Top hospitals as regional innovators: the adoption and spatial diffusion of best practices with respect to vaginal births after cesareans (VBAC)

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Abstract

During the late 20th century, the United States saw a significant rise and subsequent decline in vaginal births after cesarean (VBACs). This trend was closely tied to evolving guidance from the American College of Obstetricians and Gynecologists (ACOG), based on emerging research about VBAC safety and efficacy. In the 1970s, it was common for women who had a cesarean to undergo the procedure in all subsequent deliveries. However, from 1980 to the mid-1990s, ACOG's guidelines became less restrictive, allowing more women to attempt VBACs. This trend reversed in the late 1990s when ACOG introduced stricter conditions, leading to a decline in VBACs. We explore the spatial aspects of this shift, particularly the role of "Top 25 hospitals" as regional health innovators. We employ a Probit model for the period 1990-2002 to examine the hypothesis that regions with or near these hospitals adopted new practices, such as changes in VBAC guidelines, more rapidly. We find that counties with a top-25 hospital had a faster reduction in the share of VBACs, but little evidence that the fall of VBAC rates in surrounding counties was faster than in more remote ones.

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Paper prepared for presentation at the 63rd European Regional Science Association Meetings, Terceira Island, Azores, Portugal, 26-30 August 2024.

1. Introduction

Regional scientists have long been fascinated with the spatial dimensions of the adoption and spread of innovation. Sometimes innovations arise serendipitously, seemingly randomly and spreading instantaneously. Other times, innovations are the product of their environment, with their rollouts methodical, managed, and initially localized (Fink et al (2017)). And, of course, innovation can spread somewhere between such extremes.

We consider the spatial dimensions of the adoption and diffusion of information in health care. Many researchers have shown that the amount and types of medical care people receive in the United States vary significantly depending on where they live (e.g., Wennberg and Gittelsohn (1973), Wennberg et al (1987), Wennberg (2002)). A variety of explanations for this geographical variation have been proffered, including differences in patient attributes, heterogeneous physician training and preferences, variance in insurance reimbursement policies, and differences in statewide legal environments. Scant attention has been given to the role played by space and knowledge diffusion, *per se*.

We examine a specific innovation: the adoption of evolving information regarding vaginal births after cesareans (VBACs). Our study focuses on a period when emerging evidence contradicted the prevailing medical practice, which initially supported VBACs. From the late 1980s through the 1990s, the American College of Obstetricians and Gynecologists (ACOG), the leading professional body in the U.S., advocated for the use of VBACs. However, in the early to mid-1990s, new evidence highlighted the risks associated with VBACs. By 1998 and 1999, ACOG incorporated this new information into revised guidelines that discouraged VBACs. Thus, the 1990s was a time when institutions shaping physician practices were promoting VBACs, while evolving evidence increasingly advised against them. We utilize this divergence between evidence and medical orthodoxy to explore the sources and dissemination of the evolving information.

Our paper focuses on the role played by top Obstetrics and Gynecology (OBGYN) hospitals in the development of that information and the spatial spread of the information developed by those hospitals. We find that VBAC rates in counties with Top 25 OBGYN hospitals fell earlier than those rates in the rest of the nation, suggesting that new information regarding VBACs emerged from those hospitals and that physicians in those hospitals incorporated that information into their practices earlier than the rest of the nation. This result reflects the important role played by top hospitals in the development of medical knowledge. On the other hand, we do not find evidence of geographic spread of that information from those hospitals prior to the revised ACOG pronouncements in 1998 and 1999. We also find no evidence that the information spread earlier to counties bordering counties with a Top 25 hospital, in states with a Top 25 hospital, or in larger counties (counties with a population of 1,000,000 people or more).

Although our work examines a particular medical practice (VBAC's), it fits into the broader area of medical knowledge innovation and diffusion medical knowledge and diffusion. It is important to note that, unlike many analyses in the literature, our work does not consider the development and adoption of *new* technologies. Rather we look at the speed and extent of adoption of changing information regarding established procedures.

2. Setting and Literature Review

Physician practices in medical specialties like obstetrics and gynecology are guided by clinical practice guidelines (CPGs) issued by national specialty associations, such as ACOG. In developing CPGs, it is common for a national group of physicians to examine evidence from clinical trials and academic research, and then convene expert panels to establish non-binding practice guidelines, which serve as benchmarks for professional responsibilities related to treatment protocols. The association will share these guidelines with its membership through various channels, including journals (e.g., *Obstetrics and Gynecology*), clinical bulletins (e.g., *Clinical Updates in Women's Health Care*), and continuing education presentations at professional meetings and conferences.

Generally, CPGs reflect the evidence accumulated over years of practice regarding practices and procedures in a specific medical context (Yi et al (2021)). Because CPGs reflect the assessment of cumulative evidence proclamations at any given point in time they might lag the best knowledge in a field. Miraldo et al (2019) note that the diffusion process for innovations can be long and Ruhl and Siegal (2017) observe that CPGs "may become outdated quickly as medicine progresses." Finally, medical malpractice law may further hinder adoption of new knowledge. In this regard Frakes (2013: 275) observes that "the law may impose a source of friction on medical practice innovations…."

2.1 Evolution of Medical Practices Regarding VBACs

In 1916, Edwin Cragin published "*Conservatism in Obstetrics*," in which he examined medical practices and techniques aimed at preserving the health and well-being of pregnant women and their fetuses. One key counsel came to be known as the Cragin Dictum: "o*nce a cesarean, always a cesarean."* As the accepted standard, the Cragin Dictum influenced obstetric practices for decades in cases of cesarean-subsequent deliveries.

Over time ACOG offered various updates to its clinical management guidelines regarding VBACs, notably changing course on the Cragin Dictum orthodoxy. Between 1980 and the mid-1990s, guidelines became increasingly less restrictive, encompassing births which previously had not been considered candidates for a VBAC (Gregory et al (2010)). A 1995 ACOG *Practice Patterns Bulletin* stated that "[i]n the absence of contraindication, a woman with one previous delivery with a lower transverse uterine incision ... should be counseled and *encouraged* (italics added) to undergo a trial of labor" (ACOG, 1996, 96).[1] Gregory et al (2010) observed that the "1995 guideline was perhaps the most liberal, and strongest endorsement" of VBACs (p. 238).

During this period, some publications also argued for expanded use of VBACs (Gregory et al (2010)) and, prior to 1998, some insurers required expectant mothers to

[1] This practice is referred to at a trial of labor after cesarean (TOLAC). Under a TOLAC, women are offered a chance for vaginal delivery without abdominal surgery. In addition to lower costs, purported benefits include quicker recovery and healing, reduced risk of infection, and reduced risk of hysterectomy, placental disorders, bowel or bladder injury, and other complications that have been associated with multiple C-sections (https://www.acog.org/womens-health/faqs/vaginal-birth-after-cesarean-delivery#:~:text=What%20are%20the%20risks%20of,both%20you%20and%20your%20fetus).

undergo a VBAC (Roberts et al (2007)). The overall effect of the ACOG Bulletins, the publications, and the insurance requirements was an increase in VBAC rates from three percent in 1981 to 28 percent in 1996 (Sargent and Caughey (2017)).

While some agents were advocating for increasing VBACs, evidence against them emerged. Safety concerns surfaced, with reports of severe complications linked to uterine rupture, including cases of perinatal death and long-term neurologic impairment in newborns (Flamm (1997)). In a study in Nova Scotia, McMahon et al (1996) found that women with a prior cesarean who attempted labor faced nearly double the risk of major maternal complications compared to those who opted for an elective second cesarean.

Increases in malpractice suits resulting from failed VBACs further influenced perceptions, with some high-profile legal cases prompting a reversal in support for VBACs by key advocates in 1996 (Mozurkewich and Hutton (2000)). Schifrin and Cohen (2013) argue that fear of litigation became a significant factor driving the decline in VBAC rates after 1995. Finally, while the 1995 ACOG *Bulletin* may be viewed as the strongest endorsement of VBACs by ACOG, it did inject some caution in use of VBACs by being explicitly non-committal with respect to multiple gestation and breech presentation (ACOG (1996)).

In 1998, ACOG once again revised its guidance, recommending that women with a prior low-transverse cesarean be "offered" rather than "encouraged" to attempt a trial of labor (ACOG (1998)). A subsequent 1999 *Bulletin* tightened safety standards, requiring that physicians be "immediately" available for emergencies during VBAC attempts, a criterion that many hospitals, especially in suburban and rural areas, could not meet (ACOG (1998), (1999), Sargent and Caughey (2017), Gregory et al. (2010)). Following these changes, VBAC rates declined significantly, dropping to 8.5 percent by 2006 (ACOG (2017)).

Ultimately, then, the 1990s was a period in which the institutions important to determining physician practices were encouraging VBACs while evolving evidence suggested reductions in their use.

2.2 Previous research on the spatial dimensions of innovation in health care

A vast body of research shows great regional heterogeneity in use of a variety of medical treatments (e.g., Fisher et al (2003), Zuckerman et al (2010), Song et al (2010)). Miraldo et al (2019)) provide an excellent literature review examining variation in the adoption of assorted clinical practices and medical technologies. They identify many of the individual, institutional, and organizational factors which underlie this heterogeneity, such as select doctor and patient demographics, practitioner behavioral preferences, physician training, and hospital characteristics. They also identify spatial factors that are salient for our work, especially regarding *Health System and Ecosystem Factors* and *Networks and Collaboration*. We discuss those next.

2.2a Spatial factors affecting innovation adoption

Leading hospitals, especially those affiliated with universities or committed to research, are central to health innovation systems. These hospitals perform various critical roles as primary providers of healthcare services, key adopters and users of new technologies, and potential creators of new processes and organizational practices. Additionally, they play a vital role in education by training new healthcare professionals, serving as hubs for clinical research, and acting as significant R&D institutions (Thune and Mina (2016)). Accordingly, leading hospital are often seen as the focal point in a distributed system due to their complex division of labor and collaborative use of knowledge (Coombs et al (2003); Von Hippel (1988)).

Urbanization economies can affect the adoption of new medical innovations. Typically, urban hospitals are larger than those in non-metropolitan areas (Hatten and Connerton (1986). As a result, urban hospitals usually have larger staffs and more complex organizational structures, factors that have been shown to enhance a firm's ability to collect, scrutinize and share information (Kelley and Helper (1999)).

Previous empirical studies suggest that the size of a practice or facility significantly influences physician behavior and practice variations. For instance, Baicker et al (2006) analyzed data from the National Center for Health Statistics--which includes linked information on birth and infant death--to identify factors contributing to risk-adjusted county Cesarean rates. They find that provider density and hospital capacity explain approximately 9 percent of the variation in these rates. Goes and Park (1997) and Nystrom et al (2002) examine panel data from US hospitals, finding that larger hospitals tend to be more innovative than smaller ones.

Lu et al (2015) examine how hospital characteristics influence the adoption of innovations, using patient-level data on percutaneous coronary interventions in Taiwanese hospitals. They find that smaller hospitals and those situated near early adopters were slower to adopt the innovation. Additionally, a higher concentration of physicians in larger facilities is associated with overall practice variations (Yiannakoulias et al (2009)). This could be due to enhanced communication among staff in larger hospitals, which results in treatment decisions that are more aligned with widely accepted best practices (Verstappen et al (2004), Ketcham et al (2007)).

Differences in the characteristics of surgeons in urban versus rural areas may contribute to variations in medical practices. For instance, Yiannakoulias et al (2009) examined differences in diagnostic practices for cerebrovascular disease in Alberta, Canada. They discovered that physicians in rural and urban areas exhibited distinct practice patterns, even when accounting for the types of facilities they worked in, their medical specialization, and their workload.

Technology adoption can also be affected by the extent of spatial competition. Fudenberg and Tirole (1985) note that competitive firms may be faster adopters of new technologies if it enhances market power. In a study of the adoption of new fertility treatments, Hamilton and McManus (2005) demonstrate that a rise in competition was linked to a 19 percent increase in the likelihood of a clinic adopting fertility treatment. Aggarwall et al (2017) study of prostate cancer treatment is England suggests that increased competition and patient choice are associated with greater service specialization and faster adoption of innovative technologies in cancer surgery. The impact of these factors, however, varies by region, hospital size, and the type of cancer surgery.

2.2b Spatial factors affecting innovation diffusion

Regarding diffusion, there is extensive literature on the geographic spread of knowledge. Duranton and Puga (2004) review the microeconomic foundations of agglomeration economies. They motivate their discussion of models of learning by suggesting that being physically close to individuals with higher skills or greater knowledge fosters the acquisition of skills and promotes the exchange and spread of knowledge.

Empirical work in innovation diffusion in sectors other than healthcare is highlighted by the large literature devoted to patent spillovers. Research has shown that patent spillovers tend to cluster in specific regions, often due to the presence of specialized knowledge pools, skilled labor, and supportive infrastructure (Jaffe et al (1993)). For example, Silicon Valley's success can be attributed to the dense network of tech firms and institutions, which facilitates rapid exchange of ideas and technologies.

Geographic proximity plays a significant role in these spillovers. Firms located near each other can more easily share information and collaborate, leading to a more efficient diffusion of technological advancements. A key conclusion of Comin et al’s (2012) empirical study of technology diffusion across countries is that technology diffuses slower to locations that are farther away from adoption leaders. It is important to note, however, that while proximity can enhance knowledge sharing, the nature of the industry and the type of technology also influence how and where these spillovers occur.

In healthcare, Burke et al (2010) examine the social interactions among local physicians, specifically addressing productivity spillover and conformity pressure. They provide a theoretical framework that incorporates both patient characteristics and the influence of local social dynamics. Miraldo et al (2019) note that networks at both the individual and organizational levels can facilitate the spread of information, the adoption of new practices, and the standardization of care delivery. Many studies investigate the dynamics of individual networks by analyzing how communication and information flow between doctors. These networks' structure is significantly shaped by the tendency of individuals to interact with those who share similar characteristics, such as gender, age, seniority, or profession (MacPhee (2000), MacPhee and Scott (2002)).

Knowledge sharing often depends on key opinion leaders. Coleman, Katz, and Menzel (1957), were pioneers in the study of knowledge transmission in healthcare, emphasizing contagion, where new adopters of a treatment are inspired by doctors that had already adopted. Similarly, brokers, defined as individuals who connect otherwise unconnected people, can play a crucial role in the diffusion of important information, as does the hierarchical structure within a network (Heng, McGeorge, and Loosemore (2005), West and Barron (2005), Rangachari (2008)). In healthcare networks, a higher density can lead to more consistent performance but may sometimes result in less efficient information acquisition and diffusion through network ties (Fattore et al (2009), West and Barron (2005), Mendel et al (2009)).

3. **Empirics**

We focus on VBACs over the 1990-2002 period. Birth data is drawn from the US Centers for Disease Control and Prevention Natality Files. We limit our analysis to the subset of women who had a prior C-section and whose births were attended by a medical doctor or by a Doctor of Osteopathy (“physicians") in a hospital. A birth was associated with its state and county of occurrence. It is noteworthy that the internet was still a relatively new phenomenon in terms of information dissemination during this timeframe, especially in the earlier years. This may have resulted in slower information flows. See Schriger et al (2010) for a discussion of the evolution of medical journals available on the internet.

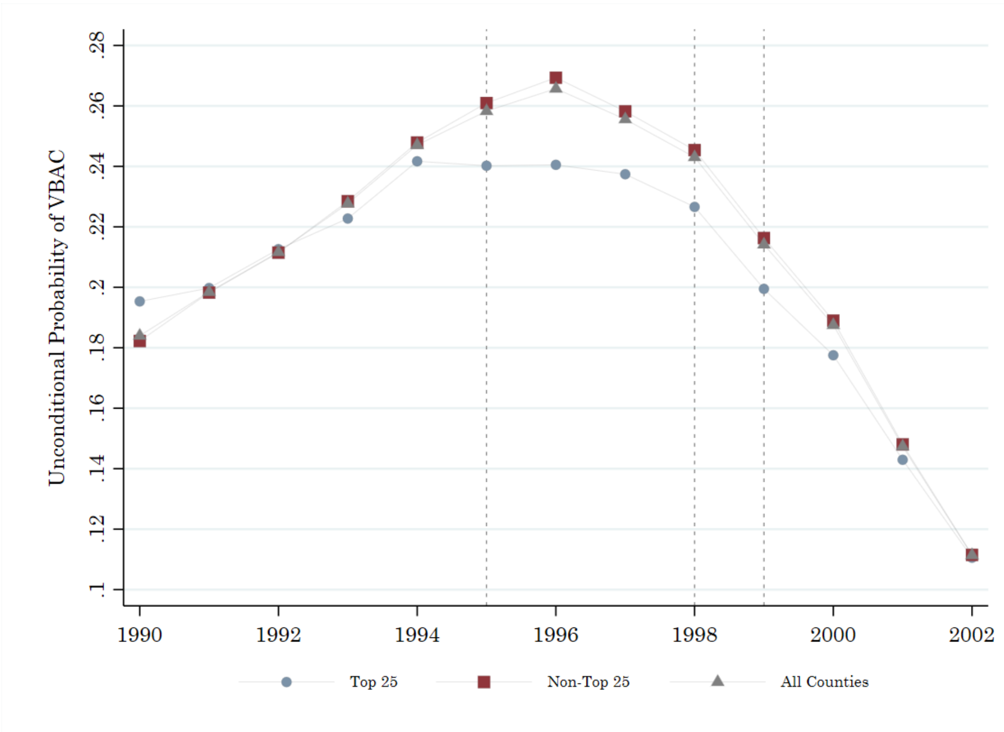
We identified counties as having a “Top Hospital” using *US News and World Report* rankings of top Gynecological hospitals between 1991 and 1996.[2] We considered four potential definitions of a “Top Hospital” using those rankings: (1) appearing in the top 25 at least three times in the 1991-1996 period, (2) appearing in the top 25 at least twice, (3) appearing in the top 30 at least three times, and (4) appearing in the top 30 at least twice. The differences in the total number of counties identified as having Top Hospital were nominal for the first three definitions. Moving from definition (1) to definition (2) added one more county, while moving from definition (2) to definition (3) added a second county. Moving to definition (4) added four more counties to those which satisfied definition (3). We ultimately chose (1) as our definition of a “Top Hospital.” Regardless of the definition used, however, the estimated parameters for our Preferred Specification (identified as Model 3 below) were substantially the same. Table A3 in the Appendix reports APEs associated with those parameters for the four different Top Hospital definitions.

To set the stage, Figure 1 presents unconditional national VBAC rates over the period 1990-2002 for i) all counties, ii) counties with a Top Hospital, and iii) non-Top Hospital counties. The vertical lines identify the timing of the relevant ACOG *Bulletins*. Overall, we see that VBAC rates increased between 1990 and 1996 and decreased thereafter. Not surprisingly, the trend for non-Top Hospital counties is like All counties. VBAC rates in Top Hospital counties, on the other hand, dropped below the national

[2] USNWR notes that: “The Best Hospitals specialty rankings are meant for patients with life-threatening or rare conditions who need a hospital that excels in treating complex, high-risk cases. These rankings are helpful if you’re looking for information about a rare condition or difficult diagnosis that isn’t treated at many facilities.” For more on hospital ranking methods see https://health.usnews.com/best-hospitals.

average early in the period with the difference becoming greater between 1995 and 1998. After the 1998/1999 ACOG Bulletins, VBAC rates in non-Top Hospital counties decreased faster and converged to rates in Top Hospital counties.

Figure 1. Unconditional VBAC probabilities in the US Over Time



Our econometric analysis begins by distinguishing births in counties which include a Top Hospital and births in other counties during the 1990-2002 period. We estimate several versions of the following equation (our "Primary Equation"):

$$Y_{is} = \delta_1 \cdot Top_i + \sum_{t=1991}^{2002} \rho_t \cdot T_{it} + \sum_{t=1991}^{2002} \pi_t \cdot T_{it} \cdot Top_i + x_i \cdot \beta + \eta_s + \epsilon_i \qquad (1)$$

where Y_{is} equals one if a birth *i* in state *s* was a VBAC, Top_i is a dummy variable which equals one if the birth was in a county with a Top Hospital, T_{it} is a year dummy variable which equals one if the birth was in year *t*, ***x*** is a row vector which includes the control variables identified below and an intercept, η_s is a state fixed effect, and e_i is a disturbance which we assume has a standard normal distribution. The time dummy variables represent a non-parametric time trend. The π_t parameters capture how VBAC rates in Top Hospital counties differed over time from rates in the other counties in the nation.

The patient control variables are informed by the literature. They include mother's age (in quadratic form), dummy variables for whether the mother is (i) Hispanic, (ii) Black, (iii) of a non-White or a non-Black race, education dummy variables for whether the mother has less than a high school diploma, has some college, and has a college diploma, dummy variables for whether the birth (a) has maternal or fetal complications, (b) is a plural birth, and (c) has a gestational period between 37 and 42 weeks.

For differences in state legal environments, we include law-related dummy variables for the presence of a cap on non-economic damages (*Cap*) in tort lawsuits and for the use of a national standard in determining a physician's duty of care to a patient (*NatStd)* (see: Frakes 2013). To capture spatial factors, we include a dummy variable for a birth in a metro area (*Metro=1*), which is defined using the USDA's Economic Research Service (ERS) Rural-Urban Continuum Codes. We model the relationship with a Probit Model and estimate the parameters using the maximum likelihood estimator. We report standard errors clustered at the state level. We do not cluster at the county level because we might expect errors within a state to be correlated.

We report the average partial effects (APEs) associated with the π_t parameters in Table 1 as well as results for several specifications, which are designed to capture the importance of state fixed effects and the control variables on results regarding VBAC rates in Top Hospital counties.[3] Model 1 excludes control variables and state fixed effects. Model 2 adds state fixed effects, while Model 3 (our preferred specification) adds control variables. Model 4 allows for county fixed effects and control variables. We also include APEs for the Top Hospital and the Metro variables. In calculating the Top Hospital by Year APEs we set the value of the Metro variable equal to one because all Top Hospital counties fall into that category.[4] The addition of the state (county) fixed effects and the control variables does not affect the estimated π_t parameters notably, suggesting that observed heterogeneity does not drive our results. We focus on the Model 3 estimated APEs.

The APEs associated with the π_t parameters can be interpreted as how the difference between Top Hospital and non-Top Hospital counties each year (say, 1995) differs from that difference in 1990. For example, the regression results for Model 3 indicate that the difference between the Top and non-Top Hospital counties in 1990 was 2.6 percent. Table A2 indicates that in 1995 VBAC rates in non-Top Hospital counties were 7.38 percent higher than they were in 1990. The 1995 0.044 APE for Top Hospital counties (in Table 1) implies that VBAC rates in Top Hospital counties were (7.38 percent - 4.4

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[3] In Appendix Table A2 we report the Model 3 APEs for the year dummy variables, in addition to APEs for the π_t parameters reported in Table 2.
[4] In Appendix Table A2 we report the Model 3 APEs for the year dummy variables, in addition to APEs for the π_t parameters reported in Table 2.

percent) = 2.98 percent higher in 1995 compared with 1990. In other words, VBAC rates were not increasing as fast in Top Hospital counties.

We make several observations about the results in Table 1. First, the APEs in 1991 and 1992 were similar and, thereafter, the absolute value of the (negative) APEs increased through 1996, indicating that doctors in Top Hospital counties were moving away from VBACs sooner than doctors in non-Top Hospital counties. Second, once ACOG shifted its position regarding VBACs in 1998/99, non-Top Hospital counties moved away from VBACs, reflected in the decreased absolute values of the differences between their rates. Finally, by 2002, the VBAC rates in Top Hospital counties had returned to their level in 1991.

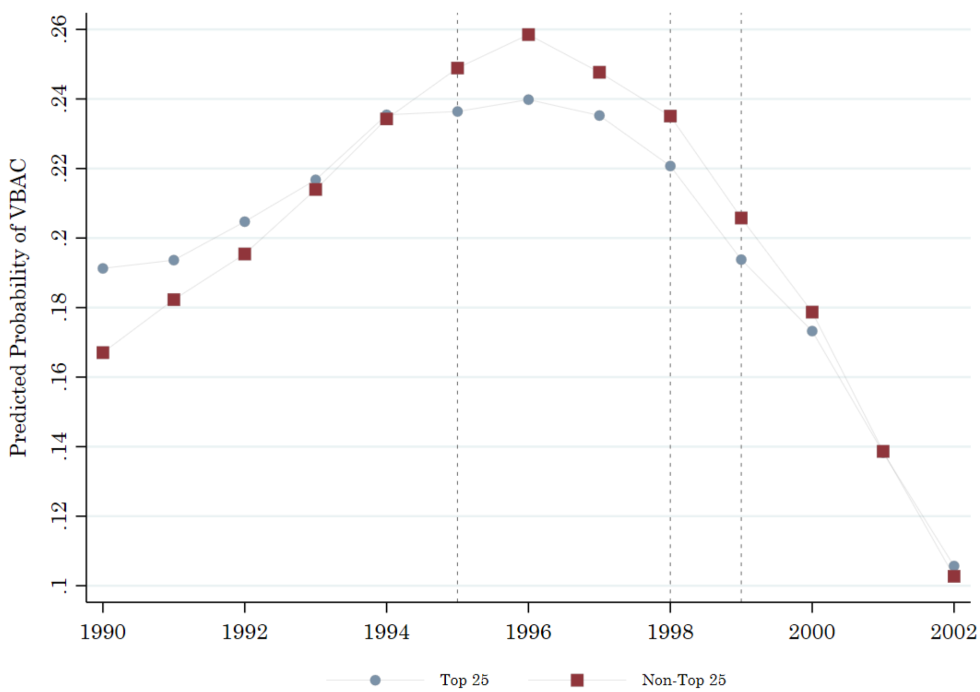
Figure 2 identifies the predicted VBAC rates for Top Hospital counties and non-Top Hospital counties calculated from the Model 3 APEs. We see that VBAC rates in counties without a Top Hospital increased at a consistent pace up to 1996, while VBAC rates in counties with a Top Hospital pulled back from VBACs sooner and faster. By the end of the period (2002) VBAC rates in both groups of counties were basically the same.

Table 1. APEs for Different Versions of the Primary Equation[a]

	Model 1	Model 2	Model 3	Model 4
Top Hospital County	0.014 0.020	0.027** 0.011	0.026** 0.011	0.226*** 0.012
Metro			0.032*** 0.004	-0.229*** 0.002
	Top x Year			
1991	-0.013 0.010	-0.014 0.011	-0.015 0.011	-0.018 0.014
1992	-0.013 0.010	-0.033* 0.020	-0.018* 0.010	-0.022* 0.012
1993	-0.0212* 0.011	-0.025** 0.011	-0.026** 0.011	-0.030** 0.012
1994	-0.022** 0.009	-0.028*** 0.009	-0.029*** 0.008	-0.034*** 0.009
1995	-0.038*** 0.009	-0.045*** 0.010	-0.044*** 0.010	-0.047*** 0.010
1996	-0.047*** 0.012	-0.052*** 0.013	-0.051*** 0.013	-0.055*** 0.013
1997	-0.038** 0.018	-0.046** 0.021	-0.044** 0.021	-0.0489** 0.023
1998	-0.036 0.024	-0.045* 0.027	-0.046 0.027	-0.053* 0.029
1999	-0.033 0.020	-0.041* 0.023	-0.042* 0.024	-0.051* 0.027
2000	-0.026 0.018	-0.033 0.021	-0.033 0.022	-0.043 0.026
2001	-0.017 0.014	-0.023 0.017	-0.024 0.017	-0.035 0.024
2002	-0.011 0.011	-0.016 0.014	-0.016 0.014	-0.027 0.022
Unconditional Mean	0.21			
N	5,267,023	5,267,023	5,245,590	5,245,589
Control Variables	No	No	Yes	Yes
State FEs	No	Yes	Yes	No
County FEs	No	No	No	Yes

[a] When calculating the Top x Year APE for a given year, we set Metro =1. Standard errors (reported below an APE) are clustered at the state level.

Figure 2. Predicted VBAC rates for Top Hospital counties and non-Top Hospital counties



We next analyze the robustness of the preceding results by gradually reducing the number of counties included in our data set.[4] We first estimate our preferred specification for Metro counties only, dropping non-metro counties. Interpretation of the estimated APEs, thus, is how Top Hospital counties differ from Metro counties without a Top Hospital. We then further winnow our dataset to include only Metro counties with populations of 250,000 people or more (we label this regression *Metro 2*). The comparison in this regression is, thus, Top Hospital and Metro 2 counties. Because this involves removing rural counties and lower-population metro counties (which we might not expect to adopt innovations as quickly) we might expect the absolute values of the Top Hospital APEs to decrease as we restrict the type of county in our population (because we are restricting the population to counties which are more likely to adopt innovations).

We report APEs for the Top Hospital by Year interactions in Table 2, with two observations. First, the impact of being in a Top-Hospital county persists across specifications. Second, we generally observe the absolute values of the differences decreasing, as we would expect.

Table 2. Time Trend APEs for Counties with a Top Hospital by Urbanicity [a]

	All Counties	Metro Counties [b]	Metro 2 Counties [c]
Top Hospital County	0.026** 0.011	0.025** 0.011	0.025** 0.011
Top Hospital x Year			
1991	-0.015 0.011	-0.014 0.011	-0.014 0.011
1992	-0.018* 0.010	-0.017* 0.010	-0.016* 0.010
1993	-0.026** 0.011	-0.025** 0.011	-0.024** 0.011
1994	-0.029*** 0.008	-0.028*** 0.008	-.0029*** 0.009
1995	-0.044*** 0.010	-0.043*** 0.011	-0.045*** 0.011
1996	-0.05*** 0.013	-0.049*** 0.014	-0.052*** 0.015
1997	-0.044** 0.021	-0.039* 0.022	-0.041* 0.023
1998	-0.046 0.027	-0.041*** 0.028	-0.041 0.028
1999	-0.042* 0.024	-0.036 0.023	-0.035 0.024
2000	-0.033 0.022	-0.027 0.022	-0.026 0.022
2001	-0.024 0.017	-0.018 0.017	-0.017 0.017
2002	-0.016 0.014	-0.012 0.014	-0.011 0.014
N	5,267,023	4,137,567	3,810,026

a Includes state fixed effects and control variables. Standard errors (reported below an APE) are clustered at the state level.
b Includes all counties designated as a metro area.
c Includes counties designated as a metro area with a population of 250,000 or more.

Spatial Effects of Innovations at Top Hospital counties

Our results so far suggest that physicians in Top Hospitals innovated and adopted VBAC innovations earlier than physicians elsewhere. We now turn to possible spread of innovations from Top Hospitals by estimating several models. First, we consider whether information (the innovation) from these hospitals spread sooner to counties which were contiguous with Top Hospital counties. Second, we consider whether VBAC rates in states with a Top Hospital dropped earlier than rates in states without a Top Hospital. This regression provides insights into whether the evolving information regarding VBACs spread within states with a Top Hospital earlier than in other states. Finally, using the ERS codes, we estimate a model which places counties into one of four categories (including Top Hospital counties) and analyze the movement of VBAC rates in the four categories. Across specifications, our results generally suggest that (other than the general nationwide spread of information regarding VBACs) spread of information about VBACs did not have geographic effects.

As noted above, we first consider spread of the innovation to counties which were contiguous with a county with a Top Hospital.[5] We estimate the following equation:

$$Y_{is} = \delta_1 \cdot Top_i + \delta_2 \cdot Sur_i + \sum_{t=1991}^{2002} \rho_t \cdot T_{it}$$

$$+ \sum_{t=1991}^{2002} \pi_t \cdot T_{it} \cdot Top_i + \sum_{t=1991}^{2002} \gamma_t \cdot T_{it} \cdot Sur_i + x_{it} \cdot \beta + \eta_s + \epsilon_i \quad (2)$$

where Sur_i equals one if a birth was in a surrounding county. The γ_t parameter captures the impact of being in a surrounding county on VBAC rates (relative to non-Top Hospital and non-surrounding counties). If information associated with the evolving information regarding VBACs was transmitted to surrounding areas sooner than to the nation, we would expect those parameters to move like the π_t parameters, except with a lag.

The APEs associated with the γ_t parameters (reported in Table 3) suggest that geographic proximity to a county with a Top Hospital did not affect VBAC rates in the surrounding counties. The APEs are generally positive and statistically insignificant. We also tested whether VBAC rates differed between Top Hospital counties and surrounding counties by estimating equation (2) for a model which limited counties in the sample to counties with a Top Hospital and surrounding counties. Regression results are reported in Table A4 in the Appendix. The regression results are consistent with results in Table 1.

Table 3. Time Trend APEs for Counties with a Top Hospital and Surrounding Counties[a]

Top Hospital County		0.025** 0.012
Surrounding County	-0.004 0.009	
Metro	0.032*** 0.004	
	Year x Surrounding	Year x Top Hospital
1991	-0.002 0.005	-0.015 0.011
1992	-0.011* 0.006	-0.019* 0.010
1993	-0.007 0.007	-0.027** 0.011
1994	0.007 0.010	-0.028*** 0.008
1995	0.014 0.013	-0.042*** 0.010
1996	0.013 0.017	-0.049*** 0.013
1997	0.011 0.018	-0.042** 0.021
1998	0.003 0.015	-0.045* 0.027
1999	0.003 0.014	-0.041* 0.024
2000	0.001 0.011	-0.032 0.022
2001	0.001 0.007	-0.023 0.018
2002	0.003 0.007	-0.016 0.015
N		5,245,590

a Includes state fixed effects and control variables. Standard errors (reported below an APE) are clustered at the state level.

We, next, consider whether the evolving information regarding VBACs spread earlier within states with a Top Hospital by estimating equation 3:

$$Y_i = \delta_1 \cdot TopState_i + \sum_{t=1991}^{2002} \rho_t \cdot T_{it} + \sum_{t=1991}^{2002} \pi_t \cdot T_{it} \cdot TopState_i + x_i \cdot \beta + \eta_s + \epsilon_i \tag{3}$$

where $TopState_i$ is a dummy variable which equals one if a state had a Top Hospital. If information/innovation spreads spatially, we might expect VBACs in those states to retreat earlier (but not as early as Top Hospital counties). The APEs associated with the π_t parameters (reported in Table 4) are generally positive and statistically insignificant, suggesting non-dissemination of information regarding VBACs in states with a Top Hospital; the presence of a Top Hospital did not appear to affect VBAC rates in the state.

Finally, we estimate a model that distinguishes three categories of counties: (i) counties with a Top Hospital, (ii) Metro area counties with a population of 250,000 or more (Metro Larger), and (iii) Metro area counties with a population less than 250,000 (Metro Smaller).[6] The reference group is non-Metro counties. We estimate an equation which has a dummy variable for each of the three categories and which interacts each dummy variable with the time dummies; basically, we estimate equation (2) except that we distinguish the three categories of counties. Comparison of these categories might reveal differential dissemination of information.

Table 4. Year APEs and Time Trend APEs for States with a Top Hospital[a]

Top State		0.091*** 0.0121
	Year	Year x Top Hospital State
1991	0.014*** 0.002	-0.006 0.006
1992	0.023*** 0.003	-0.005 0.008
1993	0.038*** 0.003	-0.007 0.009
1994	0.048*** 0.004	0.005 0.010
1995	0.055*** 0.004	0.010 0.012
1996	0.063 0.006	0.006 0.016
1997	0.055*** 0.006	0.009 0.019
1998	0.047*** 0.006	0.005 0.019
1999	0.026*** 0.007	0.003 0.019
2000	0.003 0.007	0.008 0.017
2001	-0.031*** 0.007	0.007 0.016
2002	-0.069*** 0.008	0.008 0.014
N		5,245,590

a Includes state fixed effects and control variables. Standard errors (reported below an APE) are clustered at the state level.

Estimated APEs are in Table 5 and "standardized" predicted VBAC rates for the four groups are reported in Figure 3. We "standardize" the predicted rates by subtracting from the rates for a group over the 1990-2002 period the difference between the 1990 rate for that group from the 1990 rate for the reference group. The standardization allows us to better compare the relative evolution of rates for the groups over the period. The regression results suggest some dispersion of information across Metro areas. Metro Smaller counties appear to have moved like Top Hospital counties with a lag; the change in VBAC rates for Metro Smaller counties fell below that change for Reference Group rates around 1995 while rates in Top Hospital counties fell earlier (in the early 1990s) and in larger absolute amounts. VBAC rates in Metro Larger counties appear to have dropped later (around 1997). Review of Figure 3 reflects rates in Metro Smaller counties moving more like rates in Top Hospital counties and rates in Metro Larger counties moving more like rates in the Reference Group. This result is relatively counterintuitive in that we might expect rates in Metro Larger counties to move earlier than rates in Metro Smaller counties. This result, however, is not unprecedented. It appears to be consistent with the findings in Lu et al (2015) that hospitals situated near early adopters were slower to adopt innovations.

4. Conclusion

Once a cesarean, always a cesarean? Not necessarily, but….

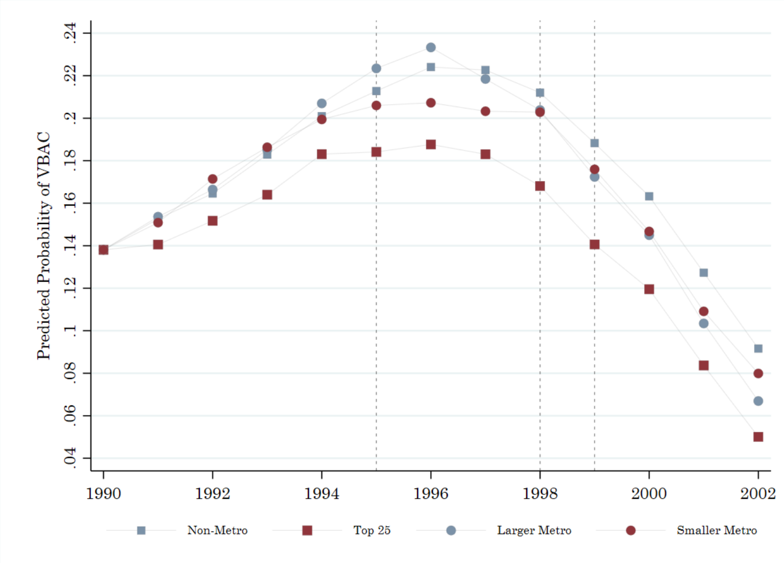
We examine the spatial adoption and diffusion of information innovations in health care, focusing on VBACs in the US in the 1990s. Previous literature suggests that leading hospitals may have more capacity to collect, process, and utilize new medical information, due to organizational capacity and staffing. Using a county-level data set on VBAC rates, our empirical results provide evidence that counties with Top Hospitals behaved in ways consistent with faster adoption of updated CPGs from ACOG regarding cesarean-subsequent deliveries. However, we do not find evidence supporting the hypothesis that innovations in medical procedures first radiate from counties with leading hospitals to geographically proximate regions before spreading to the hinterlands.

Table 5. APEs for Time Trends by Category of County[1]

	Top	Metro Larger	Metro Smaller
Top Hospital County	0.066*** 0.011		
Metro Larger County		0.044*** 0.005	
Metro Smaller County			0.029** 0.010
1991	-0.016 0.011	-0.002 0.003	-0.003 0.006
1992	-0.020* 0.011	-0.003 0.004	0.004 0.006
1993	-0.030** 0.012	-0.005 0.006	-0.001 0.007
1994	-0.032*** 0.011	-0.004 0.007	-0.008 0.012
1995	-0.046*** 0.011	-0.0004 0.007	-0.014 0.012
1996	-0.056*** 0.013	-0.003 0.009	-0.026** 0.014
1997	-0.059** 0.023	-0.016* 0.010	-0.028** 0.014
1998	-0.062** 0.030	-0.019** 0.009	-0.017 0.014
1999	-0.062* 0.027	-0.024** 0.010	-0.018 0.013
2000	-0.053** 0.024	-0.023** 0.009	-0.020* 0.011
2001	-0.044** 0.021	-0.023*** 0.008	-0.018* 0.010
2002	-0.030* 0.018	-0.016** 0.007	-0.006 0.008
N	5,245,590		

[1] Includes state fixed effects and control variables. Reference group is rural counties. Standard errors (reported below an APE) are clustered at the state level.

Figure 3. Predicted VBAC rates for Different Categories of Counties



In addition to finding that Top Hospital counties are early adopters of knowledge innovations, our results reflect the importance of accounting for means of encouraging the spread of innovations from Top Hospitals. One possible avenue of change is medical malpractice liability law. Frakes (2015) considers a variety of legal reforms that might affect medical practices and, thus, the spread of medical knowledge. For example, the law might set liability standards according to best scientific evidence rather than custom (as is the present practice in medical malpractice law).

Second, as we mention above, the period we analyzed was one in which spread of information via the internet was not prevalent. It may be worth closer examination to see if the internet has indeed "flattened" information adoption in medical communities, or if top hospitals remain regional innovation leaders. Third, our results indicate that proclamations issued by medical societies (such as the ACOG proclamations we considered) are important to physician decision making. Means of ensuring faster spread of best practices, embodied in the proclamations, may be considered.

APPENDIX

Table A1. Counties with a Top 25 Hospital At Least Three times between 1991 and 1996

Baltimore City, MD	Olmsted, MN	Dallas, TX	Suffolk, MA
Durham, NC	New York, NY	Los Angeles, CA	Cuyahoga, OH
Cook, IL	San Francisco, CA	Santa Clara, CA	Philadelphia, PA
New Haven, CT	King, WA	Orange, NC	Albemarle, VA
Erie, NY			

Table A2. APEs for Year Dummies and Top x Year interactions[1]

Top Hospital		0.026** 0.011
Metro		0.032*** 0.004
	Year[2]	Year x Top Hospital
1991	0.015*** 0.002	-0.015 0.011
1992	0.027*** 0.003	-0.018* 0.010
1993	0.044*** 0.003	-0.026** 0.011
1994	0.062*** 0.003	-0.029*** 0.008
1995	0.074*** 0.004	-0.044*** 0.010
1996	0.082*** 0.005	-0.051*** 0.013
1997	0.073*** 0.006	-0.044** 0.021
1998	0.062*** 0.006	-0.046 0.027
1999	0.04*** 0.006	-0.042* 0.024
2000	0.012* 0.006	-0.033 0.022
2001	-0.030*** 0.007	-0.024 0.017
2002	-0.074*** 0.008	-0.016 0.014
Unconditional Mean	0.2100071	
N		5,245,590

[1] Includes state fixed effects and control variables. Standard errors (reported below an APE) are clustered at the state level.

[2] In calculating these APEs, we set Top = 0.

Table A3. APEs for Different Definitions of Top Hospital x Year Interactions[1]

	Appearing in Top 25 three times	Appearing in Top 25 twice	Appearing in Top 30 three times	Appearing in Top 30 three times
Top Hospital	0.026** 0.011	0.027** 0.011	0.029** 0.011	0.024** 0.012
Metro	0.032*** 0.004	0.032*** 0.004	0.032*** 0.004	0.033** 0.004
	Top x Year			
1991	-0.015 0.011	-0.015 0.011	-0.014 0.011	-0.014 0.009
1992	-0.018* 0.010	-0.018* 0.010	-0.018* 0.010	-0.012 0.010
1993	-0.026** 0.011	-0.026** 0.011	-0.026* 0.011	-0.016 0.013
1994	-0.029*** 0.008	-0.029*** 0.009	-0.030*** 0.008	-0.017 0.013
1995	-0.044*** 0.010	-0.044*** 0.010	-0.045*** 0.010	-0.031*** 0.011
1996	-0.051*** 0.013	-0.052*** 0.013	-0.053*** 0.013	-0.036*** 0.011
1997	-0.044** 0.021	-0.044** 0.021	-0.046** 0.021	-0.034*** 0.013
1998	-0.046 0.027	-0.045* 0.027	-0.049* 0.027	-0.041** 0.018
1999	-0.042* 0.028	-0.041* 0.023	-0.044* 0.023	-0.037** 0.016
2000	-0.033 0.022	-0.033 0.021	-0.034 0.021	-0.030* 0.015
2001	-0.024 0.017	-0.024 0.017	-0.026 0.017	-0.024* 0.013
2002	-0.016 0.014	-0.016 0.014	-0.017 0.014	-0.017 0.011
Unconditional Mean	0.21			
N	5,245,590			

[1] Includes control variables and state fixed effects. Standard errors (reported below an APE) are clustered at the state level. When calculating the Top x Year APE for a given year, we set Metro =1.

Table A4. APEs for Top Hospitals (sub-population: T25 + Surrounding counties)[1]

Top	0.032** 0.011
Metro	0.030 0.022
Top x Year	
1991	-0.012 0.013
1992	-0.007 0.010
1993	-0.019 0.013
1994	-0.037** 0.016
1995	-0.058*** 0.020
1996	-0.064*** 0.024
1997	-0.056* 0.030
1998	-0.049 0.034
1999	-0.044 0.028
2000	-0.034 0.026
2001	-0.025 0.017
2002	-0.020 0.013
N	1,192,712

[1] Includes state fixed effects and control variables. Standard errors (reported below an APE) are clustered at the state level.

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