# Geographic Variation and the Adoption and Diffusion of Medical Technology: Cancer Screening and Diagnostic Imaging Among the Privately Insured

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July 2011

Preliminary – Please Do Not Cite

Note: This research was partly conducted while I was employed at the Federal Reserve Board and I am grateful for their support. I would also like to acknowledge helpful comments in the early stages from Ana Aizcorbe, Louise Sheiner, and John Stevens. All mistakes are my own.

## I. Introduction

The adoption and diffusion of medical technology has come under examination as it appears that the growth in the share of the US economy spent on health care is driven by the diffusion of new medical treatments (Newhouse 1992). Some of these treatments have been shown to be clearly cost-effective and to increase the productivity of the health care sector; many treatments seem less likely to do so (Cutler 2004, Chandra and Skinner 2011).

Skinner and Staiger (2007) found a strong correlation across states among rates of adoption of beneficial technologies, both medical and non-medical. Specifically, they found associations among the rapidity of adoption of hybrid corn in the 1930s and 1940s, the rate of use of computers in the early 1990s, and the rate of use of beta-blockers to treat heart attacks in Medicare patients in 2000. Beta-blockers were recognized as a highly cost-effective intervention for heart attacks by this time but use appeared to lag in many areas. Skinner and Staiger also found significant and positive correlations between the adoption of these beneficial technologies and measures of human and social capital: areas with higher high school graduation rates and more civic participation appear to adopt productive technologies earlier.

At the same time, many analysts blame the adoption and diffusion of medical technologies of more doubtful value for the rapid growth in health-care costs and the apparent decline in productivity growth in the health care sector. This paper will look at the question of whether regions that higher rates of use of high-value medical technologies also have higher rates of low-value medical technologies. In other words,

does the same underlying factor that predisposes regions to the early adoption of beneficial technology also predispose them to adopt all technologies, in the absence of financial incentives to do so otherwise? Or are they more selective about which technologies they adopt and allow to diffuse?

To address this question, I will examine the relationship between breast and colon cancer screening rates and the rates of use of advanced diagnostic imaging (computed tomography, magnetic resonance imaging, and ultrasound) in enrollees in private insurance in 136 MSAs in 37 states from 2002 to 2008, a period when uses of these technologies was expanding rapidly.

Breast cancer screening for women 40-69 and initial colon cancer screening for all adults at 50 were both recommended (USPSTF 2002a, USPSTF 2002b) and recognized as signals of health-care quality during this time. Diagnostic imaging has come under criticism in recent years, as it use has expanded. An analysis by the Government Accountability Office of the use of imaging in Medicare Part B found that diagnostic imaging had very high variation in its use (suggesting a reduced medical need for it) and a fast rate of growth relative to other physician services in Medicare (GAO 2008). Other research has found that the rates of use of diagnostic imaging appear to be significantly affected by the availability of diagnostic imaging machines for both privately insured patients and Medicare beneficiaries (Baker et al. 2003, Baras and Baker 2009). The available evidence therefore suggests that diagnostic imaging is a technology that contributes less to the productivity of the health care sector. In addition, as described below, I will attempt to identify specific uses of diagnostic imaging that are likely to be particularly unproductive.

I first look for support of Skinner and Staiger's results by analyzing the relationship between cancer screening rates among the privately insured in 2002 and local educational achievement among the population at large (as measured in the 2000 Census) at the MSA level. I find that mammogram rates appear to be unrelated to education and that colon cancer screening rates seem to have a nonlinear relationship to education, as both local high school dropout rates and local college graduation rates positively affect cancer screening rates.

I then move on to explore the relationship in 2002 between cancer screening rates and the rates of use of diagnostic imaging, both unconditionally and conditional on a diagnosis. For the latter, I try to identify uses of imaging that are likely to be particularly unproductive by choosing diagnoses whose rates in the enrollee population appear to be endogenous to the overall rate of imaging, on the assumption that these uses of imaging are driven more by the availability of imaging machines and are therefore less likely to be medically required. I find that cancer screening rates are positively and generally significantly correlated with the unconditional use of advanced diagnostic imaging and that mammogram rates are sometimes positively and significantly correlated with some uses of advanced diagnostic imaging conditional on a diagnosis (the use of CT scanning conditional on a diagnosis of abdominal pain or headache, and the use of MRI conditional on a diagnosis of back problems). Taken together, these results suggest that regions that adopt productive medical technologies earlier are also early adopters of medical technologies that are less likely to be productive.

Next, I examine the relationship between cancer screening rates in 2002 and the diffusion of advanced diagnostic imaging from 2002 to 2008, with a view to answering

the question of whether regions that adopt less beneficial medical technologies earlier also manage their diffusion better. Here, I find some evidence that regions that have higher cancer screening rates in 2002 had slower growth rates of the use of advanced diagnostic imaging from 2002 to 2008, but the effect is very small.

Overall, therefore, it seems that regions that adopt beneficial medical technologies earlier also adopt less productive medical technologies earlier but these same regions also manage the diffusion of those technologies slightly better after the adoption.

## II. Data

### A. Claims data

The data for the utilization of medical imaging and for the cancer screening rates come from the MarketScan claims database, a large database of medical claims for privately insured people. The database contains claims from the following kinds of plans: basic/major medical, comprehensive, exclusive provider organization (EPO), health maintenance organization (HMO), point-of-service (POS), preferred provider organization (PPO), point-of-service with capitation, CDHP, and HDHP. While the plan type is identified in both the enrollment and claims files, the individual plans are not. The MarketScan database has data from 1999 through 2008, but I only employ the data from 2002 to 2008, since the coverage of the database expanded considerably in 2002.

I also limited the analysis to enrollees who were enrolled in the same type of plan for the full calendar year. While this restriction has the drawback that these enrollees may not be

entirely representative of all enrollees in their use of medical care, it simplifies the analysis considerably, since I do not have to adjust for differing lengths of time of enrollment when calculating annual rates of cancer screening or use of medical imaging per enrollee. As most of the analysis focuses on comparing utilization of health care services across regions and over time, applying the same cross-sectional restriction across regions and over time should not affect the results substantively.

The enrollment file contains data on the enrollee's age and sex, and the three-digit ZIP code of the enrollee's residence. I only kept enrollees under age 65 (since most people in the United States aged 65 and above are covered at least partially by Medicare, and I wanted to focus on the privately insured).

All utilization rates (cancer screening and imaging) are adjusted for differences in age and sex composition across regions and over time. I put the enrollees into categories by sex and five-year age groups, resulting in 26 age-sex groups. I then calculated time- and region-constant weights for the 26 groups from the full dataset. To calculate an age- and sex-adjusted utilization rate, I calculated the rate for each group and then took a weighted average of the rates of the 26 age-sex groups, using the time- and region-constant weights.

I assigned enrollees based on their 3-digit zip code to Metropolitan Statistical Areas (MSAs) using the 2008 MSA definitions from the Census Bureau. I limited the data to MSAs where there were at least 1000 enrollees in all seven years from 2002 to 2008. The

resulting dataset contains data for 136 MSAs in 37 states. All statistics and regressions will be weighted by enrollee population in each MSA.

The claims file contains one record for each claim, each of which contains a procedure code and diagnosis codes. Procedures are encoded with either Current Procedural Technology (CPT) or Healthcare Common Procedure Coding System (HCPCS) codes, and diagnoses are encoded with ICD-9 codes.

### B. Demographic data from the Area Resource File

In this paper, I will be making use of demographic data for each MSA from the 2008 version of the Area Resource File (ARF), a file from the Health Resources Service Administration that compiles county-level data on demographics and on the county's medical system from multiple data sources. I aggregated the county-level data to the MSA level, again using the 2008 MSA definitions from the Bureau of the Census. Table 1 shows which demographic and medical system variables I use and their ultimate source. Most of the demographic data comes from the 2000 Census, with the exception of per capita income in 2000, which comes from the Bureau of Economic Analysis. Most of the medical system variables also date from 2000, with the exception of the number of teaching hospitals in an MSA, which was only available for 2006.

## III. Advanced diagnostic imaging

### A. Unconditional utilization of advanced diagnostic imaging

Advanced diagnostic imaging was defined as the use of computed tomography (CT) scanning, magnetic resonance imaging (MRI) or ultrasound. I used the Clinical Classification Software (CCS) for services and procedures to identify the use of diagnostic imaging and Table 2 shows the specific CCS codes that were used to identify the use of each modality. The Clinical Classifications Software for services and procedures was created by the Agency for Healthcare Research and Quality and classifies the CPT and HCPCS codes into 244 categories of "clinically meaningful" procedures. For the sake of simplicity, when counting scans to calculate utilization rates, I assumed that patients only received one scan per modality on a given date, so multiple claims for the same modality, same patient and same date were counted as one scan.

Table 3 shows the summary statistics for the age- and sex-adjusted unconditional utilization of and growth in utilization of CT scanning, MRI, and ultrasound. Unconditional utilization is measured by the number of scans per 1000 enrollees. Ultrasound is the most frequently used, CT scanning is the next most common and MRI is the least common of the three modalities. All three modalities of imaging saw rapid increases in their use from 2002 through 2008: CT scanning and ultrasound had average annual growth rates in their use of about 5% while MRI had an average annual growth rate of about 6% over the period. These rates translate into total growth rates over the period of between 33 and 42%; in other words the use of advanced diagnostic imaging

increased by over a third in six years. Over the same period, variation in the use of CT and MRI scans across MSAs declined by about a third while variation in the use of ultrasounds only declined about 6%.

Table 4 shows the weighted correlations in the utilization of the different modalities of imaging in 2002 and 2008. As it shows, the use of CT, MRI, and ultrasound are all highly correlated with each other in 2002, with positive and significant correlations all over 50%. The correlations have declined by 2008, but the correlation of the use of CT scanning with MRI is still fairly high, at about 65%. These positive and significant correlations in the use of different modalities are consistent with Baker et al. (2003)'s findings that diagnostic imaging technologies are complementary; they find, for example, that an increase in the availability of one modality of diagnostic imaging leads to increased use and spending on other modalities. The correlations are also consistent with Skinner and Staiger (2007)'s findings of complementarity in the adoption of both medical and non-medical technologies.

### B. Conditional utilization of advanced diagnostic imaging

While the findings for the unconditional use of imaging are consistent with other papers that found complementarity in technological adoption, they do not rule out that the correlations in the use of imaging may come from relative differences in health status among enrollees across regions. I therefore also look at the use of advanced imaging conditional on having received a diagnosis in the past three months. Since I cannot be

sure that the illness or symptom that led to the scan being ordered is always encoded the day of the scan, I do not require that the diagnosis necessarily be attached to the imaging scan in any way in the data; the scan just needs to occur less than 3 months after the diagnosis. The focus in the analysis will be on the variation between regions and over time in diagnosis and scanning rates, and these variations should be meaningful even if every diagnosis is not actually medically connected with the scan that I attach it to. Note also that, in this method, more than one diagnosis can be attached to a scan.

To define diagnoses, I use the Clinical Classification Software (CCS) for diagnoses. The CCS for diagnoses was created by the Agency for Healthcare Research and Quality and classifies ICD-9 diagnosis codes into 262 mutually exclusive, mostly homogeneous diagnosis categories (for example, "cancer of thyroid" or "acute myocardial infarction"). Some categories only represent symptoms ("headache" or "abdominal pain").

In order to distinguish uses of imaging conditional on a diagnosis that are likely to be more or less cost-effective, I separate diagnoses by whether or not their rates in the enrollee population appear to be endogenous to the availability of imaging, on the assumption that diagnoses that appear to be endogenous to the availability of imaging are being coded partly or mostly to justify the scan. I am also assuming that imaging that is being provided following a diagnosis that is encoded to justify the scan is less cost-effective than imaging following a diagnosis that appears to be exogenous to the availability of imaging. (This assumption does not require that scans following exogenous diagnoses be cost-effective; it may be that there is no use of imaging that is

cost-effective. Nor does it imply that scans following endogenous diagnoses are not cost-effective or not beneficial at all; it may be that regions with more imaging machines available may providing more medical care and catching more diagnoses.)

To detect endogenous and exogenous diagnoses, I regress the age- and sex-adjusted diagnosis rate in 2002 across all enrollees for each CCS diagnosis category on the economic, education, and race variables for the MSA taken from the ARF and shown in table 1, and the overall rates of unconditional utilization of CT scanning, MRI, and ultrasound. The overall rates of unconditional utilization of advanced imaging conditional on the demographic variables are proxying for the availability of CT scanners, MRI machines, and ultrasound machines in the MSA.[1] As Baker et al. (2003) and Baras and Baker (2009) show, the mere availability of advanced imaging machines increases their use. If a rate at which a condition or symptom is diagnosed is significantly affected by the overall rate of use of advanced imaging conditional on the demographics of the region, that strongly suggests the condition or symptom is often being diagnosed because of the availability of advanced imaging, to justify the scan.

I further restrict the conditions to having at least a 10% average rate of use of imaging following the diagnosis, to make it more likely that the diagnosis is associated with the scan, and also to conditions that are common enough that they are diagnosed in virtually all MSAs. These restrictions leave me with thirteen exogenous diagnoses (five for CT scanning, five for MRI, and three for ultrasound—the vast majority of diagnoses were

[1]The results of the 262 regressions (one for each CCS diagnosis) are not reported but are available on request.

endogenous to the availability of ultrasound) and thirteen endogenous diagnoses (five for CT, three for MRI, and five for ultrasound). They are listed in the upper and lower panels of table 5. While the subsequent analysis will focus on the endogenous diagnoses, I include both the exogenous and endogenous diagnoses in table 5 to highlight the stark differences between their levels and growth rates.

One validation of this method for identifying more and less cost-effective uses of imaging is that the most endogenous diagnosis for MRI (as measured by the magnitude of the coefficient on the overall MRI rate in the regression of diagnosis rate on demographics and imaging rates) is the CCS category “Spondylosis; invertebral disc disorders; other back problems.” The use of MRI to diagnose back problems has been specifically identified in the medical literature as a relatively unproductive use of MRI that leads to overdiagnosis and overtreatment (Baras and Baker 2009).

Two differences between endogenous and exogenous diagnoses should be noted. Exogenous diagnoses are much rarer, as shown in the first column, which shows the average diagnosis rate per 1000 enrollees in 2002. The most common exogenous diagnosis (“Hereditary and degenerative nervous system conditions other than Parkinson’s disease or multiple sclerosis”) is diagnosed, on average, in nearly three enrollees per 1000 enrollees, while the least common endogenous diagnosis (“Nausea and vomiting”) is more than three times as common, with nearly eleven enrollees per 1000 enrollees, on average, diagnosed with it. The other notable difference between endogenous and exogenous diagnoses is that the exogenous diagnoses all appear to be

well-defined diseases while five of the thirteen endogenous diagnoses represent symptoms rather than diseases (“Abdominal pain”, “Cough” [which accounts for much of “Lower respiratory disease other than lung disease due to external agents or pneumothorax”], “Headache”, “Nausea and vomiting”, and “Nonspecific chest pain”). Diagnostic imaging is, of course, often conducted to find the sources of symptoms such as abdominal pain or headache, and it is certainly not the case that every CT scan for abdominal pain is not cost-effective but the presence of so many diagnosis categories that are only symptoms among the endogenous diagnoses is further evidence that imaging for the endogenous diagnoses is likely to be less productive.

The second column shows the rate of receiving an advanced imaging scan within three months of the diagnosis being coded. The average rate of imaging conditional on the diagnosis, shown in the last row of each panel, is higher for the exogenous diagnoses (28%) than for endogenous diagnoses (16%). However, since the endogenous diagnoses are so much more common among enrollees, the rate of scans per 1000 enrollees associated with the diagnoses is much higher for the endogenous diagnoses than for the exogenous diagnoses. The last rows of the third column in Tables 5A and 5B show the sums of the scanning rates per 1000 enrollees. Note that this figure in actuality represents a maximum, not a sum, since single imaging scans can be associated with more than one diagnosis. The exogenous diagnoses are associated with, at most, nearly 5 scans per 1000 enrollees in 2002. The endogenous diagnoses are associated with, at most, nearly 86 scans per 1000 enrollees and, given the heterogeneity of the endogenous diagnoses, it is not likely that the actual total number of separate scans is much less than that.

The last three columns in Tables 5A and 5B show the same figures for 2008 for the selected diagnoses, and Tables 5C and 5D show the growth rate in the figures from 2002 to 2008. The bottom row in Tables 5C and 5D show the averages of the growth rates for the diagnoses, weighted by the diagnosis rate. Comparing the bottom row of Table 5C with the bottom row of Table 5D, we find that the rates of diagnoses that are exogenous to the availability of imaging in 2002, on average, fall 0.7% from 2002 to 2008 but the rates of diagnoses that are endogenous to the availability of imaging in 2002, grow over 16%, on average. The growth in the rate of performing advanced imaging conditional on the diagnoses is about 14% for the exogenous diagnoses and nearly 18% for the endogenous diagnoses. Overall, therefore, the growth in the scanning rate per 1000 enrollees of scans associated with exogenous diagnoses is about 14% while that of those associated with endogenous diagnoses is nearly 36%. As this figure also started from a higher base for the endogenous diagnoses, the level increase in the number of scans per 1000 enrollees from 2002 to 2008 appears to be enormously larger for the endogenous diagnoses than for the exogenous diagnoses: nearly 29 scans per 1000 enrollees for the endogenous diagnoses versus about a third of a scan for the exogenous diagnoses. (Note again, however, that these figures are maximums, not exact sums.)

In summary, the diffusion of diagnostic imaging in these data appears to match the model of productivity growth for health care described in Chandra and Skinner (2011). They cite diagnostic imaging as an example of an innovation that has high value for a subset of patients but probably low efficacy at the margin. If we accept the assumption that

imaging associated with conditions whose diagnosis rates are unrelated to the availability of imaging is more cost-effective than imaging associated with conditions whose diagnosis rates are endogenous to the availability of imaging, it has poor implications for the growth of productivity in health care that the contribution of growth in the utilization of the latter appears to outweigh the contribution of growth in the utilization of the former by nearly 100 to 1.

## IV. The utilization of imaging and health-care quality

Skinner and Staiger (2007) find evidence of complementarity in adoption of beneficial technologies, both medical and non-medical, across states and the adoption of the technologies also appears to be positively related to measures of educational and social capital measures in the state. This next section looks for further confirmation of their results by examining the relationship between the use of two technologies that are known to be productive (breast and colon cancer screening) in the claims data and education levels in the MSA.

I then move on to explore two more questions. First, do regions that adopt beneficial technologies like cancer screening more quickly also use medical technologies more that are less likely to be productive, like advanced imaging? Or are they more careful about which technologies they use? Second, is there a relationship between local education levels and the diffusion of less productive technology like advanced imaging?

A. Cancer screening rates and education

Skinner and Staiger (2007) found a significant positive relationship between the state-level rate of administration of beta-blockers following a heart attack to Medicare beneficiaries and state education levels as measured by both educational attainment levels in recent history (for which they use the Putnam education index) and the high school graduation rate in 1928. The administration of beta-blockers following a heart attack is a very cost-effective technology as the drugs are both cheap and highly effective in lowering mortality. Skinner and Staiger hypothesize that there are systematic differences across states with regard to informational exchanges among people and that these differences are related to both educational and social capital and to the ease of technology adoption. In this section, I look to see if a relationship exists between MSA education levels in the broader population as measured in the 2000 Census, and the rates of breast and colon cancer screening among the enrollees in the MarketScan claims database that is similar to what Skinner and Staiger find for education levels and beta-blockers.

There are two differences between Skinner and Staiger's analysis and mine. First, the demographic data I use comes largely from the 2000 Census and represents the population at large, while the MarketScan claims data only represents a portion of the privately insured (and not a randomly selected portion). The privately insured may differ systematically from the population at large in educational attainment levels, which would bias against finding a relationship. Skinner and Staiger used Medicare claims data and it may be argued that Medicare beneficiaries are more representative of the local population

than the privately insured since virtually every person 65 and over has Medicare regardless of income. Second, the data I use (both claims data and demographic data) are for MSAs only and my results do not reflect any data for rural areas.

Screening mammogram claims are identified in the data with the CPT codes 76092 or 77057 or the HCPCS code G0202. In claims data, single procedures often appear with multiple claims (since there is often both a physician claim and a facility claim) so, when counting mammograms, I assumed that patients had, at most, one screening mammogram per day and that multiple mammogram claims for the same patient on the same day represent just one mammogram.

The United States Preventive Services Task Force recommended in 2002 (USPSTF 2002a) that women aged 40-69 receive mammograms every one to two years. However, the benefits for mammograms increased as women get older, according to the USPSTF, so I only calculate the mammogram rate among women 50 and above. (In 2009, the USPSTF rescinded the recommendation for routine mammograms in women in their 40s. [USPSTF 2009].)

The USPSTF also recommended initial colon cancer screening for all patients at age 50 (USPSTF 2002b) who had not already had it. In their recommendation, colon cancer screening consists of one of the following: flexible sigmoidoscopy, fecal occult blood test, or colonoscopy. Flexible sigmoidoscopies are identified with the CPT codes 45330, 45331, 45333, 45334, 45335, 45337, 45338, 45339, 45340, 45341, or 45342 or the

HCPCS code G0104. Fecal occult blood tests are identified with the CPT code 82270 or the HCPCS code G0107. Colonoscopies are identified by matching the procedure codes with the CCS for services and procedures and taking those claims which match procedure 76 “Colonoscopy and biopsy.” As I did with the mammograms, I assumed that multiple colon cancer screening claims on the same date for the same patient represented just one colon cancer screening when calculating cancer screening rates.

Table 6 shows summary statistics across MSAs for the age- and sex-adjusted rates of both kinds of cancer screening in 2002. Mammogram rates were calculated over female enrollees aged 50-64 and colon cancer screening rates were calculated over both male and female enrollees aged 50-54. The mean age-adjusted mammogram rate was about 34% in 2002 and ranged from 10% to 54%. The mean age-adjusted colon cancer screening rate was about 24% and ranged from 9% to 49%. The last row of the table shows the correlation between the two cancer screening rates across MSAs in 2002: this correlation is about 35% and is significantly different from zero at a less than .1% level.

Table 7 shows the results of regressing the cancer screening rates in 2002 on demographic variables in 2000 and characteristics of the local medical system, mostly in 2000. Two measures of education are included: the high-school dropout rate in 2000 and the college graduation rate in 2000; both rates are measured among adults 25 and over. Interestingly, both education variables have the same sign in both regressions, suggesting a nonlinear relationship between education and cancer screening rates. For mammograms, the effects of both variables are negative but insignificant. For colon

cancer screening, both the high-school dropout rate and the college graduation rate affect screening rates positively and significantly, suggesting a U-shaped relationship between local education levels and colon cancer screening rates. The positive relationship between the high-school dropout rate and the colon cancer screening rate is surprising and its implication for the relationship between cancer screening rates and education is not clear.

## B. Cancer screening rates and the level of use of imaging in 2002

Next I examine whether regions that adopt beneficial technologies like cancer screening more quickly also use medical technologies more that are less likely to be productive, like advanced imaging. To do this, I look at the relationship between cancer screening rates and rates of use of advanced imaging in the claims data.

Table 8 shows simple weighted correlations between cancer screening rates and the unconditional rates of use of advanced imaging, where the weights are enrollee population in the MSA. There are positive and significant correlations of about 25% between the mammogram rate among women aged 50 to 64 and the unconditional rates of use of both CT scanning and of MRI. There are also positive and significant correlations between the colon cancer screening rate among adults aged 50 to 54 and the unconditional rates of use of both MRI and ultrasound. The correlations between the mammogram rate and the use of ultrasound and between the colon cancer screening rate and the use of CT scanning are positive but insignificantly different from zero. The positive and mostly significant correlations suggest that regions that adopt beneficial

medical technologies more quickly also adopt medical technologies that are less likely to be productive.

Table 9 shows simple weighted correlations between cancer screening rates and the rates of use of advanced imaging conditional on diagnoses that have been found to be endogenous to the rate of imaging overall, as described above. As it shows, there are positive and significant correlations between the mammogram rate among women 50 and over and the use of CT conditional on a headache diagnosis of about 29% and between the mammogram rate and the use of MRI conditional on a diagnosis of back problems of about 34%. There is also a negative and somewhat significant correlation between the mammogram rate and the use of ultrasound conditional on a diagnosis of a thyroid disorder. The rest of the correlations are insignificantly different from zero.

Taken together, the results in tables 8 and 9 suggest that regions that adopt more beneficial technologies sooner also adopt technologies that are less likely to be productive sooner; in other words, they suggest that some regions have lower barriers to the adoption of all technologies, whether productive or not, if there is no incentive in place to not use a less productive technology.

C. Cancer screening and the diffusion of advanced diagnostic imaging from 2002 to 2008

Next I examine whether there is a relationship between the use of productive technologies like breast and colon cancer screening and the rate of diffusion of advanced imaging. As discussed above, advanced imaging expanded fairly rapidly during the period covered by the claims data. The expansion of imaging did not go unnoticed by insurers, many of whom established programs to make providers justify the use of imaging, such as radiological benefit managers.[2] It is possible that the same factors that make regions adopt technologies earlier may also make them manage the growth of these technologies in a more productive way.

To test this hypothesis, I examine the relationship between cancer screening rates in 2002, the beginning of the period, and the growth in utilization of advanced imaging from 2002 to 2008 (while controlling for the initial level of use of imaging in 2002). Table 10 shows the results of regressions of the log of 1 plus the annualized growth rate of the unconditional uses of the three modalities of advanced imaging from 2002 to 2008 on the level of the unconditional use of the same modality in 2002 and the level of the age-adjusted mammogram rate for women 50 and over in 2002 or the level of the age-adjusted colon cancer screening rate for adults aged 50 to 54 in 2002. As it shows, in general, if a region has a higher mammogram or colon cancer screening rate in 2002, it has a lower growth rate of the use of advanced imaging from 2002 to 2008. The effect is

[2] See the Wall Street Journal article "Insurers Hire Radiology Police to Vet Scanning" (11/6/08), for example.

negative and significantly different from zero for mammograms and CT scanning, colon cancer screening and CT scanning, and mammograms and ultrasound and negative but insignificantly different from zero for cancer screening and MRI, and mammograms and ultrasound.

Table 11 explores the same hypothesis with the uses of imaging conditional on a diagnosis that have been identified above as less likely to be productive. For most conditional uses of imaging, there is no relationship between cancer screening rates in 2002 and the subsequent growth rates of imaging but there are exceptions: regions with higher mammogram rates have significantly lower subsequent growth rates of the use of ultrasound for nonspecific chest pain and for nonmalignant breast conditions and regions with higher colon cancer screening rates have significantly lower growth rates in the use of CT scanning for abdominal pain and for lower respiratory disease. In addition, regions with higher mammogram rates have significantly higher growth rates of the use of MRI for nervous system disorders (other than dizziness or disorders of the sense organs).

In general, the results offer some evidence in favor of the hypothesis that regions that adopt technologies earlier also manage the growth of that technology more efficiently. The effect, though significant, is quite small, however. For example, if a hypothetical region had a colon cancer screening rate in 2002 that was two standard deviations (or 12 percentage points) higher than another region, the coefficient of -.096 translates into a relative reduction in per capita spending of only $2.56, assuming average starting levels and growth rates of utilization of CT scanning and that CT scans cost, on average, $600.

## V. Conclusion

By and large, the results above show that regions who adopt productive medical technologies earlier also seem to adopt less productive medical technologies earlier, judging by their utilization rates in 2002. In other words, some regions simply appear to like all technologies more and will adopt them sooner if the incentives to adopt them are in place, as they are in the medical sector. These results contrast with those of the Dartmouth group for Medicare, which found that higher-spending areas do not have higher rates of effective care (Wennberg et al. 2002, Fisher et al. 2003).

However, there is also some evidence that regions that adopt more productive medical technologies earlier better manage the growth of the less productive technologies. This could be because of the intervention of the insurers, because physicians in the better regions are putting less weight on financial incentives, and/or because physicians in the more educated and socially connected regions are better at "learning by doing" and found more quickly that advanced diagnostic imaging did not improve outcomes and sometimes contributed to overdiagnosis and overtreatment of disorders.

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**Table 1**
**Demographic variables from the 2008 Area Resource File, aggregated to MSA level: Summary statistics**

| Variable | Source | Mean | Standard deviation | Minimum | Maximum |
|---|---|---|---|---|---|
| Per capita income in 2000 | Regional Economic Information System, Bureau of Economic Analysis | $ 30,854 | $ 5,973 | $ 14,906 | $ 58,254 |
| Population density in 2000 | 2000 Census | 722 | 710 | 12 | 2724 |
| Percent of adults 25 and over in 2000 who have not graduated from high school | 2000 Census | 6.8% | 3.1% | 2.0% | 29.4% |
| Percent of adults 25 and over in 2000 who have graduated from college | 2000 Census | 25.9% | 6.0% | 11.1% | 48.1% |
| Percent of population in 2000 that is white and non-Hispanic | 2000 Census | 67.0% | 14.7% | 14.5% | 96.3% |
| Percent of population in 2000 that is African-American | 2000 Census | 16.1% | 10.3% | 0.2% | 49.7% |
| Doctors per 1,000 population in 2000 | AMA Physician Master File | 2.406 | 0.686 | 0.670 | 7.461 |
| Percent of doctors in 2000 engaged in teaching or research | AMA Physician Master File | 3.4% | 1.7% | 0.0% | 9.5% |
| General practitioners/internists/family practitioners per 1,000 population in 2000 | AMA Physician Master File | 0.219 | 0.064 | 0.095 | 0.486 |
| Hospitals per 1,000,000 population in 2000 | AHA Survey Database in 2000 | 11.9 | 4.8 | 6.3 | 46.9 |
| Teaching hospitals per 1,000,000 population in 2006 | AHA Survey Database in 2006 | 3.7 | 2.5 | 0 | 13.7 |

Means calculated across 136 MSAs in data and weighted by enrollee population in 2002

**Table 2**

**Codes used to identify diagnostic imaging claims from the Clinical Classification Software for services and procedures**

| Modality | CCS code | Description |
|---|---|---|
| CT | 177 | Computerized axial tomography (CT) scan head |
| | 178 | CT scan chest |
| | 179 | CT scan abdomen |
| | 180 | Other CT scan |
| MRI | 198 | Magnetic resonance imaging |
| Ultrasound | 192 | Diagnostic ultrasound of head and neck |
| | 193 | Diagnostic ultrasound of heart (echocardiogram) |
| | 194 | Diagnostic ultrasound of gastrointestinal tract |
| | 195 | Diagnostic ultrasound of urinary tract |
| | 196 | Diagnostic ultrasound of abdomen or retroperitoneum |
| | 197 | Other diagnostic ultrasound |

**Table 3**
**Overall rates of utilization of diagnostic imaging**

| | CT | | | MRI | | | Ultrasound | | |
|---|---|---|---|---|---|---|---|---|---|
| **Year** | **Number of scans per 1000 enrollees** | **Standard deviation** | **Coefficient of variation** | **Number of scans per 1000 enrollees** | **Standard deviation** | **Coefficient of variation** | **Number of scans per 1000 enrollees** | **Standard deviation** | **Coefficient of variation** |
| **2002** | 61.78 | 13.31 | 0.22 | 49.26 | 10.11 | 0.21 | 166.11 | 30.13 | 0.18 |
| **2003** | 61.38 | 14.22 | 0.23 | 50.05 | 11.69 | 0.23 | 166.53 | 36.38 | 0.22 |
| **2004** | 70.08 | 13.85 | 0.20 | 58.63 | 12.66 | 0.22 | 180.62 | 34.69 | 0.19 |
| **2005** | 76.36 | 14.33 | 0.19 | 63.37 | 12.57 | 0.20 | 191.85 | 35.35 | 0.18 |
| **2006** | 81.51 | 12.18 | 0.15 | 68.20 | 10.31 | 0.15 | 204.50 | 35.31 | 0.17 |
| **2007** | 82.89 | 12.09 | 0.15 | 68.25 | 9.71 | 0.14 | 213.24 | 38.17 | 0.18 |
| **2008** | 82.98 | 12.51 | 0.15 | 69.84 | 9.54 | 0.14 | 220.21 | 37.48 | 0.17 |
| **Average annual growth rate 2002-2008** | 5.2% | -0.7% | -5.3% | 6.1% | -0.4% | -5.9% | 4.8% | 4.0% | -0.5% |
| **Total growth** | 34.3% | -6.0% | -30.0% | 41.8% | -5.6% | -33.4% | 32.6% | 24.4% | -6.1% |

Observations are MSAs. Means are weighted by number of enrollees in data resident in MSA.

**Table 4**
**Correlations in rates of unconditional use of diagnostic imaging**

| | CT | MRI |
|---|---|---|
| | **2002** | |
| **MRI** | 0.71*** | |
| **US** | 0.56*** | 0.61*** |
| | **2008** | |
| **MRI** | 0.65*** | |
| **US** | 0.19* | 0.49*** |

Statistics are weighted by enrollee population. Imaging rates are age- and sex-adjusted.
* = significant at the >1%-<=5% level
** = significant at the >.1% and <=1%
*** = significant at <=.1%

**Table 5A: Imaging-disease combinations that are likely to be more productive: diagnosis rate appears to be exogenous to overall imaging rates**
**Levels in 2002 and 2008**

| | | 2002 | | | 2008 | | |
|---|---|---|---|---|---|---|---|
| **Modality** | **CCS condition** | **Diagnosis rate per 1000 enrollees** | **Scanning rate within 3 months of diagnosis** | **Scanning rate per 1000 enrollees** | **Diagnosis rate per 1000 enrollees** | **Scanning rate within 3 months of diagnosis** | **Scanning rate per 1000 enrollees** |
| **CT** | Appendicitis and other appendiceal conditions | 1.02 | 0.24 | 0.25 | 1.26 | 0.37 | 0.46 |
| | Intestinal obstruction without hernia | 1.20 | 0.21 | 0.25 | 1.01 | 0.28 | 0.29 |
| | Cancer of kidney and renal pelvis | 0.44 | 0.36 | 0.16 | 0.56 | 0.38 | 0.21 |
| | Hodgkin's disease | 0.37 | 0.37 | 0.14 | 0.37 | 0.33 | 0.12 |
| | Aortic; peripheral; and visceral artery aneurysms | 0.89 | 0.26 | 0.23 | 1.19 | 0.33 | 0.39 |
| **MRI** | Cancer of brain and nervous system | 0.55 | 0.54 | 0.30 | 0.46 | 0.62 | 0.28 |
| | Other and ill-defined cerebrovascular disease (other than acute cerebrovascular disease and occlusion or stenosis of precerebral | 1.04 | 0.37 | 0.38 | 1.12 | 0.36 | 0.40 |
| | Transient cerebral ischemia | 1.91 | 0.30 | 0.56 | 1.63 | 0.36 | 0.59 |
| | Occlusion or stenosis of precerebral arteries | 2.39 | 0.20 | 0.48 | 2.94 | 0.21 | 0.62 |
| | Hereditary and degenerative nervous system conditions other than Parkinson's disease or multiple sclerosis | 2.97 | 0.16 | 0.47 | 3.02 | 0.16 | 0.50 |
| **Ultrasound** | Conduction disorders | 1.62 | 0.21 | 0.34 | 2.08 | 0.26 | 0.54 |
| | Spontaneous abortion | 1.32 | 0.37 | 0.49 | 0.22 | 0.40 | 0.09 |
| | Transient cerebral ischemia | 1.91 | 0.42 | 0.81 | 1.63 | 0.43 | 0.70 |
| **Mean (weighted by diagnosis rate) or sum** | | | **0.28** | **4.86** | | | **5.21** |

Diagnosis rates, scanning rates conditional on diagnosis, and scanning rates per 1000 enrollees are weighted by enrollee population

**Table 5B: Imaging-disease combinations that are likely to be less productive: diagnosis rate appears to be endogenous to overall imaging rates**
**Levels in 2002 and 2008**

| | | 2002 | | | 2008 | | |
|---|---|---|---|---|---|---|---|
| **Modality** | **CCS condition** | **Diagnosis rate per 1000 enrollees** | **Scanning rate within 3 months of diagnosis** | **Scanning rate per 1000 enrollees** | **Diagnosis rate per 1000 enrollees** | **Scanning rate within 3 months of diagnosis** | **Scanning rate per 1000 enrollees** |
| **CT** | Abdominal pain | 61.42 | 0.20 | 12.10 | 65.52 | 0.26 | 17.03 |
| | Lower respiratory disease other than lung disease due to external agents or pneumothorax (includes "cough") | 64.67 | 0.13 | 8.22 | 75.68 | 0.15 | 11.28 |
| | Headache | 35.64 | 0.19 | 6.74 | 37.77 | 0.20 | 7.63 |
| | Nausea and vomiting | 10.76 | 0.14 | 1.56 | 12.85 | 0.18 | 2.30 |
| | Pneumonia | 12.42 | 0.10 | 1.26 | 11.48 | 0.13 | 1.51 |
| **MRI** | Spondylosis; intervertebral disc disorders; other back problems | 85.29 | 0.12 | 10.08 | 97.19 | 0.12 | 11.85 |
| | Nervous system disorders other than dizziness or disorders of the sense organs | 28.36 | 0.13 | 3.81 | 31.42 | 0.15 | 4.59 |
| | Headache | 35.64 | 0.15 | 5.24 | 37.77 | 0.18 | 6.66 |
| **Ultrasound** | Deficiency and other anemia | 21.83 | 0.12 | 2.60 | 68.02 | 0.13 | 8.73 |
| | Urinary tract infections | 45.37 | 0.16 | 7.41 | 47.04 | 0.16 | 7.66 |
| | Thyroid disorders | 34.81 | 0.14 | 5.00 | 43.34 | 0.19 | 8.44 |
| | Nonspecific chest pain | 50.61 | 0.20 | 10.18 | 49.61 | 0.24 | 12.10 |
| | Nonmalignant breast conditions | 41.66 | 0.27 | 11.45 | 37.39 | 0.38 | 14.38 |
| **Mean (weighted by diagnosis rate) or sum** | | | **0.16** | **85.64** | | | **114.18** |

Diagnosis rates, scanning rates conditional on diagnosis, and scanning rates per 1000 enrollees are weighted by enrollee population

**Table 5C: Imaging-disease combinations that are likely to be more productive: diagnosis rate appears to be exogenous to overall imaging rates**

| Modality | CCS condition | Growth rates 2002-2008 | | |
|---|---|---|---|---|
| | | Diagnosis rate per 1000 enrollees | Scanning rate within 3 months of diagnosis | Scanning rate per 1000 enrollees |
| **CT** | Appendicitis and other appendiceal conditions | 23.3% | 50.7% | 85.8% |
| | Intestinal obstruction without hernia | -15.5% | 34.5% | 13.7% |
| | Cancer of kidney and renal pelvis | 26.5% | 4.5% | 32.2% |
| | Hodgkin's disease | -1.7% | -11.9% | -13.4% |
| | Aortic; peripheral; and visceral artery aneurysms | 33.6% | 25.5% | 67.7% |
| **MRI** | Cancer of brain and nervous system | -16.4% | 14.0% | -4.7% |
| | Other and ill-defined cerebrovascular disease (other than acute cerebrovascular disease and occlusion or stenosis of precerebral arteries) | 8.1% | -2.3% | 5.6% |
| | Transient cerebral ischemia | -14.3% | 22.7% | 5.2% |
| | Occlusion or stenosis of precerebral arteries | 23.1% | 5.9% | 30.4% |
| | Hereditary and degenerative nervous system conditions other than Parkinson's disease or multiple sclerosis | 1.6% | 4.9% | 6.6% |
| **Ultrasound** | Conduction disorders | 28.3% | 24.2% | 59.3% |
| | Spontaneous abortion | -83.1% | 7.2% | -81.9% |
| | Transient cerebral ischemia | -14.3% | 1.7% | -12.9% |
| **Mean (weighted by diagnosis rate)** | | **-0.7%** | **13.8%** | **13.8%** |

**Table 5D: Imaging-disease combinations that are likely to be less productive: diagnosis rate appears to be endogenous to overall imaging rates**

| | | Growth rates 2002-2008 | | |
|---|---|---|---|---|
| **Modality** | **CCS condition** | **Diagnosis rate per 1000 enrollees** | **Scanning rate within 3 months of diagnosis** | **Scanning rate per 1000 enrollees** |
| **CT** | Abdominal pain | 6.7% | 31.9% | 40.7% |
| | Lower respiratory disease other than lung disease due to external agents or pneumothorax (includes "cough") | 17.0% | 17.3% | 37.3% |
| | Headache | 6.0% | 6.9% | 13.2% |
| | Nausea and vomiting | 19.5% | 23.8% | 47.9% |
| | Pneumonia | -7.6% | 29.5% | 19.7% |
| **MRI** | Spondylosis; intervertebral disc disorders; other back problems | 14.0% | 3.1% | 17.5% |
| | Nervous system disorders other than dizziness or disorders of the sense organs | 10.8% | 8.8% | 20.5% |
| | Headache | 6.0% | 20.1% | 27.3% |
| **Ultrasound** | Deficiency and other anemia | 211.7% | 7.8% | 236.0% |
| | Urinary tract infections | 3.7% | -0.2% | 3.5% |
| | Thyroid disorders | 24.5% | 35.6% | 68.9% |
| | Nonspecific chest pain | -2.0% | 21.3% | 18.9% |
| | Nonmalignant breast conditions | -10.2% | 40.0% | 25.6% |
| **Mean (weighted by diagnosis rate)** | | **16.4%** | **17.6%** | **35.8%** |

**Table 6**
**Cancer screening rates in 2002: summary statistics**

| | Mean | Standard deviation | Minimum | Maximum |
|---|---|---|---|---|
| **Mammogram rate among women aged 50-64** | 0.34 | 0.08 | 0.10 | 0.54 |
| **Colon cancer screening rate among enrollees aged 50-54** | 0.24 | 0.06 | 0.09 | 0.49 |
| **Correlation between two cancer screening rates** | 0.35*** | | | |

Statistics are weighted by enrollee population. Cancer screening rates are age- and sex-adjusted.
* = significant at the >1%-<=5% level
** = significant at the >.1% and <=1%
*** = significant at <=.1%

**Table 7**

| | Mammogram rate among female enrollees aged 50-64 | Colon cancer screening rate among enrollees aged 50-54 |
|---|---|---|
| Log(per capita income in 2000) | 0.141 | 0.036 |
| | (0.087) | (0.056) |
| Log(population density in 2000) | 0.002 | -0.015 |
| | (0.011) | (0.009) |
| Percent of adults over 25 in 2000 who did not graduate from high school | -0.675 | 1.147 |
| | (0.434) | (0.247) |
| Percent of adults over 25 in 2000 who graduated from college | -0.108 | 0.589 |
| | (0.195) | (0.159) |
| Percent of population in 2000 who are white and non-Hispanic | 0.060 | 0.267 |
| | (0.091) | (0.065) |
| Percent of population in 2000 who are African-American | -0.241 | 0.166 |
| | (0.093) | (0.078) |
| Doctors per capita in 2000 | -22.137 | -5.543 |
| | (20.637) | (17.973) |
| Percent of doctors in 2000 who are engaged in teaching or research | 1.033 | 0.160 |
| | (0.793) | (0.581) |
| General practitioners and internists per capita in 2000 | 81.104 | -217.171 |
| | (125.031) | (103.948) |
| Log(number of hospitals per capita in 2000) | 0.034 | -0.059 |
| | (0.026) | (0.018) |
| Number of teaching hospitals per capita in 2006 | 5759.014 | 5508.660 |
| | (3147.286) | (2292.973) |
| Constant | -0.688 | -1.119 |
| | (0.942) | (0.578) |
| $R^2$ | 0.366 | 0.411 |

Robust standard errors are in parentheses. Regressions are weighted by enrollee population in 2002.

**Table 8**

**Correlations between cancer screening rates and overall imaging rates in 2002**

| **Overall rates of:** | **Mammogram rate among female enrollees aged 50-64** | **Colon cancer screening rate among enrollees aged 50-54** |
|---|---|---|
| **CT** | 0.25** | 0.08 |
| **MRI** | 0.25** | 0.22* |
| **Ultrasound** | 0.11 | 0.23** |

Weighted by enrollee population

* = significant at the >1%-<=5% level

** = significant at the >.1% and <=1%

*** = significant at <=.1%

**Table 9**

**Correlations between cancer screening rates and imaging rates conditional on a diagnosis in 2002**

| Modality | CCS condition | Mammogram rate among female enrollees aged 50-64 | Colon cancer screening rate among enrollees aged 50-54 |
|---|---|---|---|
| **CT** | Abdominal pain | 0.22* | 0.07 |
| | Lower respiratory disease other than lung disease due to external agents or pneumothorax (includes "cough") | 0.12 | 0.06 |
| | Headache | 0.29*** | -0.03 |
| | Nausea and vomiting | 0.12 | -0.02 |
| | Pneumonia | 0.13 | -0.04 |
| | | | |
| **MRI** | Spondylosis; intervertebral disc disorders; other back | 0.34*** | 0.05 |
| | Nervous system disorders other than dizziness or dis | 0.14 | 0.11 |
| | Headache | 0.04 | 0.10 |
| | | | |
| **US** | Deficiency and other anemia | -0.08 | -0.03 |
| | Urinary tract infections | -0.04 | 0.10 |
| | Thyroid disorders | -0.20* | 0.04 |
| | Nonspecific chest pain | -0.13 | -0.11 |
| | Nonmalignant breast conditions | 0.05 | 0.06 |

Weighted by enrollee population

* = significant at the >1%-<=5% level

** = significant at the >.1% and <=1%

*** = significant at <=.1%

Table 10

| | Dependent variable: Log(1+growth rate of unconditional use of imaging modality from 2002 to 2008) | | | | | |
|---|---|---|---|---|---|---|
| | CT | | MRI | | Ultrasound | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| **Initial level of growth rate of use of imaging modality in 2002** | -1.05 | -1.09 | -2.48 | -2.48 | -0.282 | -0.304 |
| | (0.186) | (0.179) | (0.378) | (0.347) | (0.118) | (0.112) |
| **Mammogram rate among female enrollees aged 50-64** | -0.045 | | -0.013 | | -0.087 | |
| | (0.023) | | (0.027) | | (0.040) | |
| **Colon cancer screening rate among enrollees aged 50-54** | | -0.096 | | -0.020 | | -0.009 |
| | | (0.024) | | (0.032) | | (0.031) |

**Table 11**

| Modality | CCS condition | Coefficient on: Mammogram rate | Coefficient on: Colon cancer screening rate |
|---|---|---|---|
| **CT** | Abdominal pain | -0.010 | -0.077 |
| | | (0.026) | (0.027) |
| | Lower respiratory disease other than lung disease due to external agents or pneumothorax (includes "cough") | 0.032 | -0.106 |
| | | (0.030) | (0.038) |
| | Headache | -0.032 | -0.047 |
| | | (0.022) | (0.026) |
| | Nausea and vomiting | 0.034 | -0.083 |
| | | (0.043) | (0.063) |
| | Pneumonia | -0.022 | -0.077 |
| | | (0.055) | (0.072) |
| **MRI** | Spondylosis; intervertebral disc disorders; other back problems | 0.007 | -0.007 |
| | | (0.028) | (0.045) |
| | Nervous system disorders other than dizziness or disorders of the sense organs | 0.067 | -0.019 |
| | | (0.029) | (0.057) |
| | Headache | 0.042 | 0.010 |
| | | (0.030) | (0.033) |
| **Ultrasound** | Deficiency and other anemia | -0.046 | -0.082 |
| | | (0.043) | (0.068) |
| | Urinary tract infections | -0.037 | 0.016 |
| | | (0.043) | (0.031) |
| | Thyroid disorders | -0.082 | 0.066 |
| | | (0.050) | (0.061) |
| | Nonspecific chest pain | -0.061 | 0.002 |
| | | (0.026) | (0.043) |
| | Nonmalignant breast conditions | -0.088 | -0.056 |
| | | (0.036) | (0.041) |

The dependent variable is the log(1+ the growth rate in the rate of imaging conditional on the CCS diagnosis). Regressions are weighted by enrollee population and also include a control for the initial level of conditional imaging.