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JNCI J Natl Cancer Inst (2017) 109(8): djw330

doi: 10.1093/jnci/djw330
First published online March 14, 2017
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The Impact of Social Contagion on Physician Adoption of Advanced Imaging Tests in Breast Cancer

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Abstract

Background: Magnetic resonance imaging (MRI) and positron emission tomography (PET) scans are widely used in breast cancer practice despite unproven benefits. We examined the extent to which social contagion is associated with adoption of these imaging modalities.

Methods: We used Surveillance, Epidemiology, and End Results–Medicare to construct peer groups of physicians who shared patients during a baseline period when these imaging modalities were starting to disseminate into practice (2004–2006) and determined the potential impact of these peer groups during a follow-up period (2007–2009). For non-early-adopting surgeons (whose patients did not receive MRI/PET during baseline), we used hierarchical logistic regression models to examine the effect of their peer group's baseline use on their use of MRI/PET during the follow-up period, adjusting for patient characteristics and hospital MRI/PET use.

Results: For MRI, there were 6424 women diagnosed in the follow-up period assigned to 986 non-early-adopting surgeons. During baseline, 9.3% of women received an MRI, varying across peer groups from 0% to 81%. Women assigned to surgeons whose peers had the highest rate of baseline MRI use were more likely to receive MRI compared with women whose surgeons' peers did not use MRI (24.9% vs 10.1%, adjusted odds ratio [OR] = 2.47, 95% confidence interval [CI] = 1.39 to 4.39). Physician peers were associated with uptake of PET imaging (OR for highest vs lowest baseline peer group PET use = 2.04, 95% CI = 1.24 to 3.36).

Conclusions: The phenomenon of social contagion may offer opportunities to better understand how new approaches to cancer care disseminate into clinical practice.

The cost of cancer care is expected to continue rising steeply and is projected to reach $158 billion by 2020 (1). While new tests and treatments are a major driver of cancer costs (2), little is known about the factors that drive diffusion of new modalities into routine cancer care. Traditional models hold that a combination of patient demand, evidence, provider preferences, and health system factors influence provider behavior. While there is some evidence that these factors influence uptake of new technologies, they do not fully explain the observed variations in practice (3–6). In order to improve the value of cancer care, it is crucial to identify novel mechanisms of the dissemination of cancer management strategies.

Received: September 15, 2016; **Revised:** November 29, 2016; **Accepted:** December 13, 2016

The theory of social contagion offers an innovative perspective for understanding the adoption of innovation in cancer care. The interpersonal context in which individuals are embedded influences their interactions with everything from pathogens to ideas, based on contact with their peers (7). Social contagion theory posits that this contact is quantifiable and predictable: Social contagion has been shown across a wide variety of behaviors and traits, including obesity (8), smoking (9), and happiness (10). Early work suggests that social contagion also impacts physician behavior (11–14). However, prior research has rarely used population-based data based on clinical encounters to construct physician networks, or incorporated social network analytic techniques (15,16).

The diffusion of advanced imaging technologies such as magnetic resonance imaging (MRI) and positron emission tomography (PET) scans into cancer care provides an opportunity for studying the potential impact of social contagion on the adoption of a new technology. These advanced imaging technologies have been adopted rapidly into breast cancer practice, despite uncertain benefits (17–21). First introduced in breast cancer around 2000, the use of perioperative MRI among Medicare beneficiaries increased to 25% in 2008–2009 (22); PET scan use grew to more than 10% by 2006 (23). Though preoperative MRIs have a higher sensitivity for detection of additional breast lesions, randomized studies have not demonstrated survival differences (24,25), and concerns have been raised about the association between MRI and more aggressive surgical care and overdiagnosis (22,26), leading the American Society of Breast Surgeons to recommend against their routine use (27). The American Society of Clinical Oncology has recommended against routine PET scans for breast cancer with a low risk of metastasizing based on retrospective studies (28).

To better understand why expensive and unproven modalities are disseminating into cancer practice, we explored whether physician patient-sharing networks were linked with the uptake of advanced imaging technology. We identified physician peer groups—representing clusters of physicians who frequently share patients with one another—and tested whether these peer groups were longitudinally associated with the adoption of MRI and PET. Because of the relative lack of data regarding the effectiveness of these tests, the decision to order them is likely based on clinical factors and physician preference, which may be influenced by interactions with peers and hospital standards and practice patterns. We hypothesized that physicians who were in peer groups with early adopters of MRI/PET scans would be more likely to subsequently use these technologies than physicians who were in groups without any early-adopting peers. We further sought to delineate the relative contribution of physician peer groups compared with patient, surgeon, hospital, and geographic region in the uptake of MRI/PET imaging.

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Methods

Overview

We conducted a retrospective study in which we constructed physician peer groups during 2004–2006 ("baseline") and examined subsequent adoption of advanced imaging technologies during a follow-up period (2007–2009). These time periods were chosen to reflect a period early in the adoption curve followed by rapid uptake (21–23). Our primary exposure was the proportion of patients assigned to each peer group who received MRI/PET during the baseline period. Among surgeons who did not have any patients who received MRI/PET during baseline, we examined the association between their peer groups' MRI/PET use during the baseline period and their patients' corresponding MRI/PET use during follow-up (Figure 1).

Data Source and Study Sample

We used the Surveillance, Epidemiology, and End Results (SEER)–Medicare linked database, which includes patient demographic and tumor-specific cancer registry data as well as Medicare claims. The Yale Human Investigations Committee determined that this inquiry did not constitute human subjects research; internal review board approval was not needed.

In order to construct peer groups, we included patients with a first diagnosis of in situ or localized breast cancer during the baseline period (2004–2006), as well as a 5% sample of female Medicare beneficiaries without cancer. We incorporated this

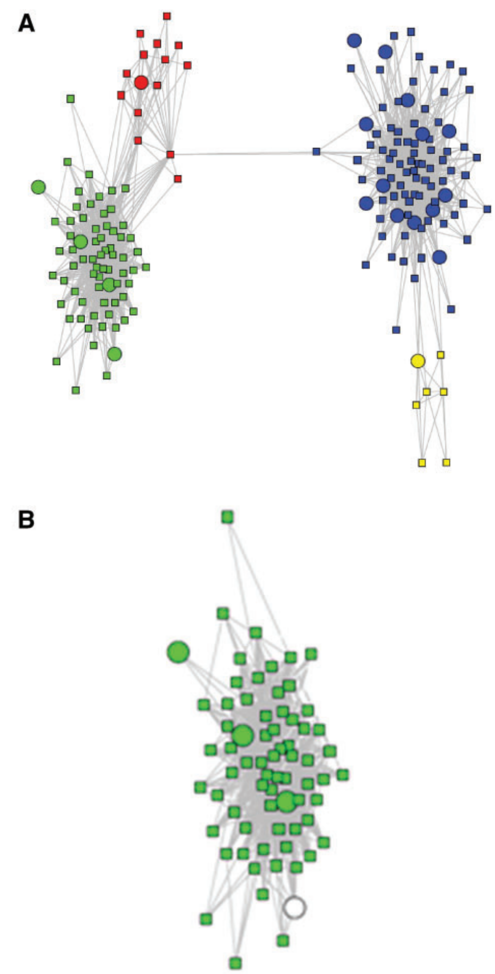

Figure 1. Illustration of peer groups within a single hospital referral region. An example of peer groups within a single hospital referral region is shown in **(A)**. Surgeons are represented by **circles**, other physicians by **squares**, and shared patients by **lines**. **Colors** denote different peer groups, and the location is determined by social distance using the Fruchterman-Reingold layout. A single peer group is shown in **(B)**. Surgeons who were early adopters of positron emission tomography (PET) scans are represented by **solid circles**, and non-early-adopting surgeons are represented by **outlined circles**.

heterogenous group in order to more fully capture patient-sharing ties and potential referral patterns. In constructing peer groups, we excluded women with breast cancer who met any of the following criteria: stage IV disease, breast cancer not the first or only primary cancer, histology not consistent with epithelial origin, younger than age 66 years or older than age 94 years, unknown month of diagnosis or diagnosis reported on autopsy or death certificate, or not continuously enrolled in Medicare Parts A and B from one year prior to diagnosis through either one year after diagnosis or until the time of their death (if they died within one year). Women from the 5% random sample of Medicare beneficiaries without cancer were required to fulfill the same age and Medicare enrollment criteria as the cancer patients and were randomly assigned an index date, which was used analogously to the date of diagnosis.

When evaluating MRI and PET use, we constructed a sample of breast cancer patients who fulfilled the above inclusion criteria but who were diagnosed during the follow-up period (2007–2009). We additionally excluded women who did not receive surgery and those with in situ disease. Finally, because we were interested in assessing the impact of social contagion among non-early-adopting surgeons, we limited the sample to patients cared for by surgeons who did not have any patients receiving MRI/PET during the baseline period (non–early adopters).

Construction of Provider Peer Groups

Our peer groups were constructed using women diagnosed during the baseline period. We included all surgeons, medical oncologists, radiation oncologists, radiologists, and primary care providers (PCPs; including obstetricians/gynecologists) who billed for care during the three months prior to diagnosis (or the index date for women without cancer) to the nine months following. Two providers who both billed for care delivered to the same patient were considered to have a patient-sharing tie (16,29).

Within each hospital referral region (HRR), we identified peer groups of physicians who most frequently shared patients with one another using the Girvan-Newman method (30–33). In this approach, physician ties that have the highest betweenness scores are iteratively removed and a goodness-of-fit test is maximized (34,35). This approach places each physician within an HRR into mutually exclusive groups that we term “peer groups.” We included physicians who cared for at least five patients and only counted two providers as linked to one another if they shared two or more patients. These thresholds helped optimize peer group stability.

Patients were assigned to a peer group based on the surgeon who performed their definitive cancer surgery. We excluded peer groups with fewer than two surgeons. For each peer group, we calculated the proportion of baseline patients who received an MRI or PET scan during the perioperative period (three months before diagnosis through three months after surgery). We defined non-early-adopting surgeons as those who did not have any baseline patients who received MRI/PET and examined the subsequent use of MRI/PET among their patients diagnosed in the follow-up period; this definition was constructed separately for each imaging technology, so that non-early-adopting MRI surgeons might have used PET and vice versa.

Variables

Our main outcomes were the receipt of MRI and PET during the perioperative period among patients diagnosed during the follow-up period and assigned to non-early-adopting surgeons. Our primary exposures were the baseline rates of MRI/PET utilization among the surgeon’s peer group. Patient covariates included age, race, marital status, and area-level median household income. Tumor characteristics included size, nodal status, stage, hormone receptor status, grade, and laterality. Comorbidity in the 12 months through one month before diagnosis was measured using a modified list of the conditions suggested by Elixhauser et al. (categorized as 0, 1 to 2, or $\geq$3) (36,37). We included whether someone had a PCP visit in the 12 months through one month prior to diagnosis as a proxy for access to care.

To account for potential variation in practice patterns across hospitals, surgeons were assigned to the hospital where they billed for inpatient care for the plurality of their assigned patients (38). Similar to peer group exposure, we calculated the proportion of patients assigned to each hospital (via their surgeon) who received MRI/PET during the baseline period.

Statistical Analysis

We summarized the characteristics of the baseline patients, physician peer groups, and non-early-adopting surgeons. Among patients diagnosed during the follow-up period whose surgeons were not early adopters of MRI/PET, we compared the characteristics of women who did and did not receive MRI/PET using chi-square tests.

To test the hypothesis that non-early-adopting surgeons are influenced by their peer group, we estimated separate hierarchical generalized linear models for MRI and PET, where the primary exposure was the peer group’s baseline MRI/PET use (39). Peer group use in baseline was categorized to allow for nonlinear associations and tested for effect using overall (Wald) tests. Models controlled for patient sociodemographic and clinical characteristics and the baseline hospital rate of MRI/PET use. These models included random effects for the surgeon, peer group, and HRR to account for clustering of data. We attempted to estimate models with an additional hospital-level random effect, with hospital assignment crossed with peer group membership, but these failed to converge under a broad range of assumptions, estimation methods, and starting values. Multiple imputation with 20 imputations was used to account for missing data (40).

To assess the proportion of overall variance in MRI/PET use among patients of non-early-adopting surgeons in the follow-up period that was explained by peer groups, we fit cross-classified null models that estimated surgeon-, peer group–, hospital-, and HRR-level variance without adjustment for any covariates; these models included crossed effects for hospital and peer group (41). We then calculated the proportion of variance explained by each level, under the assumption that the patient-level variance was $\sigma^2 = \pi^2/3$; confidence intervals were constructed for percentage explained using simulation (42).

All statistical tests were two-sided, and a P value of less than .05 was considered statistically significant.

Results

The peer groups were constructed using 141 513 patients (29 643 women who were diagnosed with breast cancer during the baseline period and 111 870 noncancer patients) and 26 479 physicians (2644 surgeons) across 118 HRRs. These physicians were assigned to 679 peer groups. Patients were assigned to peer groups based on the surgeon who performed their cancer surgery. Of the 679 peer groups, 178 and four groups were excluded because no patients were assigned during the baseline and follow-up periods, respectively; an additional 201 were excluded because they had fewer than two surgeons. The final sample included 1369 surgeons in 296 peer groups who treated 14 542 women diagnosed with breast cancer during the baseline period and 12 549 women diagnosed with breast cancer during the follow-up period.

Peer groups had a median of 56 physicians (interquartile range [IQR] = 33–87) with a median of six surgeons (IQR = 3–9) and 34 baseline patients who underwent breast cancer surgery (IQR = 18–64) (Table 1). There was a median of 4.5 peer groups per HRR (IQR = 3–8). Of the 14 542 patients diagnosed with breast cancer during baseline, 9.3% received an MRI and 8.9% received a PET scan (Supplementary Table 1, available online). The proportion of women diagnosed during the baseline period who received MRI/PET varied widely across peer groups, from 0% to 81% for MRI and from 0% to 64% for PET scans.

MRI Adoption

We identified 6424 women diagnosed during the follow-up period assigned to 986 non-early-adopting surgeons. Although none of these surgeons' patients received an MRI during the baseline period (by definition as non–early adopters), 14.3% of their patients received an MRI during the follow-up period. Women who received an MRI during the follow-up period were more likely to be younger, white, and married and have fewer chronic conditions and higher area-level household income compared with those who did not receive an MRI (Table 2). Women assigned to surgeons whose peer groups had the highest rate of baseline MRI use (>10% of patients received MRI) were more likely to receive MRI compared with patients whose surgeons' peer groups did not have any baseline MRI use (24.9% vs 10.1%) (Figure 2A).

These differences in receipt of MRI remained statistically significant in models that adjusted for patient clinical and demographic factors as well as for the hospital rate of MRI use (odds ratio [OR] for >10% vs 0% peer group MRI use = 2.47, 95% confidence interval [CI] = 1.39 to 4.39) (Table 3; Supplementary Table 2, available online). Women whose surgeons' peer groups were in the second highest category of MRI use (5%–10% of patients) were also statistically significantly more likely to receive MRI than women whose surgeons were in the lowest group (OR = 2.14, 95% CI = 1.32 to 3.47) (Table 3). Peer group explained 6.6% (95% CI = 2.3 % to 17.6%) of the variation in MRI use during the follow-up period, compared with 10.7% (95% CI = 5.8% to 18.2%) for the surgeon, 8.6% (95% CI = 3.2% to 20.9%) for the hospital, and 7.0% (95% CI = 3.1% to 15.2%) for hospital referral region (Table 4).

Table 1. Characteristics of 296 baseline peer groups used in analysis*

Characteristic	Median	IQR
No. of doctors	56.0	33.0–87.0
No. of patients	34.0	17.5–63.5
No. of medical oncologists	4.0	2.0–6.0
No. of primary care providers	28.0	14.0–48.0
No. of radiologists	15.0	7.0–24.0
No. of radiation oncologists	2.0	1.0–5.0
No. of surgeons	6.0	3.0–9.0
MRI use, %	3.2	0.0–9.2
PET use, %	6.3	2.1–13.4

*IQR = interquartile range; MRI = magnetic resonance imaging; PET = positron emission tomography.

PET Adoption

Approximately 10.4% of the 5316 women who met inclusion criteria during the follow-up period received a PET scan. Women who were younger, did not have a prior PCP visit, or had larger tumors, node-positive or hormone receptor–negative disease, and higher stage and grade were more likely to receive a PET scan (Table 2). In unadjusted analyses, women diagnosed in the follow-up period were more likely to receive PET scans when their surgeons' peer groups had the highest baseline rate of PET use (>10% of patients) compared with those whose surgeons had the lowest rate of PET use (0% of patients; 17.7% vs 8.9%) (Figure 2B).

In adjusted models, women whose surgeons' peer groups had the highest baseline rate of PET use were statistically significantly more likely to receive PET compared with women whose surgeons were in a peer group that did not use PET during the baseline period (OR = 2.04, 95% CI = 1.24 to 3.36) (Table 3). The other categories of baseline peer group PET use were not statistically significantly associated with subsequent PET use. Peer group explained 6.8% (95% CI = 2.7% to 15.1%) of the variation in subsequent PET use compared with 3.4% (95% CI = 0.5% to 18.8%) for the surgeon and 5.3% (95% CI = 1.2% to 20.6%) for the hospital (Table 4). Models that included a random effect for the hospital referral region failed to converge.

Discussion

We found that the rate of imaging in a surgeon's peer group was linked with their subsequent adoption of MRI and PET scans. Physician peer groups provide a novel way to investigate the diffusion of innovation, a key component of rising cancer costs. Our study builds on prior work applying social network analyses to insurance claims data by focusing on the diffusion of innovation among peer groups. Our previous work showed that surgeons were more likely to adopt brachytherapy when their peers were early adopters, though this work did not situate these connections within the larger context of patient-sharing peer groups (15). Past research employing cross-sectional study designs has found statistically significant variation in practice patterns across peer groups for cancer treatment, complications, and costs of care (30,31). We extend this work by looking at how this variation may impact subsequent care delivery using a longitudinal approach.

There are four main factors affecting the speed of diffusion: characteristics of the innovation, communication channels through which individuals learn about the innovation, time, and characteristics of the social structure (11). Though we are unable to determine mechanisms using claims data, it is plausible that a physician's peer group can influence many of these factors. Peer groups may reflect formal and informal communication channels, and the sharing of clinical experiences may suggest the necessity or effectiveness of the imaging modality.

Prior work has validated that pairs of physicians who share more patients with one another are more likely to report knowing one another, and peer groups may include physicians directly and indirectly (eg, surgeons who are connected to the same medical oncologist) connected to one another (29). Among women diagnosed in the baseline period, a quarter had claims for more than one surgeon. However, physicians in the same

Table 2. Characteristics of follow-up patients used in analysis

	MRI sample* (n = 6424)			PET sample† (n = 5316)		
Characteristic	Did not receive MRI No. (%)	Received MRI No. (%)	P‡	Did not receive PET No. (%)	Received PET No. (%)	P‡
No.	5506	918		4763	553	
Age, y			<.001			<.001
66–69	1134 (20.6)	316 (34.4)		1060 (22.3)	165 (29.8)	
70–74	1295 (23.5)	280 (30.5)		1164 (24.4)	139 (25.1)	
75–79	1282 (23.3)	190 (20.7)		1088 (22.8)	121 (21.9)	
80–84	1050 (19.1)	94 (10.2)		869 (18.2)	81 (14.6)	
85–94	745 (13.5)	38 (4.1)		582 (12.2)	47 (8.5)	
Race			<.001			.25
White	4778 (86.8)	836 (91.1)		4215 (88.5)	483 (87.3)	
Black	498 (9.0)	54 (5.9)		344 (7.2)	50 (9.0)	
Other	230 (4.2)	28 (3.1)		204 (4.3)	20 (3.6)	
Marital status			<.001			.52
Married	2307 (41.9)	487 (53.1)		2088 (43.8)	254 (45.9)	
Unmarried	3054 (55.5)	408 (44.4)		2496 (52.4)	282 (51.0)	
Unknown	145 (2.6)	23 (2.5)		179 (3.8)	17 (3.1)	
Income, $			<.001			.43
<33 K	1373 (24.9)	130 (14.2)		820 (17.2)	109 (19.7)	
33 K–40 K	949 (17.2)	102 (11.1)		806 (16.9)	94 (17.0)	
40 K–50 K	1330 (24.2)	260 (28.3)		1192 (25.0)	130 (23.5)	
50 K–63 K	953 (17.3)	233 (25.4)		947 (19.9)	106 (19.2)	
≥63 K	901 (16.4)	193 (21.0)		998 (21.0)	114 (20.6)	
Comorbid conditions			<.001			.06
0	2818 (51.2)	553 (60.2)		2537 (53.3)	281 (50.8)	
1–2	2031 (36.9)	296 (32.2)		1715 (36.0)	194 (35.1)	
≥3	657 (11.9)	69 (7.5)		511 (10.7)	78 (14.1)	
Primary care provider visit			.23			.03
No	390 (7.1)	55 (6.0)		320 (6.7)	51 (9.2)	
Yes	5116 (92.9)	863 (94.0)		4443 (93.3)	502 (90.8)	
Tumor size, cm			.32			<.001
<2	3378 (61.4)	582 (63.4)		3140 (65.9)	186 (33.6)	
2–5	1847 (33.5)	289 (31.5)		1440 (30.2)	288 (52.1)	
>5	253 (4.6)	36 (3.9)		167 (3.5)	66 (11.9)	
Missing	28 (0.5)	11 (1.2)		16 (0.3)	13 (2.4)	
Node positive			.21			<.001
No/unknown	4201 (76.3)	683 (74.4)		3803 (79.8)	234 (42.3)	
Yes	1305 (23.7)	235 (25.6)		960 (20.2)	319 (57.7)	
Stage			.20			<.001
I	3116 (56.6)	524 (57.1)		2947 (61.9)	122 (22.1)	
II	1813 (32.9)	315 (34.3)		1456 (30.6)	229 (41.4)	
III	577 (10.5)	79 (8.6)		360 (7.6)	202 (36.5)	
Hormone receptor status			.14			<.001
Negative	773 (14.0)	115 (12.5)		584 (12.3)	132 (23.9)	
Positive	4425 (80.4)	771 (84.0)		3954 (83.0)	405 (73.2)	
Missing	308 (5.6)	32 (3.5)		225 (4.7)	16 (2.9)	
Grade			.02			<.001
1	1412 (25.6)	238 (25.9)		1294 (27.2)	66 (11.9)	
2	2331 (42.3)	423 (46.1)		2111 (44.3)	213 (38.5)	
3–4§	1517 (27.6)	221 (24.1)		1171 (24.6)	256 (46.3)	
Missing	246 (4.5)	36 (3.9)		187 (3.9)	18 (3.3)	
Tumor laterality			.76			.70
Right-sided	2707 (49.2)	459 (50.0)		2362 (49.6)	284 (51.4)	
Left-sided/ unknown§	2799 (50.8)	459 (50.0)		2401 (50.4)	269 (48.6)	
Baseline peer group imaging use, MRI;PET, %			<.001			<.001
0;0	2382 (43.3)	269 (29.3)		981 (20.6)	96 (17.4)	
≤2;≤3	701 (12.7)	62 (6.8)		854 (17.9)	68 (12.3)	
2–5;3–5	938 (17.0)	153 (16.7)		1044 (21.9)	117 (21.2)	
5–10;5–10	971 (17.6)	264 (28.8)		1178 (24.7)	120 (21.7)	
>10;>10	514 (9.3)	170 (18.5)		706 (14.8)	152 (27.5)	

(continued)

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Table 2. (continued)

Characteristic	MRI sample* (n = 6424) Did not receive MRI No. (%)	MRI sample* (n = 6424) Received MRI No. (%)	P‡	PET sample† (n = 5316) Did not receive PET No. (%)	PET sample† (n = 5316) Received PET No. (%)	P‡
Baseline hospital imaging use, MRI;PET, %			<.001			<.001
0;0	3413 (62.0)	396 (43.1)		1790 (37.6)	174 (31.5)	
≤3;≤4	490 (8.9)	71 (7.7)		1163 (24.4)	111 (20.1)	
3–7.5;4–10	983 (17.9)	258 (28.1)		1115 (23.4)	122 (22.1)	
>7.5;10–25	620 (11.3)	193 (21.0)		684 (14.4)	143 (25.9)	
N/A;>25				11 (0.2)	3 (0.5)	

*MRI sample includes patients who were diagnosed during the follow-up period whose surgeon did not use MRI during baseline. MRI = magnetic resonance imaging.
†PET sample includes patients who were diagnosed during the follow-up period whose surgeon did not use PET during baseline. PET = positron emission tomography.
‡P values represent two-sided global (Wald) tests.
§Categories are combined because of the Centers for Medicare and Medicaid Services prohibition against displaying cell sizes < 11.

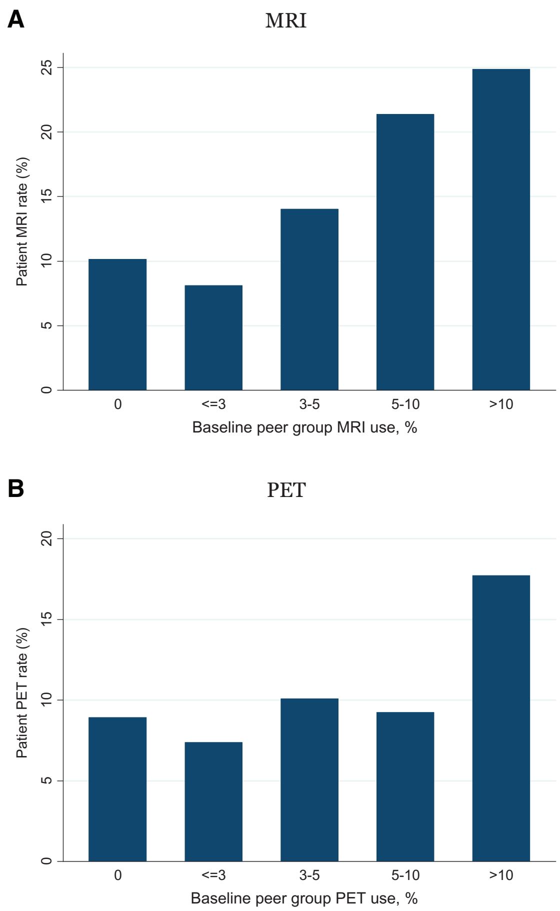

Figure 2. Patient-level magnetic resonance imaging (MRI) and positron emission tomography (PET) scans according to peer group–level MRI/PET use. **A)** Shows MRI use during the follow-up period according to baseline peer group MRI use. PET use during the follow-up period according to baseline peer group PET use is shown in **(B)**. MRI = magnetic resonance imaging; PET = positron emission tomography.

peer groups did not necessarily discuss advanced imaging technologies with one another and were not invariably aware of the imaging studies their shared patients received. An overlapping

Table 3. Adjusted association between baseline peer group–level MRI/PET use and follow-up patient-level MRI/PET use*

Baseline peer group use, %	OR (95% CI)	P†
MRI		
0	ref	.01
≤2	1.31 (0.63 to 2.73)	
2–5	1.45 (0.85 to 2.47)	
5–10	2.14 (1.32 to 3.47)	
>10	2.47 (1.39 to 4.39)	
PET		
0%	ref	.004
≤3	0.89 (0.51 to 1.54)	
3–5	1.28 (0.77 to 2.10)	
5–10	0.89 (0.55 to 1.45)	
>10	2.04 (1.24 to 3.36)	

*Adjusted for baseline peer group MRI/PET use, hospital MRI/PET rate, age, race, marital status, income, comorbid conditions, primary care provider visit, tumor size, node positivity, stage, hormone receptor status, grade, and tumor laterality. CI = confidence interval; MRI = magnetic resonance imaging; OR = odds ratio; PET = positron emission tomography.
†P values represent two-sided global (Wald) tests.

explanation for our findings is that peer groups reflect shared clinical contexts, which may provide a platform for social interaction as well as delineate available resources, constraints, and incentives (43). Because SEER-Medicare data do not have practice identifiers or participation in tumor boards, we relied on hospital assignment as a way to adjust for shared contexts, albeit incompletely. Adding baseline hospital MRI/PET utilization attenuated but did not eliminate the associations between peer group and adoption. Homophily—or the tendency for people with similar characteristics to form connections—has been demonstrated using patient-sharing approaches and may also help explain our findings (16,44). However, our finding of a longitudinal relation between baseline use and subsequent adoption, which is the first such demonstration to our knowledge, suggests that the influence of physicians by their peers may be playing a role.

We only observed an association with PET in the highest compared with the lowest baseline peer group use whereas our findings for MRI were more consistent. This may not be surprising given our focus on surgeons. In our clinical experience,

Table 4. Decomposition of variance in use of MRI and PET

	MRI		PET*
Level	% attributable (95% CI), including HRR	% attributable (95% CI), excluding HRR	% attributable (95% CI), excluding HRR
Patient	64.5 (56.8 to 70.6)	64.4 (57.3 to 70.2)	81.9 (68.7 to 87.8)
Surgeon	10.7 (5.8 to 18.2)	11.5 (6.5 to 19.6)	3.4 (0.5 to 18.8)
Peer Group	6.6 (2.3 to 17.6)	12.3 (6.2 to 22.4)	6.8 (2.7 to 15.1)
Hospital	8.6 (3.2 to 20.9)	10.1 (3.8 to 23.6)	5.3 (1.2 to 20.6)
HRR	7.0 (3.1 to 15.2)	N/A	N/A

*Positron emission tomography (PET) model could not include hospital referral region (HRR) because of model convergence problems. To make models more comparable, we ran the magnetic resonance imaging model with and without HRR. CI = confidence interval; HRR = hospital referral region; MRI = magnetic resonance imaging; PET = positron emission tomography.

surgeons are more likely to order MRIs while PET scans are more likely to be ordered by other practitioners such as oncologists. It is plausible that assigning patients to peer groups based on their medical oncologists may have yielded different results. We also note different characteristics associated with test ordering: MRI was likely to vary according to patient age, race, and comorbidity whereas PET was closely linked with clinical characteristics of the cancer, demonstrating different correlates of utilization that may impact adoption. Further, during the study period, regulations may have made it more difficult for physicians to obtain PET scans, making them somewhat less prone to peer group influence (45).

This study has several limitations. First, the extent to which peer groups correspond to actual physician interaction remains unknown. Second, the use of HRRs for constructing peer groups may not always correspond to how care is delivered and may impact the creation of peer groups (46). Our use of cross-classified models to partition variation helps account for the nested data structure. Third, our peer groups were constructed using Medicare fee-for-service claims data, so our findings may not be generalizable to other patient populations. Fourth, patients were assigned to surgeons based on treatment patterns and surgeons were assigned to hospitals based on an established algorithm, both of which may be subject to inaccuracy (38). Fifth, claims data may be associated with incomplete risk adjustment, which may be important in decisions to order imaging studies. Finally, using observational data, we are unable to determine causality; delineating the impact of shared contexts and homophily is an important next step.

The adoption of more efficient medical practice, and the abandonment of wasteful medical practice, is a key priority for the US health care system. The current study suggests that investigating the practice patterns of physician peer groups—independent of their patients' characteristics and hospital assignment—can provide analytic leverage in understanding their subsequent adoption of breast cancer imaging. Future research is needed to further identify aspects of peer groups that may be important for diffusion, which may include compositional features of the groups (eg, proportion of surgeons) and structural characteristics (eg, density of connections). It is also necessary to disentangle social contagion from shared contexts and evaluate social contagion in smaller multispecialty teams that jointly manage cancer care as a foundation for future investigations and interventions.

Funding

This work was supported by the National Cancer Institute (NCI) of the National Institutes of Health (R01CA190017). Dr. Pollack's salary is supported by the National Cancer Institute and Office of Behavioral and Social Sciences (K07 CA151910).

Notes

The content is solely the responsibility of the authors and does not necessarily represent the official views of the National Institutes of Health. The funders had no role in the design and conduct of the study; collection, management, analysis, or interpretation of the data; or preparation, review, or approval of the manuscript.

The collection of the California cancer incidence data used in this study was supported by the California Department of Public Health as part of the statewide cancer reporting program mandated by California Health and Safety Code Section 103885; the National Cancer Institute's Surveillance, Epidemiology and End Results Program under contract N01-PC-35136 awarded to the Northern California Cancer Center, contract N01-PC-35139 awarded to the University of Southern California, and contract N02-PC-15105 awarded to the Public Health Institute; and the Centers for Disease Control and Prevention's National Program of Cancer Registries, under agreement #U55/CCR921930-02 awarded to the Public Health Institute. The ideas and opinions expressed herein are those of the author(s) and endorsement by the State of California, Department of Public Health the National Cancer Institute, or the Centers for Disease Control and Prevention or their Contractors and Subcontractors is not intended, nor should it be inferred. The authors acknowledge the efforts of the Applied Research Program, NCI; the Office of Research, Development and Information, Centers for Medicare & Medicaid Services (CMS); Information Management Services (IMS), Inc.; and the Surveillance, Epidemiology, and End Results (SEER) Program tumor registries in the creation of the SEER-Medicare database. The interpretation and reporting of the SEER-Medicare data are the sole responsibility of the authors.

Drs. Gross and Yu and Ms. Soulos receive research funding from 21st Century Oncology LLC. Dr. Gross has also received funding from Medtronic and Johnson & Johnson; the authors report no other relationships or activities that could appear to have influenced the submitted work.

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