REGIONAL PATTERNS IN MEDICAL TECHNOLOGY UTILIZATION[1]

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ABSTRACT

The U.S. health-care system is characterized by the rapid adoption and diffusion of medical technologies and high regional variation in health-care utilization and spending. I examine the correlations in the adoption and utilization rates of sixteen outpatient health-care technologies of differing quality across US metropolitan areas among nonelderly adult beneficiaries of employment-sponsored insurance in 2006-2010. I find three patterns underlying their use. One relates to the high use of diagnostic and screening services, one to the high use of pharmaceuticals, and one to the low-quality management of pain. In general therefore, utilization correlates by type of technology more than quality, which may contribute to explaining the lack of relationship between spending and outcomes observed in the U.S. health-care system. I further show that these correlations are not confined to the sixteen technologies under study but relate to medical utilization across categories of services and pharmaceuticals. I also connect these patterns with local demographics. The first factor is associated with higher education, income, population density, and provider supply and with lower social capital. The second factor is also associated with higher education, income, and provider supply, but with lower population density and higher social capital. The third factor is associated with lower education, income, social capital, population density, and provider supply.

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1. Introduction

The U.S. health-care system is characterized by three notable features. The first characteristic is that there is high regional variation across the country in health-care spending, and utilization. The variation was first documented in the Medicare program (Fisher et al. 2003a, Fisher et al. 2003b, Congressional Budget Office 2008) and has also been found in the privately insured population (Baker et al. 2008, White 2012). Much of the sources of the variation are unclear (Congressional Budget Office 2008). The second characteristic is the lack of cross-sectional relationships between regional spending and regional health outcomes and between spending and health care quality. Fisher et al. (2003a, 2003b) found areas that had higher end-of-life Medicare spending and higher health-care utilization among Medicare beneficiaries had no better health outcomes. Baicker and Chandra (2004) found a negative relationship between per capita Medicare spending and health-care quality and Yasaitis et al. (2009) found no relationship between end-of-life spending and health-care quality.

The third characteristic of the US health-care system is the rapid adoption and diffusion of medical technologies. 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). Technological change in medicine has been a substantial contributor to the high growth of per capita health-care spending over the past half-century (Newhouse 1992). Skinner and Staiger (forthcoming) tie variation in treatment quality and outcomes for Medicare beneficiaries with heart attacks to differential rates of technology adoption by hospitals. Hospitals with higher rates of adoption of and faster diffusion of three beneficial technologies for heart attack treatment have better outcomes and greater improvements in outcomes. Skinner and Staiger find that adoptions of the three technologies are correlated and also find that they are correlated with other, less medically effective technologies. In an earlier paper (Skinner and Staiger 2007), they found state-level correlations in the adoptions and utilizations of several technologies, both medical and non-medical, and suggest that some regions are more generally open to the innovation and adoption of new technologies.

Skinner and Staiger (2007) only consider productive technologies but the US health-care system has also been criticized for adopting and utilizing many technologies of doubtful value.

Estimates of waste in the system have been as high as 30 percent (Fisher et al. 2003a, Fisher et al. 2003b, Skinner et al. 2005). Chandra and Skinner (2011) classify some health-care technologies by their effectiveness and suggest that Category III treatments, whose value is unknown or probably zero, contribute much of the health-care cost growth. It is also well-known from research on innovation and diffusion outside the health-care sector that firms and individuals tend to adopt new technologies when the technologies are compatible to technologies currently in use (Rogers 2003). As Chandra and Skinner (2011) discuss, many health-care technologies (in their Category II) are highly beneficial to small groups but are prone to diffuse to increasingly larger patient populations where they are less effective, resulting in a drop in their average productivity. An example is imaging technology, as we will see below. Imaging has powerful diagnostic abilities for certain patients but some uses of it have been found to be wasteful and generally not leading to any treatment of value.

This paper therefore addresses the following question: do regions that adopt and use productive medical technologies more quickly also adopt and use more quickly medical technologies that have been found to be wasteful? More generally, what is the relationship between the use of high-quality medical technologies and medical technologies of doubtful or zero value?

To answer this question, I examine the correlations in the adoption and utilization rates of sixteen outpatient health-care technologies across US metropolitan areas among nonelderly adult beneficiaries of employment-sponsored insurance. The technologies have different modalities of delivery, are used on different subpopulations and most are identified in the medical literature as having particularly low or high effectiveness. A key feature of these technologies is that they are either measured conditional on a particular diagnosis or are screenings performed on an identifiable population. Their observed aggregate rates of use therefore do not depend on the health status of a population so any observed correlation will reflect correlations in health-care practice, not the underlying health of the population.

A factor analysis model applied to the utilization rates of these technologies uncovers three factors that appear to underlie the adoption and utilization of outpatient medical technology. The first and largest factor relates to the high utilization of diagnostic and screening services, several of which have been identified as being wasteful but one of which (colon cancer screening) is regarded as more valuable. The second, nearly as large, relates to the high utilization of pharmaceuticals, whether high-quality or low-quality, and to the use of mammograms. The third and slightly smaller factor relates to two technologies that try to treat pain but that have been identified as potentially wasteful: imaging for lower back pain and to the use of opioids to treat migraines.

The technologies reviewed therefore correlate together mostly by type, as would be predicted by most theories of technological diffusion that take into account the particular incentive structure of health care, and less so by quality. To illustrate this point I create four indexes measuring different kinds of health-care quality: an appropriate services use index (that measures the use of high-value services), a service overuse index (that measures the use of wasteful services), an appropriate pharmaceutical use index (that measures high-value uses of pharmaceuticals), and a pharmaceutical overuse index (that measures wasteful uses of pharmaceuticals). The score on the first factor is significantly positively correlated with both the appropriate service use index and the services overuse index, and the score on the second factor is significantly positively correlated with both the appropriate pharmaceutical use index and the pharmaceutical overuse index.

The factor analysis shows therefore a dilemma of health care, that the tendency to adopt and use similar technologies leads to correlations between appropriate use and overuse. However, there are correlations by quality as well as the second factor loads on both mammograms and two high-quality uses of pharmaceuticals and the third factor loads on two low-quality technologies of different types.

I also show that the first two high-use factors reflect higher medical utilization of all kinds; the score on the diagnostic and screening services factor is positively correlated with the rates of use of all categories of services and the score on the pharmaceuticals/mammograms factor is positively correlated with the rates of use of all major categories of pharmaceuticals. The first two factors therefore seem to reflect widespread tendencies in medical utilization that are not limited to the technologies that happened to be included in the factor analysis. I then examine the relationship of the factors to spending. The score on the diagnostic and screening services factor is, somewhat surprisingly, not associated with higher spending on outpatient services; it turns out this is because higher utilization of services correlates with lower prices on the services. The score on the mammograms/pharmaceutical factor is associated with higher spending on pharmaceuticals both because of higher utilization of pharmaceuticals and because of higher pharmaceutical prices.

I then explore the potential causes for these patterns arising by examining their relationships to demographic characteristics of the local population and local levels of provider supply. Skinner and Staiger (2007) found that the adoption of the technologies they studied was positively correlated with local levels of education and social capital. They theorize that there is something about higher levels of education and social capital that makes populations more open to adopting new technologies and makes the adoption of them less costly. I find a somewhat more complex relationship between the utilization of health-care technology and demographic variables. The score on the first factor, which is aligned with the higher use of diagnostic and screening services, is associated with higher education, higher income, higher population density, higher physicians per capita, a higher ratio of specialist physicians to generalists and a higher percentage of physicians engaged in being trained, teaching or performing research. It is also associated with lower levels of social capital. The score on the second factor, which is aligned with higher rates of mammograms and the use of three pharmaceutical technologies (two high-value, one low-value), is also correlated with higher education, higher income, and higher physicians per capita, but also with lower population density and higher levels of social capital. The score on the third factor, which is aligned with two technologies that have been identified as wasteful ways of managing pain, is associated with lower education, lower income, lower population density, lower social capital, and lower levels of provider supply. Education, income, and provider supply therefore seem to raise health-care utilization generally, with the exception of the two technologies in the third factor. Meanwhile population density encourages services use and discourages pharmaceutical use, again with the exceptions of the two technologies in the third factor, and social capital has the reverse effects on those technologies.

These results are consistent with four other papers on technology utilization in health care and medical productivity and quality. Baker et al. (2003) examined the relationship between the availability of a variety of medical technologies and utilization of those technologies among privately insured patients. They find that availability of a technology generally raises its utilization. They also find evidence of complementarity in the use of similar technologies. Specifically, they find that availability of magnetic resonance imaging (MRI) raises utilization of computed tomography (CT) scanning, while controlling for the availability of CT scanning. I also find correlations in the use of similar technologies, especially imaging technologies.

Chandra and Staiger (2007) model the choice of either surgical or medical treatment for heart attack patients including productivity spillovers; the return on either treatment is higher in areas where the treatment is performed more. In other words, regions specialize in particular kinds of treatments. They emphasize the externalities resulting from the spillovers: patients more suitable for surgical treatment have better outcomes in areas where surgery is performed more often (a positive externality) but patients suitable for medical treatment have worse outcomes in those areas that specialize in surgery (a negative externality). My results also show an externality. Beneficiaries receive appropriate colon cancer screenings more in regions that specialize in services (a positive externality) but patients also receive inappropriate cardiac testing and Vitamin D screening more in those same areas (a negative externality). Likewise, patients with asthma and rheumatoid arthritis receive appropriate medication more in areas that specialize in pharmaceutical treatment but patients with acute bronchitis are more likely to receive inappropriate antibiotics in those same areas.

Landrum et al. (2008) examine regional correlations in the use of treatments of different quality for colon cancer. They separate treatments into recommended care, discretionary care, and nonrecommended care. Similar to what I find, they find that areas that use higher levels of recommended colon cancer care are also more likely to use discretionary and nonrecommended care.

Finally, Skinner and Staiger (forthcoming) employ a factor analysis on the correlations in the adoptions of different technologies by hospitals to treat acute myocardial infarctions (heart attacks). They find that effective medical treatments correlate together in one factor and less cost-effective surgical treatments correlate together in another factor. I also find that some medical treatments correlate together in one factor. I do not find any evidence of surgical treatments correlating together but they are studying inpatient surgical treatments for one condition while I only consider outpatient surgical treatments across different conditions.

Taken together, these results suggest a contributing factor to the lack of relationship between health-care spending and health outcomes across US regions. The tendency for regions to adopt and use particular technologies that are similar leads to some technologies being underused and others being overused across regions. Regions with higher utilization of services use more high-quality services but also use more care that is likely to add no value or even lead to more adverse outcomes. Similarly, patients residing in regions that use more pharmaceuticals are more likely to receive appropriate medications for their conditions but are also more likely to receive inappropriate medication. As I show with the regional distributions of scores in the factors, the different combinations of rates of technology use leads to different health-care experiences for patients depending on the demographics and levels of provider supply in their region.

The paper proceeds as follows. In section 2, I summarize the data on health-care utilization. In section 3, I review the medical evidence for the effectiveness and productivity of the health-care technologies whose utilization is to be measured. In section 4, I perform a factor analysis of the utilization rates of the technologies to uncover the factors underlying the adoption of technology. I then relate these to the quality indexes and to average spending. In section 5, I examine the relationship of the scores on the factors to local demographics. Section 6 concludes.

2. Background on data

For the purposes of this paper, I have pulled together regional data from multiple sources on health-care utilization, demographics, and health-care market characteristics. The analysis is at the MSA level and is limited to adults under age 65. Table 1 gives summary statistics of the health-care technology utilization rates. The rates of use of medical care are from the MarketScan claims database, a large database of medical claims of holders of private employer-sponsored insurance. The database contains claims from the following kinds of plans: basic/major medical, comprehensive, health maintenance organization (HMO), point-of-service (POS), preferred provider organization (PPO), consumer-driven health plans (CDHP), and high-deductible health plans (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 2010, but I only employ the data from 2006 to 2010, since the coverage of the database expanded considerably in 2006. Data are pooled across 2006 through 2010. 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

Table 1
Technology utilization rates 2006-2010
Summary statistics

Technology	Mean	Standard deviation	Coefficient of variation	Medical effectiveness and specification source
High-value technologies				
Screenings				
Colon cancer screening rate among adults aged 50-54 (annualized)	95.3%	16.5%	0.17	USPSTF
Mammogram rate in women aged 55-64	49.2%	5.0%	0.10	USPSTF
Pharmaceuticals				
Patients with persistent asthma receiving appropriate medication	98.0%	1.1%	0.01	NQF/NCQA
Patients with rheumatoid arthritis receiving DMARD therapy	85.3%	4.5%	0.05	NQF/NCQA
Low-value technologies				
Screenings and diagnostic services				
Prostate cancer screening rate in men aged 55-64	44.9%	5.9%	0.13	USPSTF
Vitamin D screening rate	4.7%	2.0%	0.43	Choosing Wisely (Colla et al. 2015)
Lower back pain imaging rate on low-risk patients	32.5%	6.3%	0.19	Choosing Wisely (Colla et al. 2015)
Benign prostate hyperplasia imaging rate on low-risk patients	2.7%	3.2%	1.20	Choosing Wisely (Colla et al. 2015)
Cardiac screening rate on low-risk patients	9.0%	3.8%	0.43	Choosing Wisely (Colla et al. 2015)
Cardiac testing before surgery rate on low-risk patients	29.9%	9.6%	0.32	Choosing Wisely (Colla et al. 2015)
Pharmaceuticals				
Patients with migraines receiving opioids	22.3%	4.7%	0.21	Choosing Wisely (Colla et al. 2015)
Patients with acute bronchitis receiving antibiotics	56.7%	5.6%	0.10	NQF/NCQA
Neutral treatments				
Cardiac catheterization rate post-AMI	80.6%	9.5%	0.12	
Cholecystectomy rate for gallstones	10.7%	4.2%	0.39	
Joint replacement rate for arthritis	9.7%	2.3%	0.24	
Hernia repair rate for inguinal hernia	60.7%	10.9%	0.18	

Note: Statistics are weighted by MarketScan adult population. Observations are MSAs. N=870.

Notes: USPSTF=U.S. Preventive Services Task Force. NQF/NCQA=National Quality Forum Voluntary Consensus Standards for Ambulatory Care. CMS=Center for Medicare and Medicaid Services.

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). The final sample from which the utilization rates were calculated contains a total of 59,111,411 enrollee-years. The mean number of enrollee-years across the 870 MSAs is 67,944; the smallest has about 3600 and the largest about 3.2 million.

All the health-care utilization rates are adjusted for differences in sex and age by taking means for groups by sex and five-year age ranges and then taking the mean of those rates, weighting by the MarketScan population in each group.

As Table 1 shows, there is generally considerable variation in utilization rates. Coefficients of variation are typically between 0.1 and 0.3 with some ranging higher. Two exceptions on the low end of variation are the two high-quality uses of pharmaceuticals: the percent of patients with persistent asthma receiving medication and the percent of patients with rheumatoid arthritis receiving disease-modifying anti-rheumatic drug (DMARD) therapy. The coefficient of variation of the first is only 0.01 and that of the second is only 0.05. However, as will be shown below, even that small amount of variation turns out to be important.

3. Background on health-care technologies

As Table 1 shows, I have measured the utilization rates of sixteen health-care technologies, of differing modalities and medical effectiveness. Four of them are of high medical effectiveness with a medically optimal rate of 100 percent or close to 100 percent and eight of them are of low quality, having been recommended against by provider societies and with a medically optimal rate that is probably close to zero percent. Four of them are invasive procedures conditional on a specific diagnosis with no known medically optimal rate but I include them to see if there is an overall tendency towards invasive treatment. The last column of Table 1 gives the source from which I obtained information on their medical effectiveness and on the technical specifications for identifying them in claims data.

The set of technologies includes three cancer screenings: colon cancer screening among adults aged 50-54, mammograms for women aged 55-64, and prostate cancer screening among men aged 55-64.[2] I base the effectiveness of the cancer screenings on the recommendations of the major provider associations as well as those of the U.S. Preventive Services Task Force. The most and least stringent recommendations for low-risk patients in effect for the period 2006-2010 for each screening are summarized in table 2. As it shows, the organizations are largely united in their positive recommendations for mammograms for women aged 40 and over, for colorectal cancer screening starting at age 50. There is, however, no positive recommendation for PSA testing for men.

Table 2
Summary of cancer screening recommendations in effect 2006-2010

Screening	US Preventive Services Task Force	American Cancer Society	Provider organization
Colon cancer screening (colonoscopy, fecal occult blood testing, or flexible sigmoidoscopy) in adults at age 50	Screening should start at age 50. Grade: A.	Screening should start at age 50.	ACG: Screening should start at age 50. (Update in 2009 recommended colonoscopy be offered first.)
Mammogram in women 40 and above	Every 1 to 2 years. (Updated in 2009 to limit recommendation to women 50 and above.) Grade: B.	Annually	ACOG: Every 1 to 2 years in 40s and annually starting at age 50.
Prostate cancer screening (PSA test)	Evidence insufficient to issue a recommendation.	Offer annually starting at age 50 for men who have a life expectancy of at least 10 years.	AUA: Offer annually starting at age 50 for men who have a life expectancy of at least 10 years.

ACG = American College of Gastroenterology; ACOG = American Congress of Obstetricians and Gynecologists; AUA = American Urological Association

[2] Cervical cancer screening is another potential technology to be measured and it has strong positive recommendations from the USPTF. However, the rate did not seem to be reliably measured in claims data possibly because payment for the screening was bundled in with a gynecological exam and therefore the screening was not coded separately. A factor analysis model including the cervical cancer screening rate as measured in the Behavioral Risk Factor Surveillance System showed that it did not particularly correlate with any other technology and had a high uniqueness. In addition, including data from the BRFSS reduces the sample from 870 MSAs to 199, so I do not present that model as the main result.

Based on this table, I generally measure the cancer screening rates at an annual level. However, since I want to measure correlations that result from local healthcare practices, not from them being measured on the same patients, I divide the populations being measured by age. Colon cancer screenings are measured on both men and women aged 50 to 55; since the typical patient only needs one screening during this period, I multiply the rate by 5 to obtain an annualized level. Prostate cancer screenings and mammograms are measured on men and women aged 55 to 64 respectively.

Another group of technologies comes from the National Quality Forum's National Voluntary Consensus Standards for Physician-Focused Ambulatory Care. These were released in 2008, in the middle of the period under study. The standards were developed to measure the quality of care delivered by physicians in the outpatient setting (NQF 2008). The standards were chosen not only because they related to health-care quality but because considerable variation in them existed. The NQF provided technical specifications (diagnosis and procedure codes) for identifying the specified technologies in an appendix to the standards, and I follow their specifications.

Table 3 gives more details about the three technologies taken from the NQF's standards for ambulatory care. They are all measures of pharmaceutical utilization. The first two measure whether patients are receiving appropriate medications for their conditions: the percent of patients with "persistent" asthma (where "persistent" is defined as having one of the following in the calendar year: four or more outpatient visits, an emergency room visit or an inpatient stay for asthma) receiving medication for asthma, and the percent of patients with rheumatoid arthritis receiving disease-modifying anti-rheumatic drug (DMARD) therapy for rheumatoid arthritis. The third measures a low-value use of pharmaceuticals, the percent of patients with acute bronchitis receiving antibiotics. As detailed in the table, certain patients with the conditions are excluded from the denominators of the measures because of related comorbidities (e.g., pregnancy for rheumatoid arthritis patients or infections for the acute bronchitis patients).

The next set of technologies comes from the Choosing Wisely campaign, a movement for provider societies to define poor quality and inefficient practices in their own specialties. Colla et al. (2015) created technical specifications for a number of these measures and I follow their specifications. I was not able to use all the measures in their study because they analyzed the

Table 3
Technologies from National Quality Forum's National Voluntary Consensus Standards for Physician-Focused Ambulatory Care

Technology	Requirement for denominator	Exclusion restrictions	Requirement for numerator
Patients with persistent asthma receiving appropriate medication (High value)	At least four outpatient visits or an emergency room visit or an inpatient stay with diagnosis of asthma	Diagnosis of emphysema or COPD at any time	At least one prescription for asthma medication
Patients with rheumatoid arthritis receiving disease-modifying anti-rheumatic drug (DMARD) therapy (High value)	At least two outpatient visits with a diagnosis of rheumatoid arthritis	Diagnosis of HIV or pregnancy at any time	At least one prescription for DMARD therapy
Patients with acute bronchitis receiving antibiotics (Low value)	At least one outpatient or emergency room visit with a diagnosis of acute bronchitis	Diagnosis of HIV, cystic fibrosis, cancer, chronic bronchitis, emphysema, bronchiectasis, tuberculosis at any time. Also no infections or antibiotic prescriptions in month before visit.	At least one antibiotic prescription within three days of visit

Medicare population and some of the measures were specific to the elderly. Table 4 summarizes the technologies from Choosing Wisely that I use. They are all low-value technologies and are mostly diagnostic services. One technology, prescribing opioids for migraine patients without related comorbidities (injuries or cancer), is a measure of pharmaceutical use.

The next set of technologies is a set of invasive procedures, one diagnostic, and the other three therapeutic. These are neutral technologies because an optimal level for their utilization has not been identified to my knowledge. They possibly fall into Chandra and Skinner (2012)'s Category II of treatments, those treatments that are highly effective for a subset of patients but tend to diffuse to other sets of patients for whom they are less valuable, but I know of no medical evidence one way or the other pointing to an assignment in that category. I have included them as a potential measure of any tendency to use invasive treatments and to see if there is any correlation between diagnostic services and using invasive treatments. For all four procedures, I have conditioned on a diagnosis to remove any correlation deriving from correlations in underlying health status but rather measure the tendency to provide treatment conditional on a given health status.

The first procedure is the cardiac catheterization rate after an acute myocardial infarction (AMI, or heart attack). As discussed in Chandra and Staiger (2007), AMI can be managed intensively or non-intensively. Intensive management consists of the use of procedures such as bypass surgery or angioplasty and non-intensive management consists of the use of medication alone. The first step in the intensive management pathway is cardiac catheterization, a diagnostic procedure by which a catheter is threaded through to the heart, allowing for imaging of the blockages of the coronary arteries and measurement of the heart's functioning. I follow Chandra and Staiger in measuring the catheterization rate by including catheterizations out to 30 days after admission for the AMI.

The other three procedures have not been studied in the health economics literature as much as management of AMI but are relatively common surgeries among the nonelderly adult population. They are the cholecystectomy (removal of gallbladder) rate for gallstones, the joint replacement rate for osteoarthritis, and the hernia repair rate for an inguinal hernia, the most common type of hernia. Table 5 gives the procedure and diagnosis codes used to identify these procedures.

Table 4
Technologies from Choosing Wisely (via Colla et al. [2015])
All technologies are of low value

Technology	**Requirement for denominator**	**Exclusion restrictions**	**Requirement for numerator**
Vitamin D screening	All adults	Chronic kidney disease, osteoporosis, fragility fractures, obesity at any time	Assay of Vitamin D
Imaging on low-risk patients with low back pain	Diagnosis of low back pain	Cancer, injury, trauma, neurological impairment, IV drug use, HIV, intraspinal abscess within a year before diagnosis	Imaging (X-ray, MRI or CT) of lower back within six weeks of low back pain diagnosis
Upper urinary tract imaging on low-risk patients with benign prostate hyperplasia	Diagnosis of benign prostate hyperplasia	Chronic renal failure, nephritis, kidney stones, urinary tract infections, hematuria, fever, abdominal pain within 60 days of diagnosis	Imaging of abdomen (X-ray, MRI or CT) or intravenous pyelogram within 60 days of diagnosis
Cardiac screening on low-risk patients	All adults	HIV, cancer, diabetes, drug/alcohol dependence, cardio-respiratory failure, congestive heart failure, acute myocardial infarction, angina, heart arrhythmias, stroke, hemiplegia, vascular disease, COPD, renal failure at any time or prescription for certain cardiac drugs	Electrocardiogram, cardiovascular stress test, echocardiogram, or advanced cardiac imaging
Cardiac testing before low-risk surgeries	Patients having certain low-risk non-cardiac surgeries such as hernia repair or cholecystectomy	Cardiac diagnosis with imaging	Electrocardiogram, cardiovascular stress test, echocardiogram, chest X-ray or advanced cardiac imaging
Prescription for opioids for migraines	Patients with diagnosis of migraine	Injury, back pain, abdominal pain, fractures, surgery, cancer within 60 days before migraine diagnosis	Prescription for opioid filled within 21 days of migraine diagnosis

Table 5
Diagnosis and procedure codes for invasive surgeries

Procedure	Diagnosis codes	Procedure codes
Cholecystectomy rate for gallstones	Gallstones (ICD9 codes starting with 574) or cholecystitis (ICD9 codes starting with 575)	Codes in BETOS category P1C "Major procedure – cholecystectomy"
Joint replacement rate for osteoarthritis	Osteoarthritis (codes in CCS category 203)	Codes in BETOS category P3B "Major procedure, orthopedic – hip replacement" or P3C "Major procedure, orthopedic – knee replacement"
Hernia repair rate for inguinal hernia	Inguinal hernia (ICD9 codes starting with 550)	Codes in BETOS category P5C "Ambulatory procedures – groin hernia repair"

Note: ICD9 = International Classification of Diseases Ninth Revision. CCS = Clinical Classification Software. BETOS = Berenson-Eggers Type of Service.

4. Factor analysis of technology utilization rates

A factor analysis explores whether there are patterns underlying a set of variables. It uses correlations among the variables to convert them into a lower number of factors that are expressed in terms of weights or loadings on the variables. I conduct a factor analysis of the sixteen technology utilization rates described in the previous section, with the results shown in Table 6. The factors are orthogonally rotated with a varimax rotation.

The results of a factor analysis can be somewhat open to subjective interpretation. In general, a particular factor is usually only considered significant if its variance accounts for the variance of more than one variable, that is, if its eigenvalue is greater than one. In addition, the characterization of each factor can be open to interpretation and rests on previous knowledge of how the variables relate to each other. Table 6 shows that there are two factors with eigenvalues greater than one underlying the twenty utilization rates. There is also a third factor with an eigenvalue just below one that has loadings on two technologies that are related, so I have included it in the table.

The interpretation of the three factors based on what technologies they load on is fairly clear cut, so I have labelled the columns in Table 6 accordingly. The first factor appears to be associated with diagnostic and screening services. It has high (over 0.5) and positive loadings on the following services: colon cancer screening, prostate cancer screening, Vitamin D screening, and cardiac testing on low-risk patients, and a moderately high (over 0.3) loading on the lower back pain imaging rate. It has positive but small loadings on the remaining diagnostic and screening services and negative but small loadings on the pharmaceutical technologies. It also has moderately negative loadings on three invasive treatments: the cardiac catheterization rate post-AMI, the joint replacement rate for arthritis, and the hernia repair rate for inguinal hernia.

The second factor is associated with the use of mammograms and three of the four outpatient pharmaceutical technologies. The loadings on the use of appropriate medication for asthma, appropriate medication for rheumatoid arthritis, and antibiotics for acute bronchitis are all over 0.6 and the loading on the mammogram rate is just over 0.5. The magnitudes of the loadings on all the other utilization rates are mostly below 0.4, except for the loading on joint replacement surgery which is just over 0.4.

Table 6
Factor analysis of technology utilization rates

	Factor 1: Diagnostic and screening services	Factor 2: Pharmaceuticals and mammograms	Factor 3: Mismanagement of pain	Uniqueness
Eigenvalue	2.27	2.18	0.92	
High-value technologies				
Screenings				
Colon cancer screening rate among adults aged 50-54	0.73	0.15	0.17	0.39
Mammogram rate in women aged 55-64	0.05	0.53	-0.25	0.56
Pharmaceuticals				
Patients with persistent asthma receiving appropriate medication	-0.07	0.72	0.06	0.44
Patients with rheumatoid arthritis receiving DMARD therapy	-0.05	0.61	0.00	0.59
Low-value technologies				
Screenings				
Prostate cancer screening rate in men aged 55-64	0.52	-0.10	0.02	0.60
Vitamin D screening rate	0.60	-0.02	-0.32	0.44
Diagnostic services				
Lower back pain imaging rate on low-risk patients	0.32	-0.13	0.60	0.52
Benign prostate hyperplasia imaging rate on low-risk patients	0.14	-0.05	0.07	0.88
Cardiac testing rate on low-risk patients	0.82	-0.26	0.05	0.23
Cardiac testing before surgery rate on low-risk patients	0.03	-0.39	-0.12	0.59
Pharmaceuticals				
Patients with migraines receiving opioids	-0.08	0.04	0.56	0.65
Patients with acute bronchitis receiving antibiotics	-0.16	0.69	-0.09	0.44
Neutral treatments				
Cardiac catheterization rate post-AMI	-0.35	0.14	0.06	0.75
Cholecystectomy rate for gallstones	0.12	-0.27	-0.09	0.77
Joint replacement rate for arthritis	-0.25	0.41	0.00	0.68
Hernia repair rate for inguinal hernia	-0.25	-0.10	0.11	0.87

Analysis weighted by MSA population. N=870.

The third factor, which has an eigenvalue of just under 1, has loadings of over 0.5 on two low-value technologies as identified by the Choosing Wisely campaign: the use of imaging to diagnose the causes of lower back pain and the use of opioids to treat migraines. Although they are two different types of technologies, these two technologies are related in that they both are ways to mismanage pain. As will be discussed below, the score on this factor has a different relationship with local demographic characteristics than the first two.

The last column of Table 6 shows the uniqueness of each variable, or the percent of variation in the variable that is not accounted for by the factor analysis. Several variables are not explained well by the factor model, having uniquenesses of over 75 percent: the benign prostate hyperplasia imaging rate, and three of the four invasive procedure rates: the cardiac catheterization rate post-AMI, the cholecystectomy rate for gallstones, and the hernia repair rate for inguinal hernia. The invasive treatments, in general, exhibit little correlation with each other and with the diagnostic services and pharmaceutical treatments, so there does not seem to be any sense in which some regions have a strong tendency to perform invasive treatments.

All in all, it appears that the technologies mostly correlate together by type, and only partly by quality. Cities that use diagnostic and screening services at a higher rate tend to have higher rates of both colon cancer screening (a medically higher value technology) and higher rates of multiple wasteful technologies. Cities that are strong in the second factor have higher rates of mammograms and two high-value uses of pharmaceuticals but also have higher rates of antibiotic treatment for acute bronchitis, a lower-value technology. The third factor is the only one to show technologies correlating together only by quality rather than type.

Table 8 further illustrates the correlations between appropriate use and overuse of medical technologies by showing the correlations between scores on the first two factors and indexes measuring good or bad quality of the health care being delivered. The scores on the factors show how health care is actually practiced and the levels of the indexes show how health care should or should not be practiced.

The indexes are the averages of z-scores of the utilization rates of the technologies identified as medically high-value or low-value in Tables 1 and 6. There are four indexes and Table 7 shows which technologies are included in each index.

Table 7 Medical technologies included in quality indexes	
Index	**Technologies included**
Appropriate diagnostic and screening services use	Colon cancer screening and mammogram rates
Appropriate outpatient pharmaceutical use	Appropriate medication for asthma and rheumatoid arthritis patients
Overuse of diagnostic and screening services use	All 6 diagnostic and screening services in second panels of Tables 1 and 7
Overuse of pharmaceuticals	Opioids for migraine patients and antibiotics for acute bronchitis patients

As table 8 shows, the first two factors are positively and significantly correlated with both appropriate use and overuse of services or pharmaceuticals. The score on the diagnostic and screening service factor has a positive correlation of 58 percent with the appropriate services use index and a positive correlation of 80 percent with the diagnostic and screening service overuse index. The score on the mammogram/pharmaceutical factor has an 89 percent correlation with the appropriate pharmaceutical use index and a 59 percent correlation with the pharmaceutical overuse index.

Table 9 explores whether the tendencies to use particular types of technologies that have been uncovered by the factor analysis are also reflected in overall rates of use and spending. It shows correlations between the scores on the first two factors and spending and rates of use of services and pharmaceuticals per enrollee. Services are divided into inpatient and outpatient services, and outpatient services are further divided into five exhaustive categories: non-imaging diagnostic services, therapeutic services and procedures, medical visits, lower-technology imaging (X-ray and ultrasound) services, and higher-technology imaging (computed tomography [CT], magnetic resonance imaging [MRI], and positron emission tomography [PET]).[3] Pharmaceutical use is measured by days' supply per enrollee and both utilization of all pharmaceuticals and utilization of the top six therapeutic classes of pharmaceuticals (which account for about 36 percent of all pharmaceutical utilization) by class are shown.

As the table shows, the score on the diagnostic and services factor is strongly associated with higher use of all categories of services. The correlations with therapeutic services and low-

[3] The services were classified by manually classifying the Clinical Classification Software procedure codes (https://www.hcup-us.ahrq.gov/toolssoftware/ccs_svcsproc/ccssvcproc.jsp), a system that puts the 14,000 CPT codes into about 200 procedure categories. A list of how each CCS code was classified is available upon request.

Table 8
Correlations among scores on factors and quality indexes

	Appropriate outpatient services use index	Appropriate outpatient pharmaceutical use index	Overuse of outpatient services index	Overuse of outpatient pharmaceuticals index
Factor 1: Diagnostic and screening services	0.58***	-0.08*	0.80***	-0.19***
Factor 2: Pharmaceuticals and mammograms	0.52***	0.89***	-0.32***	0.59***

Significance level of correlations: * = .05, ** = .01, *** = .001.
Note: Correlations are weighted by MSA population.

Table 9
Correlations between scores on first two factors and overall spending and utilization

	Factor 1: Diagnostic and screening services	Factor 2: Pharmaceuticals and mammograms
Total spending per enrollee	0.13***	-0.01
Inpatient spending per enrollee	-0.10**	-0.24***
Outpatient services		
Spending per enrollee	0.06	0.03
Services per enrollee:		
All services	0.64***	-0.30***
Non-imaging diagnostic services	0.76***	-0.45***
Therapeutic services	0.30***	-0.06
Medical visits	0.66***	-0.27***
Low-technology imaging (X-ray and ultrasound)	0.14***	-0.26***
High-technology imaging (CT, MRI and PET)	0.62***	-0.43***
Price index	-0.30***	0.15***
Pharmaceuticals		
Spending per enrollee	0.38***	0.17***
Days' supply per enrollee of:		
All pharmaceuticals	0.08*	0.36***
Statins	0.28***	0.32***
Antidepressants	-0.12***	0.67***
ACE inhibitors	-0.08*	0.49***
Misc gastrointestinal drugs	-0.11***	0.23***
Beta blockers	-0.11***	0.19***
Contraceptives	0.31***	0.48***
Price index	0.15***	0.18***

Significance level of correlations: * = .05, ** = .01, *** = .001. Correlations are weighted by MarketScan population.

technology imaging services per enrollee are somewhat lower than with the other categories but all correlations with service use rates are positive and significant. The natural conclusion to draw is therefore that the tendency to use diagnostic and screening services that was uncovered by the factor analysis of a few selected services is widespread across different kinds of services for different medical conditions.

It does not appear, however, that the tendency to use diagnostic and screening services more necessarily induces higher spending on outpatient services, however, since the correlation between the score on the diagnostic and screening services factor and spending per enrollee on outpatient services is insignificantly different from zero. The last row in the outpatient services panel of Table 9 shows the reason why there is no relationship between utilization and spending: the correlation between the score on the diagnostic and screening services factor and a service price index is significantly negative.[4] In other words, cities that use services more also spend less per service, resulting in a net effect of zero of utility of higher services on spending per enrollee on services. This inverse relationship between utilization and prices among the privately insured has been noted elsewhere (Baker et al. 2003, Dunn et al. 2013, Dunn 2015).

The score on the diagnostic and services factor is also positively correlated with pharmaceutical spending, although the correlation with overall utilization is somewhat lower and some of the correlations with the utilization of individual therapeutic classes are significantly negative. It is also positively correlated with the pharmaceutical price index.[5] The score on the diagnostic and services factor has a slight negative correlation with inpatient spending and, on net, has a slight positive correlation with total spending. As the above discussion shows, however, this correlation results from its positive correlation with pharmaceutical prices (the cause of which is unclear), not from any relationship with spending on or utilization of outpatient services.

The second factor, the factor with high loadings on mammograms and three uses of pharmaceuticals, appears to be negatively related to most categories of services use but positively related to pharmaceutical use, pharmaceutical prices, and pharmaceutical spending. Nearly all of the correlations with rates of service use are significantly negative and all of the

[4] The service price index is calculated as a Laspeyres index across all services (as identified by Common Procedural Terminology [CPT] codes) with local prices and using national quantities as weights.

[5] The pharmaceutical price index is also calculated as a Laspeyres index across all formulations of prescription drugs (as identified by National Drug Code [NDC]) with local prices and using national quantities as weights.

correlations with pharmaceutical use are significantly positive. Again, however, there is no relationship between the score on the factor and spending on outpatient services because the score on this factor is also associated with higher outpatient service prices. It also has a significantly negative relationship with inpatient spending and the net effect is that there is no relationship between the score on this factor and total spending. The third factor (whose results are not shown) has no significant correlation in either direction with total spending.

The conclusion to draw from Table 9 therefore is that some regions have a propensity for using services and use all categories of them at a higher rate while different regions have a propensity for using pharmaceuticals and use all categories of them at a higher rate. The regions that use more services use both more wasteful services and more valuable services. However, the effect of higher service use on spending on services is effectively zero because of the inverse relationship between service use and service prices. Likewise, the regions that use more pharmaceuticals seem to use both more wasteful pharmaceuticals, such as antibiotics for bronchitis, and more valuable pharmaceuticals. These regions, however, have significantly higher pharmaceutical spending, due to both higher utilization and higher prices.

5. Correlates of technology utilization

As discussed in the introduction, Skinner and Staiger (2007) found an association between the dates and rates of adoption of several productive technologies, both medical and non-medical, and local levels of such demographic variables as income, education, and social capital. The focus of this section is what demographics and characteristics of local health-care markets such as the levels of provider supply seem to relate to the factors identified by the factor analysis. To explore this question, I show how the scores on the factors vary with important demographic variables such as education rates, social capital, and income. I also show how the scores on factors vary regionally.

Table 10 gives summary statistics for the demographic and provider supply variables and shows the ultimate source of the data for each variable. The demographic variables included in the regressions are listed in the top panel of Table 10. All of the demographic variables except for social capital are from the American Community Survey 2006-2010 5-year estimates and are

Table 10
Demographic and market characteristics
Summary statistics

Demographics	**Mean**	**Standard deviation**	**25th percentile**	**75th percentile**	**Source**
High school graduation rate	85.7%	4.7%	83.5%	88.6%	ACS 2006-2010 5-year estimates
College graduation rate	28.5%	7.7%	23.5%	33.8%	ACS 2006-2010 5-year estimates
Putnam social capital index	-0.273	0.513	-0.550	-0.080	www.bowlingalone.com
MarketScan adult population	67,944	215,302	9,445	43,976	ACS 2006-2010 5-year estimates
Population density (1000 per square mile)	0.634	0.678	0.167	0.781	ACS 2006-2010 5-year estimates
Median household income	$53,185	$10,052	$46,430	$59,876	ACS 2006-2010 5-year estimates
Health-care market characteristics					
Doctors per 10,000 population	27.41	11.35	20.98	32.60	AMA Physician Master File via AHRF (2005, 2010)
Ratio of specialists to generalists	3.63	2.56	2.17	4.23	AMA Physician Master File via AHRF (2005, 2010)
Licensed pharmacists per 1,000 population	0.99	0.27	0.86	1.11	State licensing boards via AHRF (2009)
Hospitals per 10,000 population	0.19	0.11	0.12	0.21	AHA via AHRF (2006-2010)
Hospital beds per 1,000 population	3.28	1.42	2.45	3.73	AHA via AHRF (2006-2010)
Percent of physicians who are primarily engaged in training, teaching or research	13.0%	7.6%	5.8%	19.2%	AMA Physician Master File via AHRF (2006-2008, 2010)

Notes: Statistics are weighted by MSA population. N=870 except for the Putnam social capital index for which N=867 (Hawaii and Alaska are dropped) and licensed pharmacists for which N=847 (Alabama is dropped). AHRF=Area Health Resource File. ACS=American Community Survey. AMA=American Medical Association. AHA=American Hospital Association.

measured at the MSA level. The provider supply variables come from different sources via the Area Health Resource File.

As social capital is not a concept commonly used in the economics literature, I will give a brief background here. Putnam (2000), from where I draw the index used to measure social capital in this paper, defines social capital as the value of social networks and their associated trust, reciprocity, and cooperation. This work emerged from his earlier study of Italian regional governments (Putnam et al. 1994) where he and his coauthors found that the governments operated more efficiently in areas where there were higher levels of trust among strangers and a higher level of participation in associations. Halpern (2005) reviews the concept of social capital and its relationship with other variables such as economic performance, government efficiency, educational attainment, and health outcomes. The consensus of the various research literatures is that social capital has positive relationships with all of these. Halpern also cites an empirical example of social capital positively influencing the adoption of a productive technology (Isham 2002).

Putnam’s index is based on a collection of variables measuring civic participation and levels of trust among individuals. Some of the variables are responses to questions from three different surveys about people’s lifestyles: the Roper Social and Political Trends survey, the DDB Life Style survey, and the General Social Survey (GSS). The questions generally relate to the number of times the survey respondent participated in community activities outside the home, socialized with non-family members, and how honest or trustworthy the survey respondent thinks most people are. The index also includes measures of nonprofit organizations per capita and the average voter turnout in the presidential elections of 1988 and 1992. Most of the measured variables date from the 1980s and 1990s.

The index is measured at the state level and only for the lower 48 states. To convert the variable to MSA level, I assigned each state's level to its counties and then took the average over the counties within each MSA, weighting by the counties' population. For the MSA containing the District of Columbia (for which there is no social capital index), I took the weighted average of the other counties within the MSA which are within the states of Virginia, Maryland, and West Virginia. The regressions using the social capital index drop MSAs in the states of Hawaii and Alaska since those states do not have social capital indexes.

A vector of health-care market characteristics describing provider supply per capita is also included. The variables are listed in the second panels of Table 10. The numerators of the per 10,000 population and percent variables and the ratio of specialists to generalists are taken from the Area Health Resource File (AHRF) where they are measured annually at the county level; I aggregated them to the MSA level and averaged them across years. The number of licensed pharmacists in each county was also taken from the AHRF and aggregated to the MSA level but as it was only reported for the year 2009, I simply use that number as a proxy for the 2006-2010 average. This variable is missing data for the state of Alabama, so MSAs located in Alabama are dropped from the statistics involving this variable. The population estimates for the denominators are the Census Bureau's intercensal population estimates which are available annually. I calculated the per capita variables for each year and took the averages over what years were available.

Table 11 shows how the means of the demographic variables vary by quartile of the scores on the three medical technology utilization factors and table 12 shows the same for the means of the provider supply variables. Table 13 shows how the scores of the factors distribute across economic regions as defined by the Bureau of Economic Analysis. Table 13 is illustrated graphically by Figure 1.

The first factor, which represents higher use of diagnostic and screening services, is associated with higher levels of college education, income, and population density, more physicians per capita, a higher ratio of specialists to generalists and a higher percent of physicians involved in academic medicine (being trained or teaching or doing research). It is also associated with lower levels of social capital and fewer hospitals and hospital beds per capita. New England has the highest scores in the first factor on average by far and the Plains and Rocky Mountain regions have the lowest.

The second factor, which represents higher use of mammograms and three of the four pharmaceutical technologies (two high-quality, one of low quality), is associated with higher education (both high school and college), higher income, higher social capital, and more physicians and pharmacists per capita. It is also associated with lower population density and fewer hospitals and hospital beds per capita. New England and the Plains regions have the highest scores in this factor on average and the Mideast region has the lowest.

Table 11
Variation of means of demographic variables by quartiles of scores on technology utilization factors

	Factor 1: Diagnostic and screening services	**Factor 2: Pharmaceuticals and mammograms**	**Factor 3: Mismanagement of pain**
High school graduation rate: Mean for 1st quartile of score on factor	84.9%	83.6%	87.3%
Mean for 2nd quartile of score on factor	87.0%	84.6%	87.2%
Mean for 3rd quartile of score on factor	85.0%	86.2%	83.8%*
Mean for 4th quartile of score on factor	85.9%	88.4%*	84.7%
College graduation rate: Mean for 1st quartile of score on factor	22.5%	25.1%	31.9%
Mean for 2nd quartile of score on factor	28.9%*	30.0%*	30.8%*
Mean for 3rd quartile of score on factor	28.9%	28.3%	26.9%*
Mean for 4th quartile of score on factor	33.6%*	30.8%*	24.3%*
Putnam social capital index: Mean for 1st quartile of score on factor	-0.050	-0.459	0.100
Mean for 2nd quartile of score on factor	-0.244*	-0.335*	-0.115*
Mean for 3rd quartile of score on factor	-0.295	-0.363	-0.420*
Mean for 4th quartile of score on factor	-0.499*	0.065*	-0.656*
Population density (1000 per square mile): Mean for 1st quartile of score on factor	181.9	762.5	1062
Mean for 2nd quartile of score on factor	593.0*	955	682.7*
Mean for 3rd quartile of score on factor	729.7	495.9*	406.2*
Mean for 4th quartile of score on factor	1024.3	381.0*	386.7
Median household income: Mean for 1st quartile of score on factor	$46,673	$50,011	$57,330
Mean for 2nd quartile of score on factor	$52,396*	$56,419*	$58,018
Mean for 3rd quartile of score on factor	$53,567	$52,813*	$50,558*
Mean for 4th quartile of score on factor	$60,017*	$54,049	$46,811*

Statistics are weighted by MarketScan population. *=mean is significantly different from quartile below at at least the 5% level.

Table 12
Variation of means of provider supply variables with quartiles of scores on technology utilization factors

	Factor 1: Diagnostic and screening services	Factor 2: Pharmaceuticals and mammograms	Factor 3: Mismanagement of pain
Physicians per 10,000 population: Mean for 1st quartile of score on factor	20.0	26.5	32.3
Mean for 2nd quartile of score on factor	29.5*	28.0	29.7
Mean for 3rd quartile of score on factor	27.7	25.9	24.0*
Mean for 4th quartile of score on factor	32.3*	29.4*	23.6
Ratio of specialists to generalists: Mean for 1st quartile of score on factor	1.79	4.37	4.61
Mean for 2nd quartile of score on factor	3.51*	3.59	4.11
Mean for 3rd quartile of score on factor	3.23	3.34	2.86*
Mean for 4th quartile of score on factor	5.98*	3.25	2.96
Hospitals per 10,000 population: Mean for 1st quartile of score on factor	0.26	0.21	0.17
Mean for 2nd quartile of score on factor	0.19*	0.16*	0.16
Mean for 3rd quartile of score on factor	0.16	0.19	0.20*
Mean for 4th quartile of score on factor	0.14	0.19	0.22
Hospital beds per 1,000 population: Mean for 1st quartile of score on factor	3.48	3.69	3.27
Mean for 2nd quartile of score on factor	3.49	3.05*	3.07
Mean for 3rd quartile of score on factor	3.04*	3.21	3.12
Mean for 4th quartile of score on factor	3.1	3.14	3.66*
Pharmacists per 1,000 population: Mean for 1st quartile of score on factor	0.85	0.98	1.07
Mean for 2nd quartile of score on factor	1.10*	0.98	0.96*
Mean for 3rd quartile of score on factor	1.00*	0.96	0.95
Mean for 4th quartile of score on factor	1.01	1.06*	1.00
Percent of physicans primarily engaged in teaching or research: Mean for 1st quartile of score on factoı	7.0%	12.5%	14.0%
Mean for 2nd quartile of score on factor	15.3%*	14.7%*	14.6%
Mean for 3rd quartile of score on factor	14.2%	13.1%	12.6%
Mean for 4th quartile of score on factor	15.1%	11.9%	10.8%

Statistics are weighted by MarketScan population. *=mean is significantly different from quartile below at at least the 5% level.

Table 13
Regional distribution of scores on factors

BEA region	Factor 1: Diagnostic and screening services			Factor 2: Pharmaceuticals and mammograms			Factor 3: Mismanagement of pain		
	Mean	95% confidence interval		Mean	95% confidence interval		Mean	95% confidence interval	
New England (CT, ME, MA, NH, RI, VT)	1.52	[1.07	1.97]	0.872	[0.685	1.06]	-0.698	[-0.886	-0.510]
Mideast (DE, DC, MD, NJ, NY, PA)	0.45	[0.242	0.658]	-0.793	[-1.02	-0.564]	-0.703	[-0.793	-0.613]
Great Lakes (IL, IN, MI, OH, WI)	-0.436	[-0.533	-0.339]	0.236	[0.143	0.329]	0.006	[-0.082	0.094]
Plains (IA, KS, MN, MO, NE, ND, SD)	-0.835	[-0.937	-0.733]	0.819	[0.692	0.946]	-0.544	[-0.677	-0.412]
Southeast (AL, AR, FL, GA, KY, LA, MS, NC, SC, TN, VA, WV)	0.243	[0.146	0.339]	0.065	[-0.027	0.157]	0.77	[0.702	0.838]
Southwest (AZ, NM, OK, TX)	0.044	[-0.102	0.189]	-0.291	[-0.420	-0.162]	0.382	[0.300	0.465]
Rocky Mountain (CO, ID, MT, UT, WY)	-0.749	[-0.986	-0.512]	0.718	[0.550	0.887]	-0.367	[-0.529	-0.206]
Far West (AK, CA, HI, NV, OR, WA)	-0.318	[-0.412	-0.223]	0.034	[-0.125	0.192]	-0.59	[-0.688	-0.492]

Statistics are weighted by MarketScan population.

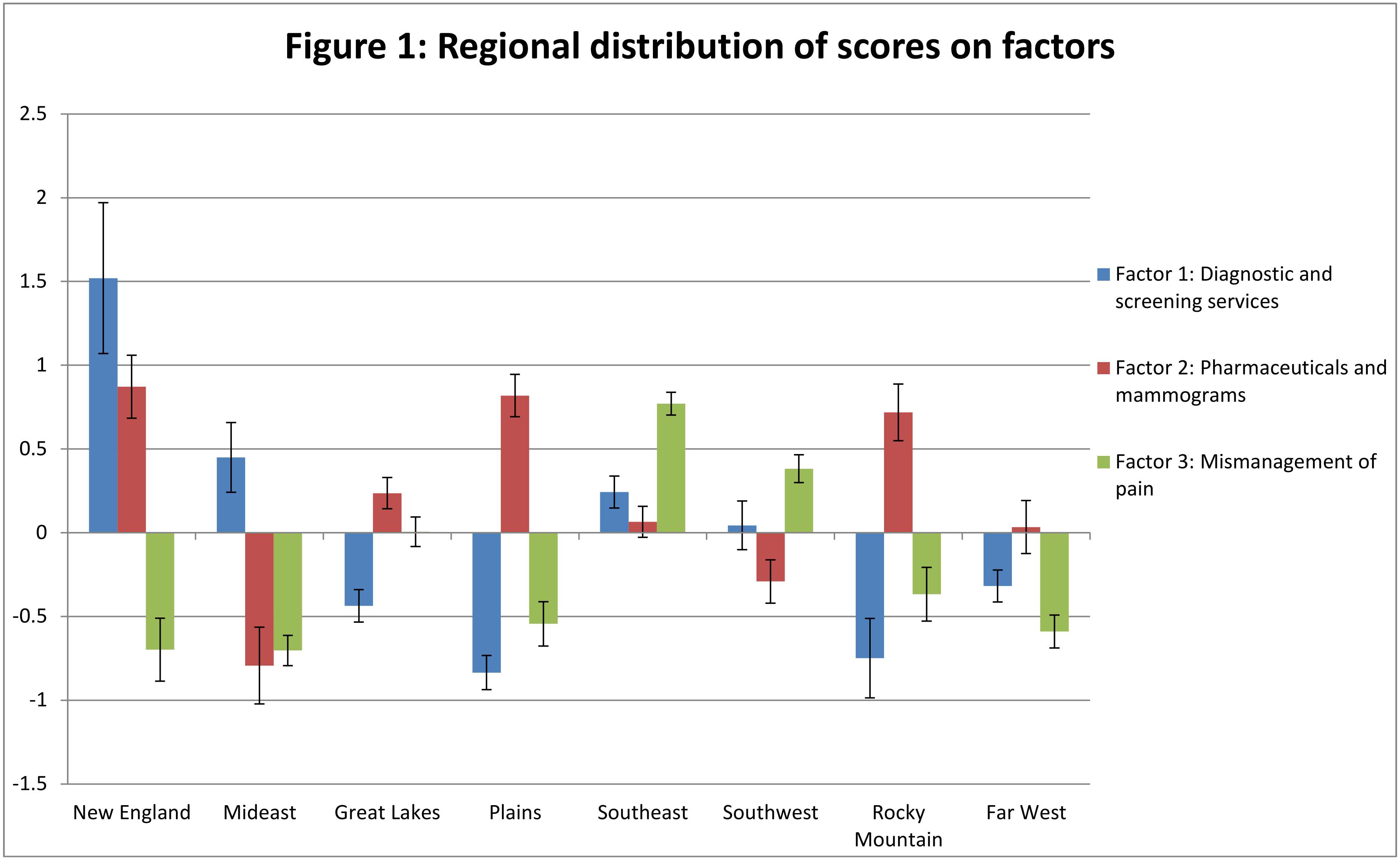
Figure 1: Regional distribution of scores on factors
2.5
2
1.5
1
0.5
0
-0.5
-1
-1.5
New England
Mideast
Great Lakes
Plains
Southeast
Southwest
Rocky Mountain
Far West
Factor 1: Diagnostic and screening services
Factor 2: Pharmaceuticals and mammograms
Factor 3: Mismanagement of pain

The third factor, which represents the use of two low-quality technologies that mismanage pain (imaging for back pain and opioids for migraines), is associated with lower education (both high school and college), lower social capital, lower income, lower population density, a lower supply of physicians, a lower ratio of specialists to generalists, a lower percent of physicians involved in academic medicine, and more hospitals and hospital beds per capita. The Southeast region has the highest scores in this factor on average by far and the two northeasternmost regions (New England and Mideast) have the lowest.

Taken together, these results suggest that demographics like education, social capital, income, and population density affect medical technology utilization in a complex way. Higher population density, higher income, and higher college education are connected to the increased use of many services, both valuable and wasteful, yet they have a negative relationship with the use of imaging for back pain. Higher education, income and social capital seem to raise the selectivity of technology utilization but none of them reduces all wasteful technologies or raises all valuable technologies, and they influence health-care quality in different ways. Higher high-school education and income are associated with the higher use of mammograms and two high-value uses of pharmaceuticals and also reduce the use of the two low-value technologies associated with the mismanagement of pain but are also associated with the increased use of wasteful antibiotics for acute bronchitis. Higher college education and income are associated with the higher use of several low-value services but also with the higher use of colon cancer screening and the lower use of the two low-value technologies associated with the mismanagement of pain. Higher social capital meanwhile is associated with the lower use of all wasteful services and lower rates of the technologies that mismanage pain but also with lower rates of colon cancer screening and higher rates of antibiotics for acute bronchitis.

The two technologies associated with the mismanagement of pain have different relationships to the demographic and provider supply variables than the other wasteful technologies, which probably relates to why they were revealed in a different factor than the other technologies in the factor analysis. While the other technologies, services in particular, are generally associated with higher levels of provider supply, the score on the third factor correlates with lower numbers of physicians per capita, a lower ratio of specialists to generalists, and fewer pharmacists per capita. Similarly, while higher pharmaceutical use is generally associated with a higher level of high-school education, the greater use of opioids to treat migraines is correlated with a lower level of high-school education. More notably, a higher score on the third factor, unlike the other two factors, is associated with a number of lower social indicators across the board: lower education, lower social capital and lower income. It is unclear why higher rates of college education and income seem to raise the use of some wasteful technologies such as Vitamin D screening or cardiac screening but lower the use of others like back pain imaging and opioids for migraines. It may be that education makes the adoption of technology easier (as Skinner and Staiger [2007] suggest) but that the latter technologies have been in use for longer and knowledge of their lack of effectiveness is more widespread among the more educated. In other words, education makes it easier to both adopt and de-adopt technologies more quickly. An alternative explanation is that the negative medical effects of back pain imaging and opioid use are greater than the effects of other wasteful services and the educated are more aware of the magnitude of those effects. An analysis over time would help separate those explanations.

In summary, therefore, demographics seem to correlate with and influence health-care utilization although the exact mechanism by which they do so is impossible to establish with the data here. Education has been shown in previous work to affect health-care technology utilization at an individual level, however (Lichtenberg and Lleras-Muney 2006, Lleras-Muney and Glied 2008). The result of the effects of the different combinations of demographics formed across the US is very different health-care experiences for patients, as summarized in Table 13 and Figure 1. New England, which has the highest levels of income, college education, and physician supply, has relatively high rates of utilization of both services and pharmaceuticals (both appropriate and inappropriate) yet has one of the lowest average scores on the factor relating to the mismanagement of pain. The Mideast region, with the highest population density and relatively high levels of physician supply, has higher use of services (excluding mammograms but both appropriate and inappropriate) but lower rates of mammograms and of pharmaceutical use. The middle northern regions (Great Lakes, Plains and Rocky Mountain), with the highest levels of social capital and high-school graduation rates and relatively low levels of population density, have higher rates of mammograms and pharmaceutical use (both appropriate and inappropriate) but lower rates of service use excluding mammograms (both appropriate and inappropriate). The southern regions (Southeast and Southwest), with the lowest levels of income, college education, and social capital, have medium scores in the first two factors but have the highest rates of the mismanagement of pain. Finally, the Far West region, which generally has the lowest levels of provider (physician, hospital and pharmacist) supply, has relatively low rates of all categories of health-care use.

6. Conclusion

I have conducted a factor analysis of the regional rates of use of sixteen health-care technologies of differing type and quality by privately insured adults across 870 MSAs in the years 2006 to 2010 to assess how medical technologies correlate. The analysis finds three factors underlying the use of the sixteen technologies:

1. The first relates to the use of diagnostic and screening services other than mammograms and loads on both a high-value service (colon cancer screening) and several low-value services.
2. The second relates to the use of mammograms for screening breast cancer and three pharmaceutical technologies, two of which are of higher value (appropriate medication for asthma and for rheumatoid arthritis) and one of which is low value (the use of antibiotics to treat acute bronchitis).
3. The third relates to two technologies that are of different types but which have both been identified as low-value ways for managing pain: the use of imaging to try to diagnose the causes of low back pain and the use of opioids to treat migraines.

Five technologies exhibit high uniqueness and are not explained well by the factor analysis, being uncorrelated with each other or any other of the technologies. These are the imaging of the upper urinary tract for patients with benign prostate hyperplasia and the four invasive technologies: cardiac catheterization after a heart attack (AMI), cholecystectomy for gallstones, joint replacement for osteoarthritis, and hernia repair for inguinal hernia.

Technologies therefore seem to correlate together by type more than by quality. This propensity to use similar technologies leads to a problem in health care since technologies that are similar in type are not necessarily similar in their effects on health outcomes. I illustrate this point by constructing quality indexes from the data and then showing how they correlate with the scores on the factors. Regions that use more diagnostic and screening services tend to use both more of services that are appropriate (such as colon cancer screening) and more wasteful services, and regions that use more pharmaceuticals use more pharmaceuticals both when they are appropriate and when they are not. I also show that the first two factors correspond to higher utilization of all categories of services (for the first factor) and of all major classes of pharmaceuticals (for the second factor) so the factors appear to correspond to tendencies in utilization that show up across all outpatient health care. These correlations may partly explain therefore why we see so little connection between aggregate health-care utilization and health outcomes in the US health-care system; regions with higher utilization have more wasteful utilization that does not contribute to (or subtracts from) health outcomes, while regions with lower utilization have lower rates of the valuable utilization that improves health outcomes.

In the last section of the paper I examine the correlations of these factors with demographics and provider supply. The results show that there is a complex relationship between such variables as income, education, social capital, population density and physician supply, and health-care technology utilization. Income, college education, provider supply and population density are correlated with the higher use of the diagnostic and screening services in the first factor while higher social capital seems to discourage their use. Levels of education (both high-school and college), income, physician supply, and social capital are positively associated with the second factor while population density has an inverse relationship with it. A higher score on the third factor meanwhile is associated with three negative social welfare indicators: lower income, lower education, and lower social capital, and also with lower levels of physician supply. Education, income, and provider supply therefore appear to induce higher levels of health-care utilization generally, while population density raises service use (other than mammograms) and lowers mammogram rates and pharmaceutical use and social capital has the opposite effects. The two technologies that the third factor loads on are exceptions to these effects as they have negative relationships with education, income, social capital, population density, and provider supply. It is unclear why they pattern differently; possibly they are medically worse than the low-value technologies in the first two factors.

The results in the last section show that patient demand (as affected by income, education, social capital, and population density) and provider supply have influences on the variation in utilization. A further potential contributing factor that is impossible to test for is the tendency of both physicians and patients to adopt more quickly and use technologies that are similar to ones they already use because those technologies have benefits that are easier to understand and because they are easier to learn. Rogers (2003) terms this "trialability" or "compatibility." The first factor, it should be noted, encompasses several different modalities (blood tests and different types of imaging) so the similarity here would be one of physician and patient knowledge of the tests and beliefs about the importance of finding problems and treating them versus watching and waiting. The physician preferences may derive from both the patient's welfare and the physician's income being positively weighted in the physician's utility function, as developed by Chandra and Skinner (2012) and Skinner (2012). Compatibility would also explain why three pharmaceutical technologies are correlated as captured by the second factor but it would not explain why the second factor also loads on the mammogram rate and the first factor does not. It could also explain why two technologies of different types correlate together as shown by the third factor; it may reflect correlating incorrect beliefs on how to manage pain. Compatibility may play a role in the correlations in the three factors but it is clear that patient demographics influencing demand and the levels of provider supply are also important.

As summarized in Table 13, the combination of influences from patient demand, provider supply, and technological compatibility lead to different health-care utilization levels and quality for patients at the regional level: patients in the New England region receive high levels of services and pharmaceuticals both appropriate and inappropriate but are less likely to have their back pain or migraines mismanaged, patients in the Southeast and Southwest regions receive the reverse care, and patients in the Far West region use relatively low levels of all health-care technologies.

These results have potential ramifications for health-care policy going forward. First, they suggest that simply cutting payments across categories of services and pharmaceuticals will do little to improve the productivity or quality of health care. Providers will likely reduce appropriate and inappropriate uses of services or drugs at the same rate. Rather, they offer more support for approaches that address quality directly and tie reimbursement to it more explicitly, as described in Cutler (2014). Rewarding treatments for which the evidence is positive and penalizing treatments for which the evidence is absent or negative would help overcome the correlations in demand and preferences that lead to the patterns observed here.

This paper was by nature exploratory and does not offer a fully characterized model of health-care treatment choices. Going forward, it suggests some avenues for further research in this area. First, do treatments pattern in the same way in the Medicare system? If they do, does that patterning help explain the lack of relationship between spending and outcomes observed by

Fisher et al. (2003a, b)? A second issue is how these patterns shift over time. There is further the question of whether low-value technologies are deadopted more quickly in more educated areas and whether that would explain why the low-value technologies in the third factor (back pain imaging and opioids for migraines) pattern differently from the other low-value technologies considered here. Finally, if more detailed regional data that ties individual health-care utilization with individual demographics becomes available, the relationships between technology utilization patterns and demographics such as income and education could be explored more fully.

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