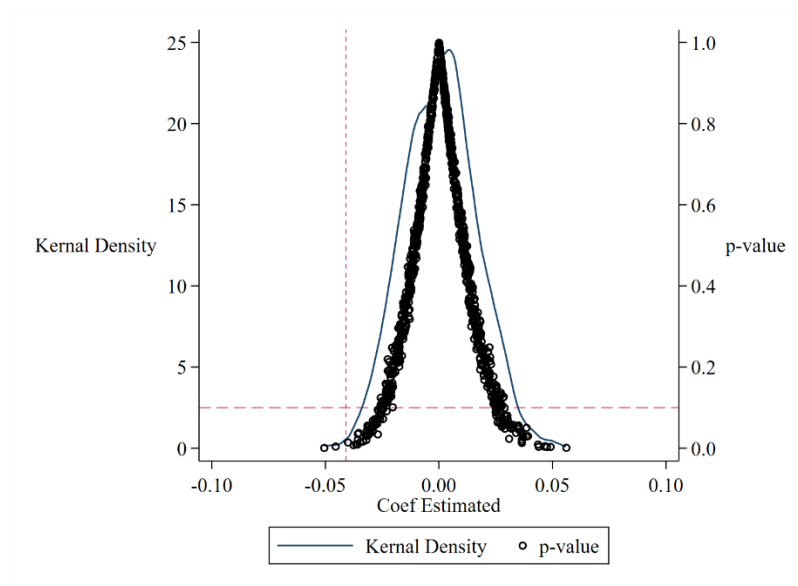


Table C1: Impact of PE Ownership based on PE Experience

Dependent variable	(1) Care Value	(2) Log(Operating Costs)	(3) Experiential Quality	(4) Mortality Rate	(5) Readmission Rate
Post	0.031** (0.012)	0.006 (0.016)	0.312* (0.186)	-0.099 (0.104)	0.048 (0.085)
Post×PE_Ownership	-0.065*** (0.021)	-0.215*** (0.037)	-1.880*** (0.337)	0.143 (0.180)	-0.112 (0.160)
Post×PE_Ownership×High-Exper_PE	0.039* (0.023)	0.232*** (0.040)	1.764*** (0.441)	0.237 (0.248)	0.195 (0.204)
Observations	5,077	5,077	5,077	5,077	5,077
Number of Hospitals	427	427	427	427	427
Adjusted R-squared	0.036	0.231	0.314	0.503	0.551
Controls	YES	YES	YES	YES	YES
Hospital FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
Marginal Effect of Low-Experience PE	-0.065*** (0.021)	-0.215*** (0.037)	-1.880*** (0.337)	0.143 (0.180)	-0.112 (0.160)
Marginal Effect of High-Experience PE	-0.026* (0.015)	-0.017 (0.025)	-0.116 (0.366)	0.376* (0.205)	0.083 (0.155)
Difference Between High and Low Experience PE (p-value)	0.086	<0.001	<0.001	0.341	0.340

Notes: Robust standard errors clustered at hospital level in parentheses. In this set of model specifications, we are unable to include *Post×High-Exper PE* because it is collinear with *Post×PE_Ownership×High-Exper PE*. *** p<0.01, ** p<0.05, * p<0.1.

Table C2: Leads/Lags Model Regression Results

Dependent variable	(1) Care Value	(2) Log(Operating Costs)	(3) Experiential Quality	(4) Mortality Rate	(5) Readmission Rate
Pre(-3+)×PE_Ownership	0.009 (0.016)	-0.004 (0.025)	0.538 (0.351)	0.068 (0.173)	0.140 (0.165)
Pre(-2)×PE_Ownership	-0.009 (0.013)	-0.010 (0.022)	-0.401 (0.279)	-0.090 (0.119)	0.108 (0.102)
Post(0)×PE_Ownership	-0.025* (0.015)	-0.083*** (0.030)	-0.118 (0.248)	0.175 (0.129)	-0.017 (0.091)
Post(1)×PE_Ownership	-0.037** (0.015)	-0.061*** (0.023)	-0.610** (0.304)	0.298* (0.173)	0.096 (0.111)
Post(2)×PE_Ownership	-0.059*** (0.022)	-0.117*** (0.043)	-1.073** (0.524)	0.455* (0.233)	0.194 (0.172)
Post(3+)×PE_Ownership	-0.042 (0.045)	-0.036 (0.073)	-1.146 (0.764)	0.604** (0.268)	0.380 (0.271)
Observations	5,077	5,077	5,077	5,077	5,077
Number of Hospitals	427	427	427	427	427
Adjusted R-squared	0.036	0.217	0.313	0.504	0.552
Controls	YES	YES	YES	YES	YES
Hospital FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES

Notes: Term “Pre(-*i*)×PE_Ownership” indicates *i* years prior to the start year for the treatment group. The term “Post(*i*)×PE_Ownership” indicates *i* years after the PE acquisition year for the PE_ownership group. “Post(0)×PE_Ownership” indicates the start year for the PE_Ownership group. “Pre(-1)×PE_Ownership” is omitted baseline period. We do not report coefficients of “Pre(-*i*)” and “Post(*i*)” due to space limitations; complete regression results are available upon request. Robust standard errors clustered at hospital level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table C3: Effect on PE Ownership on Care Value using Heckman Selection

Dependent Variable	(1) Care Value
Post	0.024* (0.012)
Post×PE_Ownership	-0.111* (0.057)
IMR	0.048 (0.033)
Observations	4,274
Number of Hospitals	421
Adjusted R-squared	0.046
Controls	YES
Hospital FE	YES
Year FE	YES

Notes: Robust standard errors clustered at hospital level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table C4: Impact of PE on Care Value using Alternate DEA Inputs and Outputs

Dependent variable	(1) Care Value	(2) Log(Operating Costs)	(3) Experiential Quality	(4) Mortality Rate	(5) Readmission Rate
Post	0.009 (0.012)	-0.006 (0.020)	0.491** (0.200)	-0.115 (0.103)	-0.072 (0.093)
Post×PE_Ownership	-0.036** (0.014)	-0.062** (0.025)	-0.907*** (0.306)	0.269* (0.157)	-0.018 (0.123)
Observations	5,119	5,119	5,119	5,119	5,119
Number of Hospitals	430	430	430	430	430
Adjusted R-squared	0.099	0.204	0.285	0.495	0.533
Controls	YES	YES	YES	YES	YES
Hospital FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES

Notes: The number of observations in this table differs from the baseline tables because we reconstructed the matched control sample for the PE ownership sample to account for the changes in care value because of alternate DEA inputs and outputs. Robust standard errors clustered at hospital level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table C5: Impact of PE Ownership on Alternative Care Value Measures

Dependent variable	(1) Cost-Adjusted Quality	(2) Cost-Adjusted Experiential Quality	(3) Cost-Adjusted Quality (Mortality)	(4) Cost-Adjusted Quality (Readmission)
Post	0.042 (0.036)	0.064 (0.044)	0.038 (0.055)	0.024 (0.053)
Post×PE_Ownership	-0.089* (0.052)	-0.124* (0.069)	-0.154* (0.082)	0.012 (0.075)
Observations	5,077	5,077	5,077	5,077
Number of Hospitals	427	427	427	427
Adjusted R-squared	0.109	0.206	0.475	0.394
Controls	YES	YES	YES	YES
Hospital FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

Notes: Cost-adjusted quality (mortality) is measured by using the standardized inverse of mortality rate minus standardized operating cost. Cost-adjusted quality (readmission) is measured as the standardized inverse of readmission rate minus standardized operating cost. The higher the cost-adjusted quality (mortality) or cost-adjusted quality (readmission), the higher the care value. Robust standard errors clustered at hospital level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table C6: Moderating Impact of Health Information Sharing on Alternative Care Value Measures

Dependent variable	(1) Cost- Adjusted Quality	(2) Cost- Adjusted Experiential Quality	(3) Cost- Adjusted Quality (Mortality)	(4) Cost- Adjusted Quality (Readmission)
Post	0.065 (0.046)	0.138** (0.062)	0.001 (0.072)	0.056 (0.067)
Post×InfoShare_High	-0.061 (0.056)	-0.159** (0.075)	0.043 (0.089)	-0.067 (0.085)
Post×PE_Ownership	-0.223*** (0.079)	-0.248** (0.109)	-0.230* (0.137)	-0.191* (0.114)
Post×PE_Ownership×InfoShare_High	0.241** (0.106)	0.258* (0.144)	0.128 (0.172)	0.336** (0.151)
Observations	4,691	4,691	4,691	4,691
Number of Hospitals	375	375	375	375
Adjusted R-squared	0.115	0.208	0.483	0.416
Controls	YES	YES	YES	YES
Hospital FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Marginal Effect of PE at Low InfoShare	-0.223*** (0.079)	-0.248** (0.109)	-0.230* (0.137)	-0.191* (0.114)
Marginal Effect of PE at High InfoShare	0.017 (0.070)	0.010 (0.093)	-0.102 (0.105)	0.145 (0.098)
Difference Between High and Low InfoShare (p-value)	0.024	0.073	0.459	0.027

Notes: Cost-adjusted quality (mortality) is measured by using the standardized inverse of mortality rate minus standardized operating cost. Cost-adjusted quality (readmission) is measured as the standardized inverse of readmission rate minus standardized operating cost. The higher the cost-adjusted quality (mortality) or cost-adjusted quality (readmission), the higher the care value. Robust standard errors clustered at hospital level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table C7: Exogeneity Test Results for Instrumental Variable

Dependent variable	(1) Care Value	(2) Log (Inpatient Visit)	(3) Log (Inpatient Days)	(4) Total Physician FTE	(5) Total Nurse FTE	(6) Total Other Clinician FTE
Neighbor InfoShare	-0.016 (0.027)	-0.059 (0.051)	-0.082 (0.054)	-3.284 (3.565)	-28.342 (17.843)	-4.778 (3.713)
Observations	5,064	5,064	5,064	5,064	5,064	5,064
Number of Hospitals	426	426	426	426	426	426
Adjusted R-squared	0.030	0.362	0.427	0.009	0.102	0.021
Controls	YES	YES	YES	YES	YES	YES
Hospital FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES

Notes: Robust standard errors clustered at hospital level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table C8: 2SLS Estimation of the Moderating Impact of Health Information Sharing on Care Value

Dependent variable: Care Value	(1)	(2)
Post	0.068*** (0.025)	0.073*** (0.024)
Post×InfoShare_High	-0.087** (0.039)	-0.096*** (0.037)
Post×PE_Ownership	-0.111*** (0.041)	-0.126*** (0.042)
Post×PE_Ownership×InfoShare_High	0.137** (0.066)	0.165** (0.067)
Observations	4,678	4,678
Number of Hospitals	374	374
Controls	YES	YES
Hospital FE	YES	YES
Year FE	YES	YES
Marginal Effect of PE at Low InfoShare	-0.111*** (0.041)	-0.126*** (0.042)
Marginal Effect of PE at High InfoShare	0.026 (0.030)	0.039 (0.031)
Difference Between High and Low InfoShare (p-value)	0.039	0.013

Notes: In column (1), the IV is the average level of health information sharing at neighboring hospitals (to the focal hospital) in the same HRR. In column (2), the IV represents the average level of inter-hospital IT at neighboring hospitals in the same HRR. The number of observations decreases from 4,691 to 4,678 in Column (1) and (2) due to missing values in the corresponding instrumental variables. Robust standard errors clustered at hospital level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table C9: Moderating Impact of Intra-hospital IT on Care Value

Dependent variable	(1) Care Value	(2) Log(Operating Costs)	(3) Experiential Quality	(4) Mortality Rate	(5) Readmission Rate
Post	0.032* (0.019)	-0.045* (0.024)	0.241 (0.324)	0.102 (0.177)	-0.138 (0.132)
Post×Intra IT_High	-0.003 (0.020)	0.059** (0.028)	0.032 (0.390)	-0.302 (0.197)	0.259 (0.159)
Post×PE_Ownership	-0.040 (0.027)	-0.030 (0.049)	-0.676 (0.521)	-0.032 (0.260)	0.146 (0.210)
Post×PE_Ownership×Intra IT_High	-0.003 (0.032)	-0.051 (0.056)	-0.136 (0.636)	0.480 (0.325)	-0.154 (0.258)
Observations	4,853	4,853	4,853	4,853	4,853
Number of Hospitals	389	389	389	389	389
Adjusted R-squared	0.036	0.225	0.311	0.504	0.563
Controls	YES	YES	YES	YES	YES
Hospital FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
Marginal Effect of PE at Low Intra-hospital IT	-0.040 (0.027)	-0.030 (0.049)	-0.676 (0.521)	-0.032 (0.260)	0.146 (0.210)
Marginal Effect of PE at High Intra-hospital IT	-0.042*** (0.016)	-0.081*** (0.029)	-0.813** (0.367)	-0.448** (0.195)	-0.009 (0.151)
Difference Between High and Low Intra-hospital IT (p-value)	0.928	0.368	0.830	0.140	0.550

Notes: Robust standard errors clustered at hospital level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table C10: Impact of PE Ownership and Information Sharing on Inpatient Volume and Inpatient Days

Dependent Variable	(1) Log(Total Inpatient Visits)	(2) Log(Inpatient Days)	(3) Log(Total Inpatient Visits)	(4) Log(Inpatient Days)
Post	-0.004 (0.029)	0.014 (0.019)	-0.030 (0.044)	0.000 (0.029)
Post×InfoShare_High			0.040 (0.054)	0.031 (0.033)
Post×PE_Ownership	-0.002 (0.043)	0.011 (0.028)	0.021 (0.061)	0.057 (0.046)
Post×PE_Ownership×InfoShare_High			-0.013 (0.085)	-0.084 (0.058)
Observations	5,077	5,077	4,691	4,691
Number of Hospitals	427	427	375	375
Adjusted R-squared	0.022	0.426	0.022	0.434
Controls	YES	YES	YES	YES
Hospital FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Marginal Effect of PE at Low InfoShare			0.021 (0.061)	0.057 (0.046)
Marginal Effect of PE at High InfoShare			0.008 (0.061)	-0.027 (0.036)
Difference Between High and Low InfoShare (p-value)			0.883	0.150

Notes: We use log transformation to reduce the skewness of the dependent variable. Robust standard errors clustered at hospital level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table C11: Summary of Robustness Checks

Concerns	Tests and Results of additional analyses	Location
Potential endogeneity may arise from complex interactions or nonlinear relationships among covariates, which may not be fully captured by the parametric models (e.g., logistic regression) typically used in PSM.	Test: Double machine learning to more flexibly control for covariates that may jointly affect treatment selection and outcomes. Findings: Result remain consistent with baseline results	Appendix B and Table B1
There may be substantial differences between the treated and control hospitals in the years prior to the treatment.	Test: Whether treated and control hospitals exhibit parallel trends. Findings: Results support the validity of the parallel trend assumption.	Figure C1 & Table C2
Observed effects may be due to pre-existing trends or spurious correlations, rather than the actual treatment.	Test: Placebo tests are conducted by randomly assigning treated hospitals. Findings: The DID estimator does not systematically generate spurious treatment effects.	Figure C2
In settings with staggered treatment timing, the two-way fixed effects model may yield biased estimates	Test: Alternative estimators that are robust to treatment effect heterogeneity. Findings: Results are qualitatively similar to baseline results.	Appendix D and Tables D1 & D2
Unobserved variables may bias the estimate of PE's impact even though we employ methods such as PSM and DML, which mainly rely on observed characteristics.	Test: A two-step Heckman selection model Findings: Results are consistent with baseline results.	Table C3
Selection of DEA input variables may drive our results	Test: Alternate DEA input variables using the number of staffed beds. Findings: Results are consistent with baseline results.	Table C4
The DEA measure accounts for multiple inputs and multiple outputs. A simplified measure may be more straightforward to measure care value.	Test: Alternative measure of care value using standardized quality minus standardized operating cost. Findings: Results are qualitatively similar to baseline results.	Table C5 & Table C6
The exogeneity assumption of our IV may not be valid.	Test: Exogeneity test using care value, patient flow, and staff level. Findings: IV does not have a direct effect on care value, patient flow, and staff level of the local hospital, suggesting that the exogeneity assumption of our IV is valid.	Table C7
The validity of the original IV strategy	Test: 1. IV using the average level of InfoShare of neighboring hospitals in the same HRR. 2. Alternate IV using the average level of Inter-hospital IT of neighboring hospitals in the same HRR. Findings: Results remain qualitatively consistent with those reported in Table 5.	Table C8
The moderating effect attributed to health information sharing may instead be driven by hospitals' internal IT capabilities.	Test: Examine the moderating impact of Intra-hospital IT on care value. Findings: Intra-hospital IT does not moderate the impact of PE on care value	Table C9
Observed changes in operating costs after PE ownership may be confounded by changes in patient volume.	Test: Examine changes in patient flow before and after PE acquisition. Findings: PE ownership does not significantly alter overall patient flow.	Table C10

Appendix D: Heterogeneity Robust Estimators

In staggered DID settings, the standard TWFE estimator can yield biased estimates, particularly when treatment effects are heterogeneous across units or vary over time (Baker et al. 2022). To address this issue, we implement two alternative estimation strategies that are robust to treatment effect heterogeneity. First, we apply the two-stage DID estimator introduced by Gardner (2022). This method mitigates the bias by residualizing the outcome variable in the first stage through a regression on unit and time fixed effects. In the second stage, the residualized outcome is regressed on the treatment indicator, isolating the treatment effect while accounting for fixed heterogeneity. We apply this estimator to our baseline model (i.e., equation (2)), and the results are presented in Table D1. They are qualitatively similar to the ones reported in our baseline table.

Table D1: Heterogeneity Robust Estimation of Impact of PE on Care Value

Dependent variable	(1) Care Value	(2) Log(Operating Costs)	(3) Experiential Quality	(4) Mortality Rate	(5) Readmission Rate
Post×PE_Ownership	-0.052*** (0.016)	-0.072** (0.026)	-1.031** (0.329)	0.317* (0.156)	0.0163 (0.129)
Observations	5,077	5,077	5,077	5,077	5,077
Number of Hospitals	427	427	427	427	427
Controls	YES	YES	YES	YES	YES
Hospital FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES

Notes: Robust standard errors clustered at hospital level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Second, we implement the group-time average treatment effect estimator proposed by Callaway and Sant'Anna (2021). This method identifies valid control groups for each treated cohort and time period and estimates group-time-specific, average treatment effects. These effects are aggregated to obtain the overall average treatment effect. We apply this estimator to the same baseline model, and the corresponding results are reported in Table D2. These results are qualitatively consistent with our baseline findings.

Table D2: Alternate Heterogeneity Robust Estimation of the Impact of PE on Care Value

Dependent variable	(1) Care Value	(2) Log(Operating Costs)	(3) Experiential Quality	(4) Mortality Rate	(5) Readmission Rate
Post×PE_Ownership	-0.059* (0.021)	-0.059* (0.029)	-0.655 (0.455)	0.458* (0.182)	0.155 (0.133)
Observations	5,054	5,054	5,054	5,054	5,054
Number of Hospitals	425	425	425	425	425
Controls	YES	YES	YES	YES	YES
Hospital FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES

Notes: Robust standard errors clustered at hospital level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Appendix Reference

Xu, Y., Ghose, A., & Xiao, B. (2024). Mobile Payment Adoption: An Empirical Investigation of Alipay. *Information Systems Research*, 35(2), 807–828. <https://doi.org/10.1287/isre.2021.0156>