

Supplementary Information for

Randomized Trial Shows Healthcare Payment Reform Has Equal-Sized Spillover Effects on Patients Not Targeted by Reform

Liran Einav, Amy Finkelstein¹, Yunan Ji, Neale Mahoney

¹ To whom correspondence may be addressed. Email: afink@mit.edu.

This PDF file includes:

Supplementary text

Tables S1 to S3

Supplementary Information Text

Appendix A: Additional Details on Data and Sample Definition

A1. Description of Data Files

1. Main CMS Data

We use the 2013-2017 Master Beneficiary Summary Files (MBSF), Inpatient (IP) files, and Medicare Provider Analysis and Review (MedPAR) files from the Center for Medicare and Medicaid Services (CMS).

The MBSF provides basic demographics on all Medicare enrollees including age, race, sex, Medicaid enrollment, and whether the individual receives Medicare through TM or MA.

The IP file contains claims-level data on hospital inpatient services used by TM enrollees, including information on the provider, dates of admission and discharge, length of stay, diagnoses, procedures, and discharge destinations for each inpatient admission.

The same data in the IP file are available at the admission-level in the MedPAR file. Different from the IP file, MedPAR also contains data on hospital inpatient services used by MA enrollees. As CMS pays a fixed amount per patient to her MA private insurer, who in turn reimburses claims submitted by providers, CMS does not directly observe MA claims. However, for MA patients the MedPAR file contains “information-only” claims on inpatient hospital admissions (encounter data); these claims show up in MedPAR due to “shadow billing” (or “no pay” billing). Hospitals are required to submit MA claims to CMS to receive indirect medical education (IME), graduate medical education (GME), or disproportionate share hospital (DSH) payments. MedPAR appears to include over 90% of MA inpatient admissions.¹ However, MA data in MedPAR only include payment information for services paid on a fee-for-services basis and do not include spending for any service that is included in a capitated payment.² Practically, 42% of the MA admissions appear to have zero spending in the data.³ Given that, we only use MedPAR for non-spending outcomes, i.e. discharge destinations. The MedPAR data have been used in several previous studies of the MA population. (Afendulis et al. 2013, Kumar et al. 2018, Wilcock et al. 2019).

2. Other CMS Data

We obtain program-specific information from the CMS website.⁴ These data include the CJR treatment status, and quarterly indicators for participation in the Bundled Payment for Care Improvement (BPCI) program. We merge these data with the Medicare data through the CMS Certification Number (CCN) for each hospital. Since the HCCI data only contain encrypted provider numbers, HCCI performed the merge on our behalf with the data we provided.

3. HCCI

Our HCCI data contain enrollment and claims from 2013-2017 on Medicare Advantage, Employer-Sponsored Insurance, and Individual Market plans provided by three insurers: Aetna, Humana and UnitedHealthcare (hereafter, “HCCI insurers”). The data contain the universe of enrollees and claims

¹ <https://journals.plos.org/plosmedicine/article?id=10.1371/journal.pmed.1002592>

² http://www.medpac.gov/docs/default-source/reports/jun19_ch7_medpac_reporttocongress_sec.pdf

³ <https://www.wpsgha.com/wps/portal/mac/site/claims/guides-and-resources/proper-billing-hmo/>

⁴ <https://innovation.cms.gov/initiatives/CJR>
<https://innovation.cms.gov/initiatives/bundled-payments/>

covered by these three insurers but exclude enrollees in highly capitated plans, Special Needs Plans, plans with various data issues, and other limitations (Curto et al. 2019). The data are stored at a secure data enclave in the National Opinion Research Center (NORC) at the University of Chicago.

The HCCI data contain four main files: enrollment, inpatient claims, outpatient claims, and physician claims.

The enrollment file is at the enrollee-month level, and contains monthly indicators for enrollment, age (in 10-year bins), gender, enrollee zip code, dual eligibility status, and whether the enrollee is at or over 65 years of age. It also contains an indicator for Medicare Advantage plans, an indicator for individual market policies, as well as an indicator for eligibility based on End Stage Renal Disease (ESRD) for Medicare Advantage enrollees. The data do not contain insurer identifiers. We identify Medicare Advantage enrollees in HCCI based on the Medicare Advantage indicator, and Employer-Sponsored Insurance (ESI) enrollees as enrollees whose plans are neither labelled Medicare Advantage nor individual market plans. In our ESI sample, we exclude admissions where the private insurer is the secondary payer on any subclaim.

We use the three claims files – inpatient, outpatient, and physician – to measure medical spending. The unit of observation is a subclaim (or a claim line), payable by one of the HCCI insurers to a medical provider. For each subclaim, we observe the amount paid to the provider from HCCI insurers, as well as any deductible, coinsurance, and copayment.

To construct LEJR index admissions, we use the inpatient file. An inpatient admission can include one or more subclaims, and admissions can be identified as unique patient ID-admission ID combinations. The inpatient data contain information on dates of admission and discharge, length of stay, discharge status code which contains information on the discharge destination, and diagnosis-related groups (DRG). The data also contain several variables that help us identify the type of facilities: we use the detailed service category (`hcci_det_cat`) variable to identify SNFs; we use the provider category code (`provcat`), which indicates the specialty of the healthcare professional or facility, to identify acute care hospitals. We use discharge status codes in the inpatient file to identify the discharge destination from index LEJR admissions.

A2. Hospital and patient eligibility criteria

Hospital eligibility: We restrict the sample of hospitals in the HCCI data using the same criteria that we applied to the TM sample. To be eligible for CJR, hospitals must be paid under Medicare’s inpatient prospective system and not participate in Model 1 of BPCI or in Phase 2 of Models 2 or 4 of BPCI. In the analysis period, 10.1% of LEJR episodes in MedPAR MA, 11.6% in HCCI MA, and 12.6% in HCCI ESI in eligible MSAs are excluded due to the hospital eligibility criteria.

Patient eligibility: We apply the analogous CJR-eligibility criteria to LEJR patients in MA and ESI as we applied to TM patients *mutatis mutandis*. For MA, we define LEJR episodes to be “CJR-eligible” if the patient is enrolled in MA during the entire episode, their eligibility for Medicare is not based on End Stage Renal Disease (ESRD), and Medicare is the primary payer. For ESI, the patient must be enrolled in ESI during the entire episode, below 65 years of age, and ESI must be the primary payer, which we identify through the primary payer indicator variable.

The episode is cancelled if the patient is readmitted during the episode to an acute care hospital for LEJR, in which case the original episode is cancelled and the readmission triggers a new episode, or if the patient initiates a new LEJR episode under any of the BPCI models during the episode. The episode is also cancelled if the patient dies during the episode; however, in HCCI data, the discharge codes for death became redacted starting from 2015. Considering that death in episode rarely takes place (less than 2% of

LEJR episodes in TM), in the HCCI data, in both pre- and post- periods, we do not cancel episodes if the patient dies.

Among LEJR episodes that pass the hospital eligibility criteria, 4.0% of LEJR episodes in MedPAR MA, 4.1% in HCCI MA, and 7.8% in HCCI ESI in eligible MSAs are excluded due to the patient eligibility criteria.⁵ Combining the hospital and patient exclusions, in the analysis period, 86.3% of LEJR episodes in MedPAR, 84.8% in HCCI MA, and 80.6% in HCCI ESI would have otherwise qualified for CJR.

Furthermore, we follow Finkelstein et al. (2018) and CMS (2015) and exclude a small number of categories of spending in episode that are not covered by the CJR bundle. Those primarily consist of spending on hospital admissions during the episode for reasons unrelated to LEJR, such as oncology, trauma, or surgery for chronic or acute diseases.

Appendix B. Construction of Specific Variables

1. Discharge Destinations

In both HCCI and CMS data, we use discharge status codes associated with the index admission to create discharge destination outcomes. In HCCI data, 6.67% of MA LEJR admissions and 2.32% of ESI LEJR admissions in 2016-17 have more than one discharge status codes reported; for those admissions we use the discharge status code associated with the last subclaim within the admission. This problem is not present in IP and MedPAR data, where we are able to assign a unique discharge code to each admission.

Our primary outcome of interest is share discharged to institutional post-acute care (PAC), which includes discharges to skilled nursing facilities (SNF), long-term care facilities (LTCH), and inpatient rehabilitation facilities (IRF).

We also analyze the share of patients discharged to each of the other major discharge locations: home health care, home without home health care, and other destinations, which include Medicare-approved swing beds, inpatient care at another acute care hospital, and other less common destinations such as psychiatric hospitals, hospices, and federal hospitals.

2. Spending and Utilization

In the Medicare data, we define total episode spending as Medicare spending in the index admission and 90 days post-discharge from the index admission, except for services unrelated to LEJR which are excluded from the episode (CMS 2015). We only include payments by Medicare and exclude any patient cost-sharing.

In the HCCI data, we identify SNF spending by the HCCI detailed service category variable – any admission with the variable value “SNF” that does not occur in an acute care hospital. When constructing length of stay in SNF, we top-code SNF days with a length of more than 100 days to 100 because TM benefits run out on day 100. We focus on SNF spending and SNF days, rather than institutional PAC spending and length of stay, as our outcomes in the HCCI data because we are unable to separately identify IRF and

⁵ Both the numerator and the denominator do not count episodes that are already excluded due to hospital eligibility criteria.

LTCH from other institutional claims based on the service category variable in the HCCI data to construct institutional PAC spending and length of stay.

Appendix C. Spillover Effects on MA Patients in the HCCI Data

We compare spillover effects on MA patients in the CMS data and the HCCI data in Panel A of Appendix Table A1. The effects of CJR for MA patients are broadly similar but less precisely estimated in the HCCI data relative to the CMS data. In the HCCI data, discharges to institutional PAC decline by 1.2 percentage points (smaller than the of 3.3 percentage points decline in the CMS data). The estimate is much less precise, with a 95% confidential interval of -3.7 to 1.4 percentage points, failing to reject both zero and the point estimate from the CMS data. Likewise, the point estimates suggest declines in days in SNF, episode spending in SNF, and overall episode spending for MA patients in HCCI that are qualitatively similar, but slightly smaller, than those from the CMS data, with 95% confidence intervals that include 0 and the CMS point estimates.

Our preferred interpretation is that the HCCI results for the MA sample fail to reject the benchmark established by the more precise CMS estimates. This is natural given that the HCCI sample is based on approximately 64,000 episodes versus about 230,000 in the CMS data. An alternative explanation is that the spillover effects onto MA patients is smaller for the particular insurers in the HCCI data. UnitedHealthcare, for example, had launched a bundled payment programs for LEJR prior to the start of CJR, potentially diminishing the scope for spillover effects from the program we study (Whitman 2016).

While we cannot rule out this alternative, several pieces of evidence point against it. First, as discussed previously in Table 1, the share discharged to institutional PAC in the control group is similar for the two groups (28% in CMS data, 27% in HCCI data), suggesting that the three insurers in the HCCI data and their patient population are broadly similar to the overall MA population.

Second, in Panel B of Table S1, we show that an “apples to apples” comparison within the CMS data for the three HCCI insurers compared to the remaining insurers shows no evidence of systematic differences. To identify HCCI insurers in the CMS data, we use the Part C contract number variable in the MBSF file, matched to CMS plan directory.⁶ Specifically, we include any MA plan with “Aetna,” “Humana,” or “UnitedHealth” in either the legal entity name or organization marketing name. Unfortunately, the Part C contract number variable is only available in our data in 2015 and 2016. Therefore, we are not able to directly replicate our baseline analysis from Table 2 (which analyzes admissions from April 1, 2016 to September 15, 2017 and uses data from 2013 and 2014 to construct the lagged outcomes) restricting to these three insurers. Instead, we estimate a version of the baseline model where we analyze admissions from April 1 to September 15, 2016, and use the six months in 2015 before CJR announcement to construct the lagged outcomes.

Specifically, Panel B compares our baseline results in 2016 (where we use lagged outcomes from 2013-2014), alternative results in 2016 (where we use lagged outcomes from the pre-CJR announcement months in 2015), and alternative results in 2016 restricting to the three HCCI insurers (also with lagged outcomes from the pre-CJR announcement months in 2015). The baseline result from 2016 shows a statistically significant 2.6 percentage point decline in share discharged to institutional PAC. The alternative

⁶ https://securemed-medicarehelp.org.netdna-ssl.com/wp-content/uploads/2015/10/MA_Contract_Directory_by_Name_2015_09.pdf

specification reports quantitatively similar results, albeit with less precision. Restricting to HCCI insurers greatly reduces the precision but does not appear to affect the point estimate.

These analyses show that there do not appear to be systematic differences in impact between the three HCCI insurers compared with the remaining insurers. Taken together with our other analyses, it appears that that the lack of precision for the MA patients in the HCCI data is a likely result of the much smaller sample size.

Table S1. Impact of CJR on Medicare Advantage patients

Panel A: Impact of CJR on Medicare Advantage patients in CMS and in HCCI data								
Sample:	CMS Medicare Advantage				HCCI Medicare Advantage			
Outcome	Control mean	Treatment effect	95% CI	p-value	Control mean	Treatment effect	95% CI	p-value
Share discharged to institutional PAC	0.283	-0.033	[-0.051, -0.017]	0.0001	0.271	-0.012	[-0.037, 0.014]	0.366
Share discharged to home health	0.365	0.004	[-0.031, 0.039]	0.8100	0.370	0.022	[-0.022, 0.066]	0.318
Share discharged home	0.336	0.042	[0.007, 0.077]	0.0200	0.346	0.000	[-0.046, 0.046]	0.990
Share discharged to other destinations	0.016	-0.003	[-0.008, -0.000]	0.0500	0.013	-0.007	[-0.013, 0.000]	0.037
Share discharged to SNF					0.255	-0.003	[-0.029, 0.022]	0.799
Number of days in SNF					5	-0.2	[-0.692, 0.330]	0.485
Episode spending in SNF					2,081	-79	[-290, 131]	0.457
Total episode spending					20,765	-160	[-892, 572]	0.667
Number of CJR episodes	1163	-5	[-155, 135]	0.89	350	27	[-61, 116]	0.541

Panel B: Impact of CJR on Medicare Advantage patients in CMS data, restricting to HCCI insurers						
Sample:	CMS MA: 2016 Baseline		CMS MA: 2016 Alternative		CMS MA: 2016 HCCI Insurers	
Outcome	Control Mean	Treatment Effect	Control Mean	Treatment Effect	Control Mean	Treatment Effect
Share discharged to institutional PAC	0.296	-0.026	0.296	-0.019	0.301	-0.023
		[-0.048, -0.003]		[-0.041, 0.003]		[-0.055, 0.008]
Share discharged to home health	0.368	0.025	0.368	0.086	0.367	0.148
		[-0.035, 0.029]		[-0.027, 0.033]		[-0.037, 0.041]
Share discharged home	0.32	0.843	0.32	0.841	0.317	0.930
		[-0.003, 0.073]		[-0.014, 0.051]		[-0.019, 0.071]
Share discharged to other destinations	0.017	0.036	0.017	0.264	0.015	0.259
		[-0.008, 0.004]		[-0.004, 0.006]		[-0.010, 0.004]
Number of CJR episodes	344	0.485	344	0.781	133	0.376
		[-37, 31]		[-30, 28]		[-11, 29]
		0.857		0.925		0.360

Notes: Panel A reports results from estimating equation (1). Specifically, it reports MSA-level estimates from a regression of the row outcome on an indicator for CJR, controlling for strata fixed effects, two lags of the outcome variable, and pre-period missing dummies. CI and p-value are based on heteroskedasticity-robust standard errors. The left panel replicates the CMS Medicare Advantage estimates from Table 2 in the paper; the right panel reports estimates using the HCCI Medicare Advantage data. The sample is all LEJR admissions between April 1, 2016 and September 15, 2017 that would have qualified for CJR, in the CMS Medicare Advantage and HCCI Medicare Advantage data, respectively. See notes to Table 1 for variable definitions.

Panel B replicates the CMS MA analysis in Table 2 in three different samples: 2016 baseline, which is the same sample as in Table 2 but includes only admissions between April 1 and September 15 of 2016; 2016 alternative, which uses admissions between January and June of 2015 to generate the lagged outcome, instead of 2013 and 2014; 2016 HCCI insurers is the same as "2016 alternative" except that the sample includes only the three insurers found in the HCCI data.

Table S2. Correlation between TM and MA treatment effects

Outcome: share discharged to institutional PAC

	Mean treatment effects (SD)		
	CMS TM	CMS MA	Correlation
Panel A: without hospital-specific trend	-0.022 (0.103)	-0.012 (0.110)	0.599 (0.026)
Panel B: with hospital-specific trend	-0.019 (0.215)	-0.013 (0.262)	0.173 (0.039)

Notes: Table reports the episode-weighted mean and standard deviation of hospital-specific treatment effects for the CMS TM and MA samples, respectively, and the correlation in hospital treatment effects between these two samples. Estimates in Panel A are based on estimating equation (2) estimates in Panel B are based on equation (3). The standard errors for the correlation are based on a parametric bootstrap procedure with 500 bootstrap draws.

Table S3. Impact of CJR on Other Conditions

Sample: all CMS TM hip and femur procedures except major joint (DRGs 480-482)

Outcome: share discharged to institutional PAC

% operated by LEJR physicians	Control mean	Treatment effect	95% CI	p-value
93%	0.824	-0.001	[-0.014, 0.012]	0.87

Notes: Table reports results from estimating equation (1). Specifically, it reports MSA-level estimates from a regression of the outcome on an indicator for CJR, controlling for strata fixed effects, and two lags of the outcome variable. CI and p-value are based on heteroskedasticity-robust standard errors. The sample is all hip and femur procedures except major joint admissions in TM between April 1, 2016 and September 15, 2017, that would have otherwise qualified for CJR. On average, for doctors who treat LEJR patients, LEJR makes up 42% of their total procedures.

Among other top procedures performed by LEJR doctors, the most common is hip and femur procedures except major joint, which makes up 13% of all procedures performed by the average LEJR doctor. The next most common procedures (lower extremity and humerus procedure, and major joint and limb reattachment procedure of upper extremity) make up 4% and 3% of an average LEJR doctor's portfolio, respectively.⁷ We focus on hip and femur procedures except major joint, which we define as inpatient admissions with DRGs 480-482. As reported in the table, 93% of these procedures are performed by a physician who also treats LEJR patients, and 82% of these patients are discharged to institutional post-acute care.

⁷ Authors' analysis of the 2016 Medicare data.