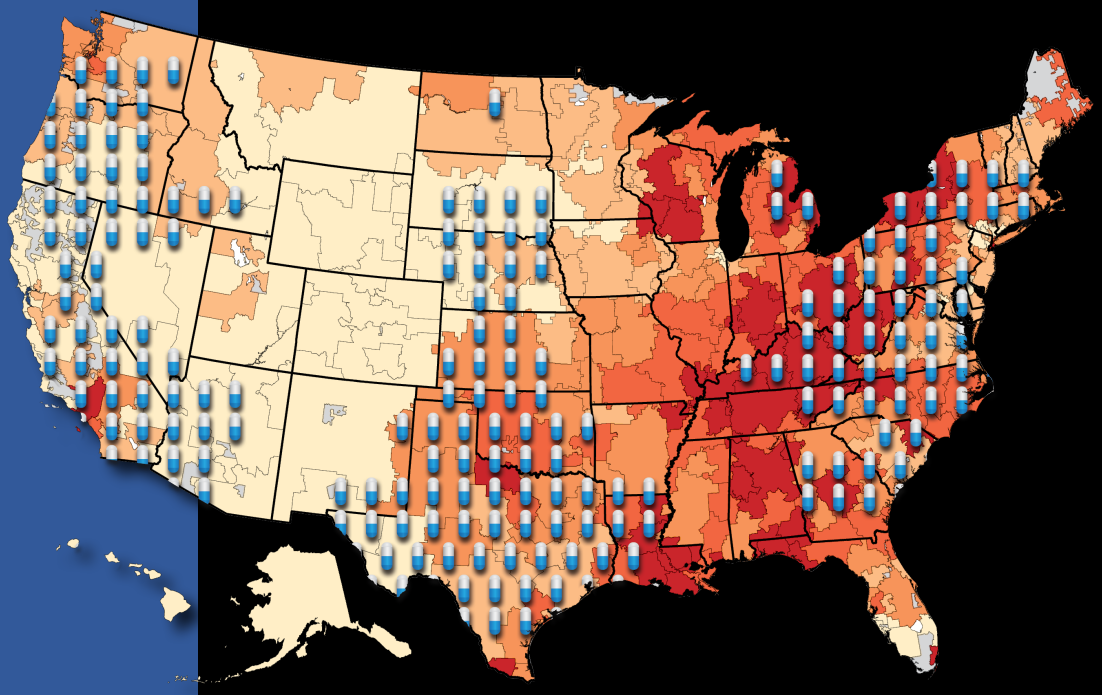
# The Dartmouth Atlas of Medicare Prescription Drug Use

*A Report of the Dartmouth Atlas Project*



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# The Dartmouth Atlas of Medicare Prescription Drug Use

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# The Dartmouth Atlas of Medicare Prescription Drug Use

## Introduction

Prescription drugs are a key and growing component of health care. Many currently available drugs have the potential to reduce the burden of illness or improve quality of life for patients with a wide spectrum of diseases. At the same time, all prescription drugs have the potential for adverse effects, including interactions with other drugs. One goal of prescription drug therapy, and, by extension, a goal of prescription drug insurance programs, is to make the benefits of drug technology widely available while minimizing the use of medications that may be unnecessary, unwanted, or harmful.

The importance of prescription drugs to the health of the elderly motivated the development of the Medicare Part D prescription drug program as part of the Medicare Modernization Act of 2003. The primary goal of this program is to ensure that Medicare beneficiaries will not forego necessary prescription drugs because they cannot afford them. Part D plans have been widely embraced by beneficiaries since the program was implemented in 2006; in 2012, 37 million Americans were enrolled in a Part D plan.[1] Prescription drugs currently account for 11% of annual Medicare spending, or approximately 60 billion dollars; they are expected to comprise almost 20% of the total Medicare budget by 2020.[1]

Little is known about patterns of prescription drug use among beneficiaries enrolled in Part D, or how drug technology interacts with other services covered by Medicare. While the presence of variation in prescription drug use is likely to be similar to that observed in other types of medical care (and reported in prior Dartmouth Atlas of Health Care reports), differences in the design of the Part D benefit and the diverse roles of prescription drugs in health care may lead to differences in the patterns of drug use variation compared to services covered under Medicare Parts A (acute care in health care facilities such as hospitals) and B (professional services such as physician visits and procedures). Some prescription drugs have the potential to reduce the use of other Medicare services such as hospitalizations and even surgery. Optimal use of these drugs could result in lower use of services covered under Parts A and B. In other cases, higher prescription drug use may arise from higher use of non-prescription services and thus mirror variation observed in inpatient and outpatient care.

Medicare Part D is a complex benefit that differs significantly from the fee-for-service insurance provided under Medicare Parts A and B (see box, next page). Under Part D, the federal government subsidizes premiums paid to private insurance plans that compete for enrollees, and each region has several plans from

which beneficiaries may choose. Some of these plans offer the minimum coverage required by the Centers for Medicare and Medicaid Services (CMS), while others offer varying levels of protection from deductibles, co-insurance, and coverage gap payments in exchange for higher premiums. As a result, beneficiaries enrolled in different Part D plans within and across regions may pay broadly varying premiums and face significantly different out-of-pocket expenses at the time of drug purchase.

## Brief Overview of Medicare Part D

Medicare Part D shares many features of the more familiar and long-standing Medicare Parts A and B. Eligibility requirements are the same, and the program is funded by taxpayer dollars and monthly premium payments by enrollees. Similar to Part B, Part D enrollment is voluntary, beneficiaries' monthly premiums increase with income, penalties are imposed on those without alternative coverage who initially opt out but later enroll in the program, and the basic benefit design includes deductibles as well as patient cost-share responsibilities (i.e., co-insurance and co-payments).[2,3]

Unlike Medicare Parts A and B, Medicare Part D plans are designed and administered by several private insurers. These insurers compete for enrollees in exchange for a risk-adjusted monthly payment for each beneficiary they enlist. In 2013, in each of the 34 regional Part D benefit markets, companies offered roughly 30 unique plans; over 1,000 plans were offered nationally. These plans vary with regard to premiums, cost-share, deductibles, and formularies, but all must meet or exceed minimum standards of coverage established by the Centers for Medicare and Medicaid Services. Beyond this minimum standard, the individual insurers determine the details of their plan offerings. This flexibility allows beneficiaries to choose the plan that best suits their finances and prescription drug needs. A consequence of the premium-subsidized, capitated program model is that high-volume or high-cost prescription drug use by patients does not directly translate to increased taxpayer spending in the near term, but instead will be reflected in future premiums paid by taxpayers and beneficiaries.[1]

Medicare Part D includes a low-income subsidy for beneficiaries who meet income eligibility criteria. The subsidy substantially reduces deductibles, prescription cost-share, and premiums. Beneficiaries at or below 150% of the federal poverty level may apply for and receive a subsidy, which varies according to individual income.

Part D plans vary in how they manage prescription drug utilization beyond the incentives that result from beneficiary cost-share responsibilities. For example, plans may require prior authorization before specific drugs can be dispensed; they may use tiered co-payments for different drugs; or they may implement step-therapy protocols that require a trial of one medication or drug class before a different, more expensive drug can be used. Individual plans often employ these benefit design features in diverse combinations and may use different designs for specific drugs and drug classes. The result of this flexibility is that a broad range of prescription plans and plan formularies may be offered in each region. At the same time, some of the largest plans are available nationwide. This means that patients within a single region may have very different prescription drug benefits under Part D, while other patients separated by large geographic distances may have nearly identical benefits.

The structure of the different Medicare insurance "Parts" likely affects patterns of utilization across the spectrum of medical services. Fee-for-service Medicare Parts A and B provide uniform coverage and price structure for services across regions; thus, regional differences in spending are largely due to variation in the volume of services delivered. In contrast, the variety of prescription drug plans available within and across regions introduces the potential for greater diversity in practice and spending. At the same time, Part D plans offer physicians no direct incentive to prescribe. Plans often provide incentives for patients to be cost-conscious consumers, but they do not reward physicians monetarily for prescribing decisions. This is in sharp distinction to the fee-for-service model that pays the treating physician directly for providing a service. The effect of these different incentive models on care utilization is difficult to predict.

In this report, the Dartmouth Atlas of Health Care framework and methods are applied to the study of prescription drugs in Medicare Part D. As the population ages and prescription drugs take on an increasing role in health and health care, a detailed evaluation of how drugs are used in Part D is needed to understand the quality and value of the care being delivered. This report will describe current prescribing practices, including patterns of regional variation in prescription drug use, across a spectrum of drug classes.

Previously, the Dartmouth Atlas has classified health care services according to the factors that primarily drive their provision or consumption: effective care, preference-sensitive care, and supply-sensitive care. Applying this taxonomy, the Atlas team has documented extensive regional variation in procedures and services provided under Medicare Parts A and B.[4] Building on this work, this report categorizes prescription drug use in an analogous way, by relative value or efficiency: (1) treatments that are widely believed to be *effective*, (2) treatments that may involve a high degree of prescriber or patient *discretion* due to diagnostic and therapeutic uncertainty, and (3) treatments with good evidence of potential *harm* in specific populations.

■ Effective care is supported by evidence that it reduces the risk of important clinical outcomes such as heart attacks, kidney disease, and fractures. These drugs generally have highly favorable benefit-to-risk ratios in the target populations. Ideally there would be little variation in the use of effective care.

■ Discretionary medications have less certain benefits, but may be effective in a subset of individual patients; in others, the benefits are unclear. For some patients, such drug use will involve meaningful tradeoffs involving both side effects and cost. The decision to use these drugs may depend on physician practice styles and physicians' interpretations of patient preferences. Even with shared decision-making that fully incorporates patient preferences regarding the risks and benefits of treatment, some variation in the use of these drugs is expected.

■ Potentially harmful medications are those for which the risks generally outweigh the benefits of use. These drugs may be necessary in rare cases, but should generally be avoided in patient populations where they have been shown to be potentially harmful. As with effective care, there should be very little variation in the use of these medications.

The report will then focus on prescription drug spending, including the influence of volume and drug selection on regional drug spending. The relationship of Part D spending to other Medicare spending will also be explored. While spending is not the primary focus of this report, its consideration provides an understanding of prescription expenditures as a component of the overall Medicare budget.

The role of prescription drugs in health, health care, and health spending is growing. Optimal use of prescription medications depends upon a clear understanding of how drugs are currently used and how they could be used more effectively. The information contained in this Atlas report will identify some of the factors that influence overall prescription drug use and those that affect different broad categories of drugs. This report will also identify high-performing regions that may serve as models for prescribing in the United States.

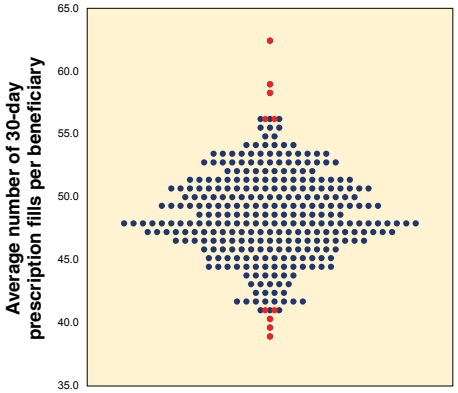
## References

1. The 2013 Annual Report of the Boards of Trustees of the Federal Hospital Insurance and Federal Supplementary Medical Insurance Trust Funds. 2013. (Accessed at http://downloads.cms.gov/files/TR2013.pdf.)

2. Part D Benefit Parameters. 2012. (Accessed September 18, 2013, at http://www.cms.gov/Outreach-and-Education/Training/CMSNationalTrainingProgram/Downloads/2013-Part-D-Benefits-Parameters-Job-Aid.pdf.)

3. Medicare 2013 costs at a glance. 2012. (Accessed September 20, 2013, at http://www.medicare.gov/your-medicare-costs/costs-at-a-glance/costs-at-glance.html - collapse-4811.)

4. The Dartmouth Atlas of Health Care. The Dartmouth Institute for Health Policy and Clinical Practice, Center for Health Policy Research, 2013. (Accessed January 4, 2013, at http://www.dartmouthatlas.org/.)




| | |
|---|---|
| Miami, FL | 62.8 |
| Lexington, KY | 59.2 |
| Huntington, WV | 58.1 |
| Alexandria, LA | 56.5 |
| Owensboro, KY | 56.5 |
| Phoenix, AZ | 41.0 |
| Boulder, CO | 40.7 |
| San Mateo County, CA | 40.6 |
| Albuquerque, NM | 39.7 |
| Grand Junction, CO | 38.6 |

**Figure 1. Overall use of prescription medications by hospital referral region (2010)**

Each blue dot represents one of 306 hospital referral regions in the U.S. Red dots indicate the five regions with the highest rates and the five with the lowest rates of overall prescription drug use.

## Does prescription use vary across regions of the United States?

Little is known about variation in prescription drug use across U.S. hospital referral regions. For twenty years the Dartmouth Atlas has demonstrated wide regional variation in health services utilization that cannot be explained by patient needs or preferences alone. This variation largely reflects regional differences in the use of medical services of uncertain benefit, rather than differences in the use of effective care. As outlined in previous Atlas publications, local health care capacity and practice style appear to drive much of this observed variation. The extent to which prescription drug use varies and mirrors the utilization patterns of non-prescription services is not known, but it warrants exploration as the use of prescription medications gains an increasingly important role in health care.

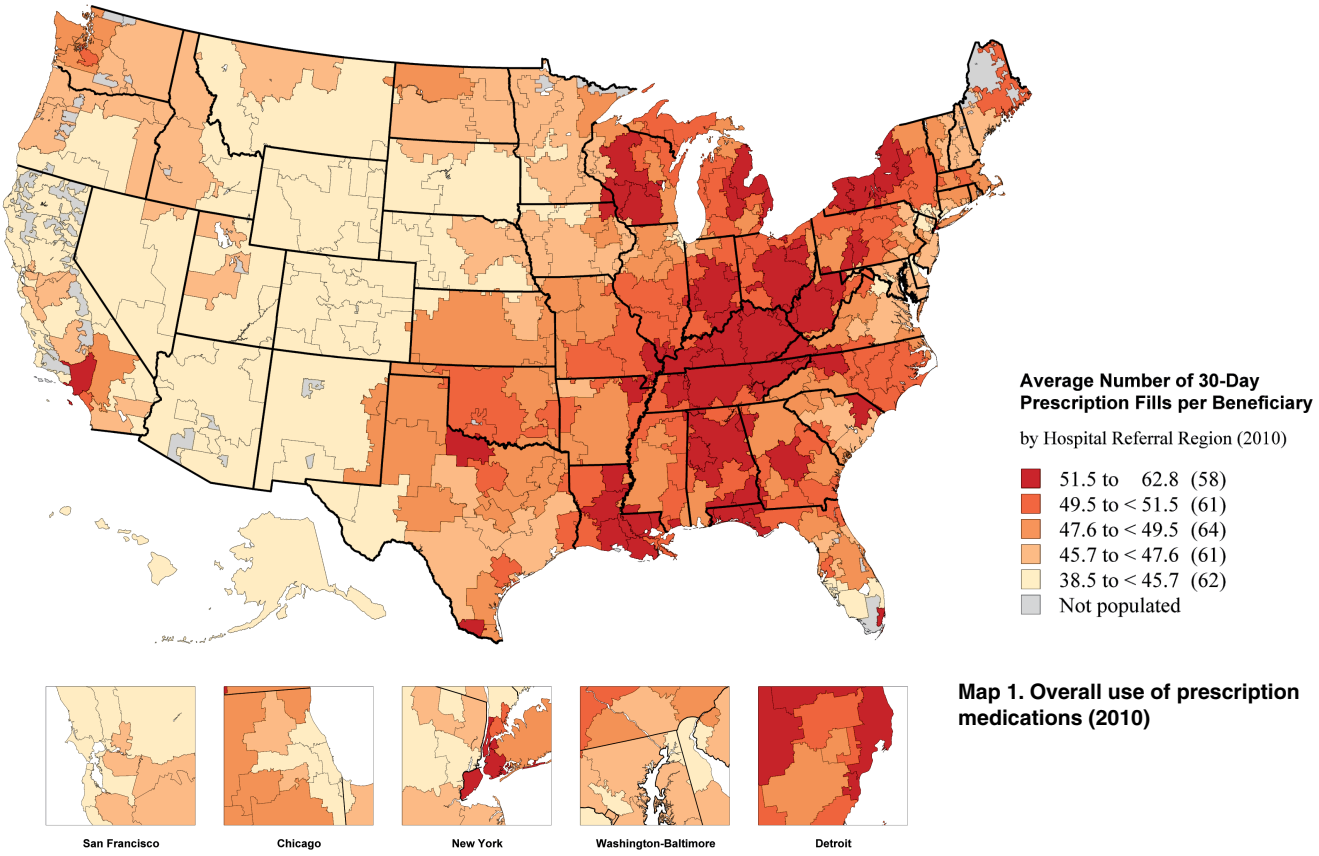
In general, total prescription drug use is high among Medicare beneficiaries enrolled in the Part D program. The average Medicare patient enrolled in Part D filled 49 standardized 30-day prescriptions in 2010; however, the number of prescriptions filled per patient across hospital referral regions varied by a factor of more than 1.6 (Figure 1). The average beneficiary in Miami, Florida filled about 63 prescriptions in 2010, while the average beneficiary in Grand Junction, Colorado filled just 39 prescriptions (Map 1).

### Medicare Part D Enrollees

The Medicare Part D program was introduced more than 40 years after the implementation of Medicare Parts A and B. As a consequence, at the time of Part D implementation, Medicare beneficiaries largely fell into one of three long-established groups defined by prescription coverage status: those with no prescription insurance, those with Medicaid prescription insurance, and those with commercial prescription insurance purchased independently or provided as an employment or retirement benefit by employers.

After the implementation of Part D, prescription coverage changed for Medicare enrollees, but not uniformly. The poorest beneficiaries, who were eligible for Medicaid, transitioned to Medicare Part D plans through an automatic enrollment process that followed a voluntary enrollment period. Those with higher incomes but no prescription drug coverage and those employed by or retired from companies not sponsoring coverage were invited to enroll in one of many Part D plans available in their region. Premium and cost-share subsidies were offered to those with incomes under 150% of the federal poverty level as an additional enrollment incentive.[1,2]

In contrast, most beneficiaries with prescription drug insurance provided as part of employment or retirement benefits retained this coverage arrangement. This was in part due to payments made to employers by the federal government to encourage continued coverage. The proportion of Medicare beneficiaries receiving prescription insurance through




**Map 1. Overall use of prescription medications (2010)**

employers has gradually diminished since the introduction of Part D, to 15% in 2012.[3]

These incentives and disincentives resulted in selective Part D enrollment. This selection is reflected in beneficiary characteristics. Compared to non-Part D enrollees, on average, Part D enrollees are older, and more likely to be female and non-Caucasian. In general, they also have higher Parts A and B expenditures and higher comorbidity scores.

**Characteristics, Morbidity Scores, and Average Medicare Spending of Older Beneficiaries Fully Enrolled in Part D vs. Those Not Enrolled in Part D**

| | Full-Year Enrollment in Medicare Part D | No Enrollment in Medicare Part D |
|---|---|---|
| Average Age | 75.4 | 74.9 |
| % Female | 64% | 52% |
| % White | 81% | 87% |
| Average RxHCC Score | 0.94 | 0.80 |
| Average Part A Spending | $4,313 | $3,006 |
| Average Part B Spending | $5,050 | $3,816 |

The differences in demographic characteristics and comorbid disease burden between Part D enrollees and non-enrollees are important to consider when examining the variations in drug use documented in this report. The enrolled population is not a random selection of Medicare beneficiaries in general, but rather a slightly sicker and poorer subset. As such, they may represent the most vulnerable beneficiaries, and thus those most in need of careful study and documentation of care intensity and quality.

In order to improve patient care and to maximize the value of Part D spending, it is critical to understand the source of this variation. If low overall prescription drug use reflects a failure to provide effective care, then reform efforts should target regions at the bottom of the total utilization ranking. On the other hand, the variation may be driven by the use of medications with uncertain benefits or by the use of prescription medications in situations where there are other reasonable treatment choices. In these instances, it is vital to establish that the decision to prescribe the drugs reflects the preferences of informed patients—expressed through shared decision-making—and is not the result of other regional and provider factors that may lead to unnecessary prescribing. Whether these differences in utilization represent differences in access to care that patients need, or the use of medications that many could or should do without, is the subject of subsequent sections of this Atlas.

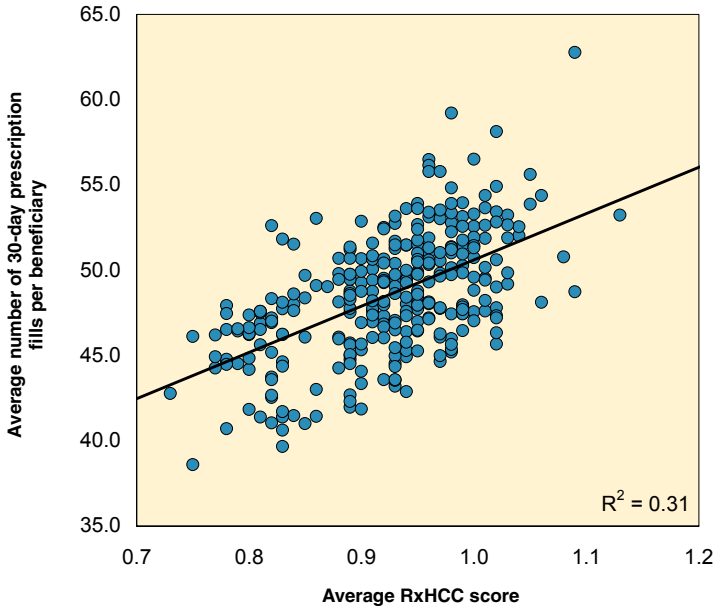



**Figure 2. Relationship between average disease severity and the number of 30-day prescription fills per beneficiary among hospital referral regions (2010)**

There was a moderate correlation between a region's average RxHCC score and the average number of prescriptions filled by Medicare beneficiaries in 2010 ($R^2$=0.31). Thirty-one percent of the variation in prescription fills was explained by disease burden as measured by the RxHCC score. For more information about the $R^2$ statistic, please see the section entitled "Utilization, variation, and association—how to interpret the measures."

## Could differences in disease burden explain variation in prescription drug use?

Many observers will assume that the regional variation in prescription drug use reflects differences in the disease burden across Medicare beneficiaries. Populations do differ with respect to health status, and, as Figure 2 shows, prescription volume in 2010 was correlated with disease burden as measured by the prescription drug hierarchical conditions category (RxHCC) score. The RxHCC score is calculated using individual age, sex, and documented co-morbid diseases, and is used by the Centers for Medicare and Medicaid Services (CMS) to predict total drug spending.

A closer look at this relationship, however, suggests that variation in disease states is not the sole, or even primary, explanation for the variation in prescribing behavior. Although disease burden, measured by the RxHCC, was correlated with the number of prescriptions filled, there was considerable overlap in prescription volume across the spectrum of RxHCC values. This is illustrated in Figure 3, which shows the number of prescription fills in each quintile of RxHCC scores. This figure also shows that there was clinically significant variation in prescription drug use within regions that had the same or similar average RxHCC values.

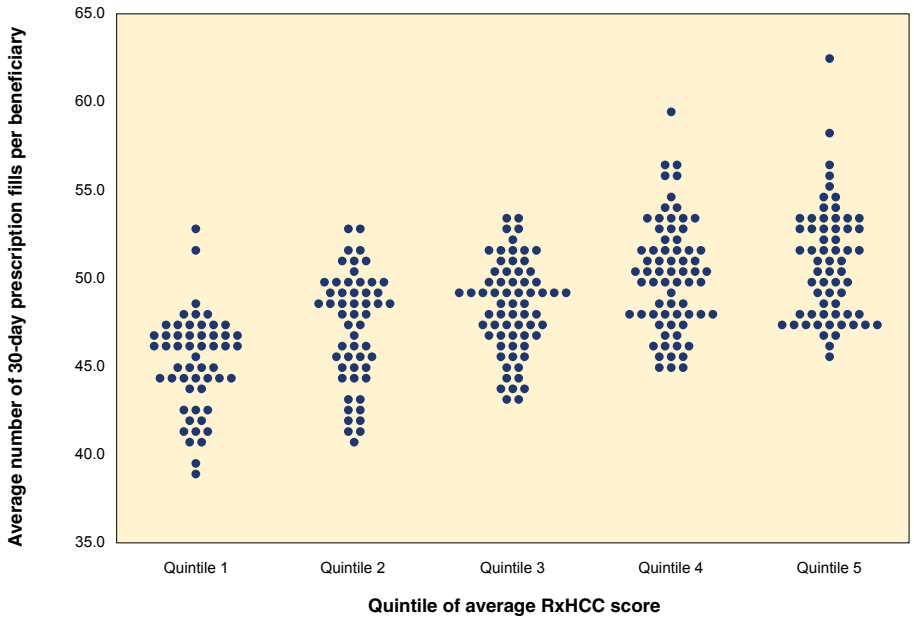



**Figure 3. Prescription fills by quintile of RxHCC score (2010)**

The data presented in Figure 3 suggest that, as with other medical services examined in prior Atlas work, variations in prescription drug utilization are not entirely explained by the disease burden of populations, but rather reflect other regional factors including prescriber practice styles and, perhaps, patient preferences. Subsequent sections of this Atlas will explore these sources of variation in more detail.

## References

1. Part D Benefit Parameters. 2012. (Accessed September 18, 2013, at http://www.cms.gov/Outreach-and-Education/Training/CMSNationalTrainingProgram/Downloads/2013-Part-D-Benefits-Parameters-Job-Aid.pdf.)

2. Medicare 2013 costs at a glance. 2012. (Accessed September 20, 2013, at http://www.medicare.gov/your-medicare-costs/costs-at-a-glance/costs-at-glance.html - collapse-4811.)

3. The 2013 Annual Report of the Boards of Trustees of the Federal Hospital Insurance and Federal Supplementary Medical Insurance Trust Funds. 2013. (Accessed at http://downloads.cms.gov/files/TR2013.pdf.)

## Variation in effective prescription care

Effective drug therapy is generally accepted to have benefits that outweigh the associated risks and costs in specific patient populations. Effective prescription care is often codified in performance measures used to assess the quality of health care delivery. It is not possible to achieve 100% adherence to effective care recommendations because contra-indications to treatment may exist and because patients may decline to fill a prescription for a recommended medication; however, these do not occur commonly and would not be expected to vary regionally in an insured population. Therefore, it is reasonable to expect very little variation in the use of effective care among Part D beneficiaries across hospital referral regions. Figure 4 shows the variation in four measures of effective drug therapy for two patient cohorts: those who have had a heart attack and patients with diabetes. The following section will discuss the variations in these measures in greater detail.

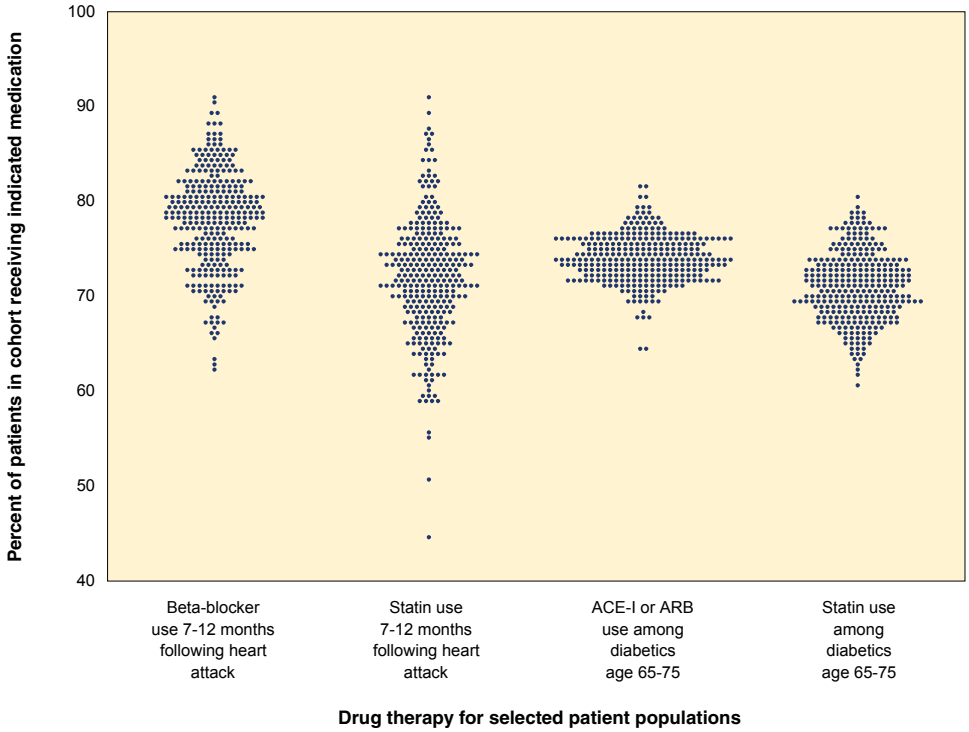



**Figure 4. Use of effective drug therapy for heart attack patients (2008-10) and patients with diabetes (2010) among hospital referral regions**

The figure shows the percentage of Part D beneficiaries in each patient cohort receiving indicated medications. For heart attack patients, medication use was measured 7-12 months following discharge from the hospital after a heart attack in 2008 or 2009 in order to assess whether therapy continued beyond the immediate period after discharge. Effective care for diabetics was measured for 2010 in patients age 65 to 75.

It is important to note that the Medicare data in this report consist only of prescriptions that were actually filled. There is no record of prescriptions that were written but not filled. The measures in this report may therefore underestimate physicians' treatment intentions. Ultimately, however, the use of medications is what matters, and both physicians and health systems are responsible for addressing factors beyond the act of prescribing itself that impact the quality of care actually received by patients.

## Effective care for cardiovascular disease

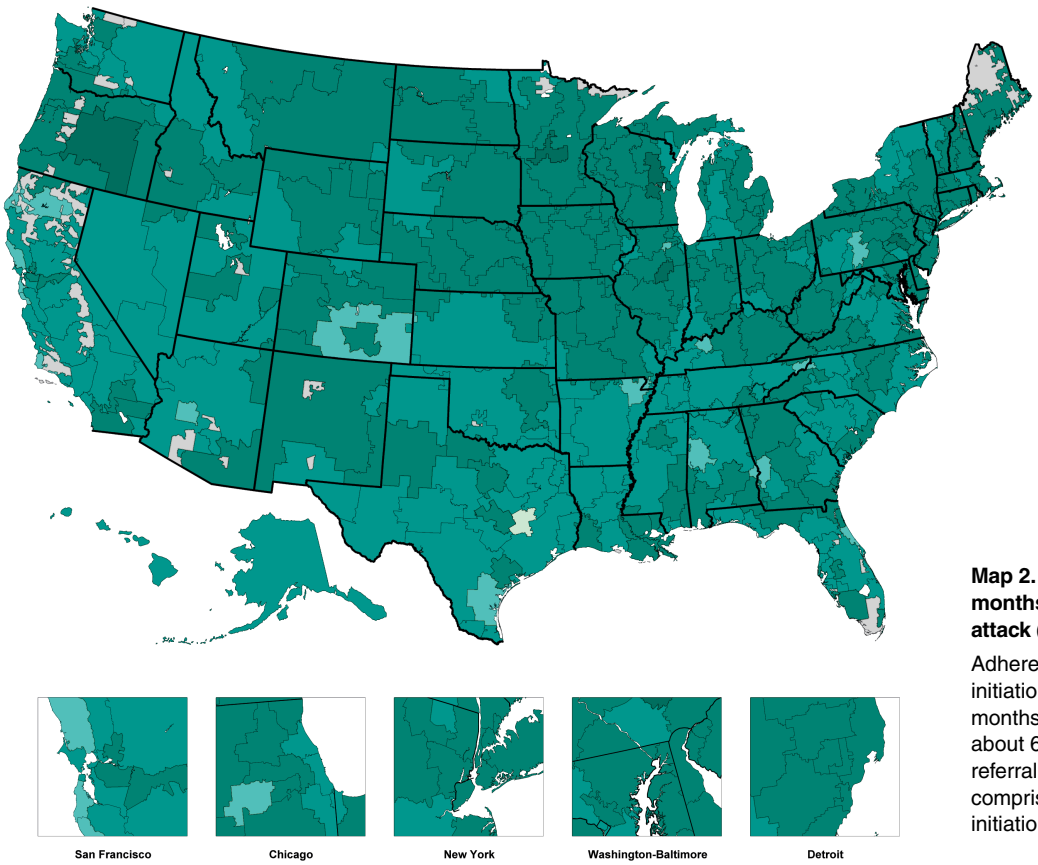
Cardiovascular disease remains the number one killer of Americans and is associated with significant morbidity among survivors.[1] Those who suffer an acute myocardial infarction (i.e., a heart attack) are at increased risk for additional events in the future;[2] prevention of these second cardiovascular events is a top priority. Fortunately, drugs such as beta-adrenergic receptor antagonists (beta-blockers, which regulate heart rate and rhythm) and HMG-CoA reductase inhibitors (statins, which are cholesterol-lowering drugs) have been shown to reduce the risk of future cardiovascular events among those who survive an initial heart attack.[3-5] These drugs do not have significant side effects in most patients and have few contra-indications. The vast majority of patients who have a heart attack should therefore be treated with a beta-blocker and a statin in the months following hospital discharge after a heart attack.[6,7]

The focus of quality measurement for beta-blocker use after a heart attack was modified recently. Initially, the National Committee for Quality Assurance (NCQA) set the standard that all patients without a contra-indication to therapy hospitalized for a heart attack should be given a prescription for a beta-blocker within seven days of hospital discharge. In May 2007, NCQA announced that it would no longer use this quality measure because near-universal uptake of effective practice had been achieved: 94% among Medicare beneficiaries and 98% in the commercially insured.[8,9] Recognizing that the benefits of beta-blockers require ongoing therapy, NCQA shifted its focus for this quality metric to *persistence* of use up to six months after hospital discharge.[10] This focus on continued long-term treatment is consistent with recommendations from the American Heart Association to continue beta-blocker therapy for at least three years following a heart attack.[7] To capture the use of beta-blocker therapy in each hospital referral region, this section of the Atlas describes two measures: 1) how many patients hospitalized for a heart attack filled at least one prescription for a beta-blocker in the first six months after hospital discharge (treatment initiation), and 2) how many filled at least one prescription in the period 7 to 12 months after hospital discharge (treatment persistence).

*Use of beta-blockers after a heart attack*

The use of beta-blockers more than six months after discharge among patients hospitalized for a heart attack is both lower and more varied than the rate of beta-blocker use at discharge reported previously by NCQA (94%). In the U.S., 78.5% of heart attack survivors filled at least one prescription for a beta-blocker in the 7 to 12 months following a hospital discharge in 2008 or 2009. In the San Angelo, Texas hospital referral region, 91.4% of heart attack patients were still using beta-blockers more than six months after their heart attacks; in Salem, Oregon, 62.5% of patients filled a beta-blocker prescription 7-12 months after a heart attack (Figure 4). The range between regions at the 10th and 90th percentile was 71.1% to 84.8%.

The rates of treatment in the second six months following a heart attack were only slightly lower than the rates in the first six months. Nationally, 84.3% of heart attack survivors received a beta-blocker in the first six months following hospitalization, with a range of 61.1% to 97.0%. These rates are significantly lower than the treat-




**Percent of AMI Patients Filling At Least One Beta-Blocker Prescription in the First Six Months Following AMI**

by Hospital Referral Region (2008-10)

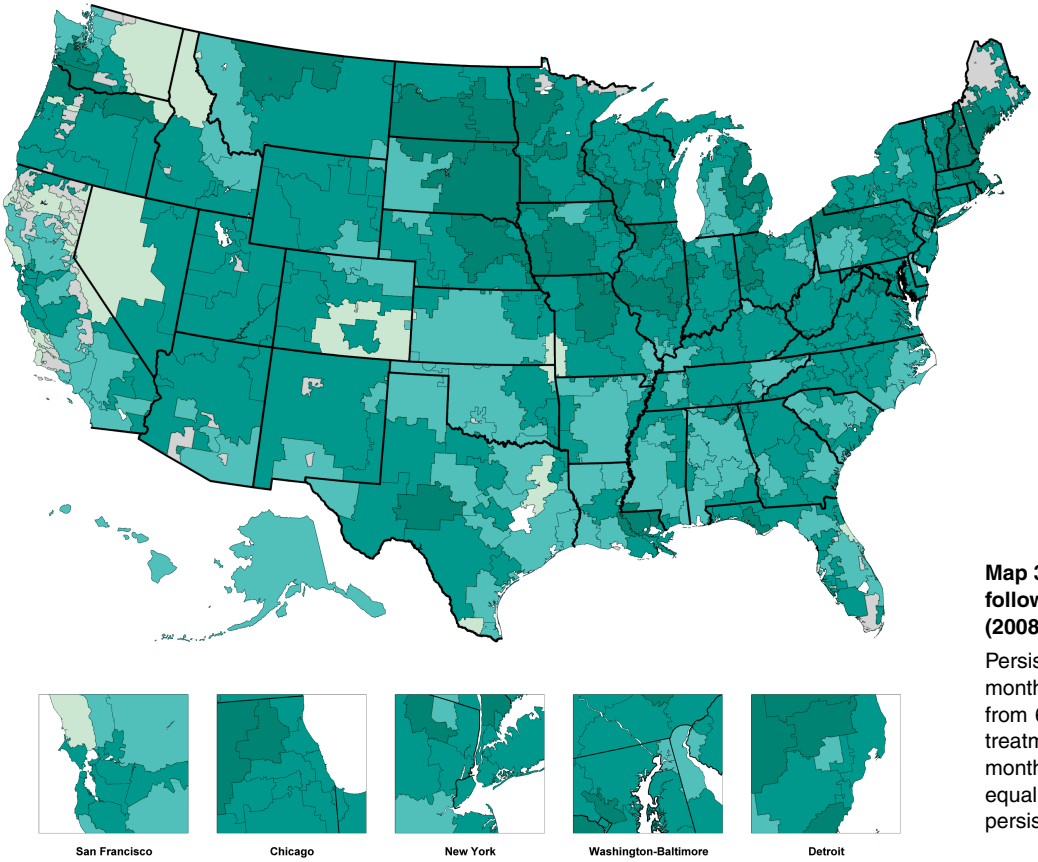
| | |
|---|---|
| 92% or More | (6) |
| 84% to < 92% | (161) |
| 76% to < 84% | (122) |
| 68% to < 76% | (16) |
| Less than 68% | (1) |
| Not populated | |

**Map 2. Use of beta-blockers within the first six months following hospitalization for a heart attack (2008-10)**

Adherence to recommendations for the initiation of beta-blocker therapy in the first six months following a heart attack ranged from about 60% to more than 92% across hospital referral regions. Maps 2 and 3 use a fixed scale comprising equal ranges to demonstrate both the initiation and persistence of treatment.

ment rates reported by NCQA in 2007 and suggest that the primary barrier to ongoing beta-blocker therapy is a failure to initiate treatment, not a failure of treatment persistence. Furthermore, the overwhelming majority of patients who started treatment with a beta-blocker in the first six months also filled a prescription in the second six months (90.1% nationally, with a range of 71.4% to 100%). Maps 2 and 3 show the variations in initiation (Map 2) and persistence (Map 3) of beta-blocker treatment across hospital referral regions.

The ability of clinicians in some hospital referral regions to initiate therapy in nearly all survivors demonstrates that treatment contra-indications, which are unlikely to vary substantially across regions, are not the sole explanation for the observed variation in beta-blocker therapy. Additionally, the fact that most patients are able to continue therapy once it is initiated suggests that significant side effects are not the primary obstacle to effective care in this population.




**Percent of AMI Patients Filling At Least One Beta-Blocker Prescription in the 7-12 Months Following AMI**

by Hospital Referral Region (2008-10)

| | |
|---|---|
| 92% or More | (0) |
| 84% to < 92% | (42) |
| 76% to < 84% | (164) |
| 68% to < 76% | (86) |
| Less than 68% | (13) |
| Insufficient data | (1) |
| Not populated | |

**Map 3. Use of beta-blockers 7-12 months following hospitalization for a heart attack (2008-10)**

Persistence of beta-blocker use in the second six months of hospitalization for a heart attack ranged from 63% to 91%. No region maintained a level of treatment persistence above 92% in the second six months. Maps 2 and 3 use a fixed scale comprising equal ranges to demonstrate both the initiation and persistence of treatment.

*Use of statins after a heart attack*

The pattern of statin use after a heart attack was similar to that of beta-blocker use. Across the U.S., 72% of heart attack survivors filled a statin prescription in the second six months after discharge, ranging from 44.3% of patients in the Abilene, Texas hospital referral region to 91.3% in the Ogden, Utah region (Figure 4). The range between the 10th and 90th percentiles was 64.2% to 79.4%.

Similar to beta-blocker therapy, the low rate of statin use after a heart attack appears related to decisions made in the first six months after hospital discharge. Nationally, 76.9% of heart attack survivors filled a prescription for a statin within six months of hospital discharge (range 53.6% to 95.7%). Patients who started therapy were also likely to continue into the second six months, with a median persistence of 89.6% and a total range of 69.8% to 100%.

**Table 1. Rank and utilization of beta-blockers and statins 7-12 months following hospitalization for a heart attack among highest-ranked regions for beta-blocker use (2008-10)**

| Region | Rank: Beta-blocker use | Beta-blocker use | Rank: Statin use | Statin use |
|---|---|---|---|---|
| San Angelo, TX | 1 | 91.4% | 56 | 77.1% |
| La Crosse, WI | 2 | 90.6% | 15 | 82.8% |
| Reading, PA | 3 | 89.6% | 241 | 67.4% |
| Sioux Falls, SD | 4 | 89.4% | 218 | 69.1% |
| Metairie, LA | 5 | 88.5% | 216 | 69.2% |
| Paterson, NJ | 6 | 88.3% | 48 | 77.7% |
| Great Falls, MT | 7 | 88.2% | 17 | 82.4% |
| Muncie, IN | 8 | 87.1% | 50 | 77.4% |
| Baton Rouge, LA | 8 | 87.1% | 136 | 73.1% |
| Danville, PA | 10 | 87.0% | 52 | 77.3% |

**Table 2. Rank and utilization of statins and beta-blockers 7-12 months following hospitalization for a heart attack among highest-ranked regions for statin use (2008-10)**

| Region | Rank: Statin use | Statin use | Rank: Beta-blocker use | Beta-blocker use |
|---|---|---|---|---|
| Ogden, UT | 1 | 91.3% | 166 | 78.3% |
| Idaho Falls, ID | 2 | 89.7% | 208 | 75.9% |
| Neenah, WI | 3 | 88.0% | 40 | 84.0% |
| Bloomington, IL | 4 | 87.5% | 139 | 79.2% |
| Appleton, WI | 5 | 87.2% | 68 | 82.1% |
| Medford, OR | 6 | 86.5% | 58 | 82.4% |
| Provo, UT | 7 | 86.1% | 101 | 80.6% |
| Marshfield, WI | 8 | 85.5% | 63 | 82.3% |
| Lebanon, NH | 9 | 85.4% | 16 | 86.0% |
| Waterloo, IA | 10 | 84.6% | 150 | 78.9% |

*How does the use of beta-blockers relate to the use of statins?*

Optimally, nearly all heart attack survivors would receive both beta-blockers and statins since each of these two drug classes reduces the risk of a subsequent, potentially life-threatening event. Regions that excelled in beta-blocker use after a heart attack, however, did not necessarily achieve similar results with statin therapy, despite the fact that these are both treatments for the same condition in the same patients. As Figure 5 shows, there was only a weak correlation ($R^2$=0.11) across hospital referral regions between the percentage of heart attack survivors receiving a beta-blocker and those receiving a statin.

The poor correlation between beta-blocker and statin use was present even among the highest performing regions. As Tables 1 and 2 show, there were no regions among the top 10 in both beta-blocker and statin use in heart attack survivors. Only four regions made the top 20 of both lists. The 3rd, 4th, and 5th ranked regions for beta-blocker use were ranked 241st, 218th, and 216th respectively in statin use. Meanwhile, the top four ranked regions for statin use were ranked 166th, 208th, 40th, and 139th respectively for beta-blocker use.

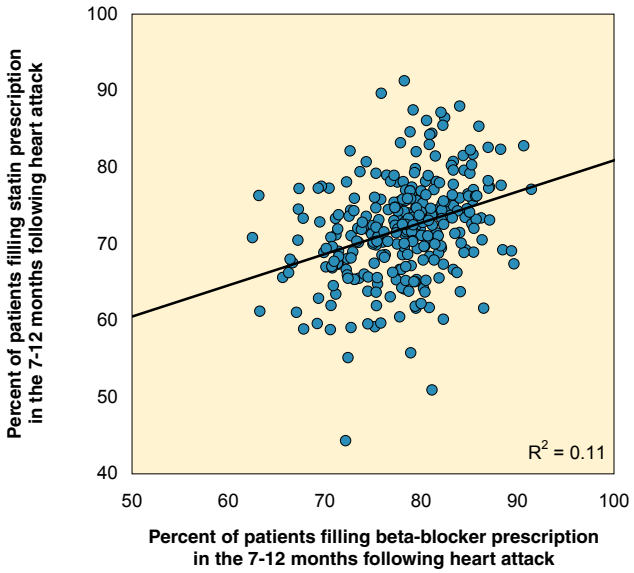



**Figure 5. Relationship between use of beta-blockers and statins in the 7-12 months following a heart attack (2008-10)**

## Effective care for patients with diabetes

Diabetes affects almost one in five U.S. adults over age 65 and is the leading cause of chronic kidney disease, including end-stage renal disease requiring hemodialysis.[11,12] Diabetes is also associated with a dramatically increased risk of cardiovascular disease. Prescription drugs can help reduce the risk of potentially life-limiting complications of diabetes. Angiotensin converting enzyme inhibitors (ACE-I) or angiotensin receptor blockers (ARBs) can reduce the risk of progressive kidney dysfunction among patients with early signs of diabetic kidney disease.[13,14] These drugs also help reduce blood pressure, which, if elevated, can contribute to an increased risk of heart disease and stroke. Statins can reduce the risk of cardiovascular disease among diabetic patients with any additional risk factors for heart disease.[15] Because early kidney disease, hypertension, and other risk factors for cardiovascular disease are common in people with diabetes, both an ACE-I or an ARB and a statin are indicated for the majority of these patients.[16]

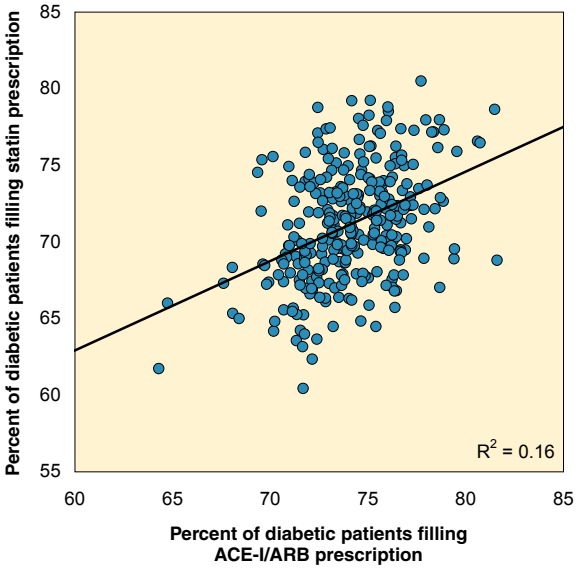



**Figure 6. Relationship between ACE-I/ARB use and statin use in diabetic beneficiaries age 65-75 (2010)**

*Use of ACE-I/ARBs among Medicare beneficiaries with diabetes*

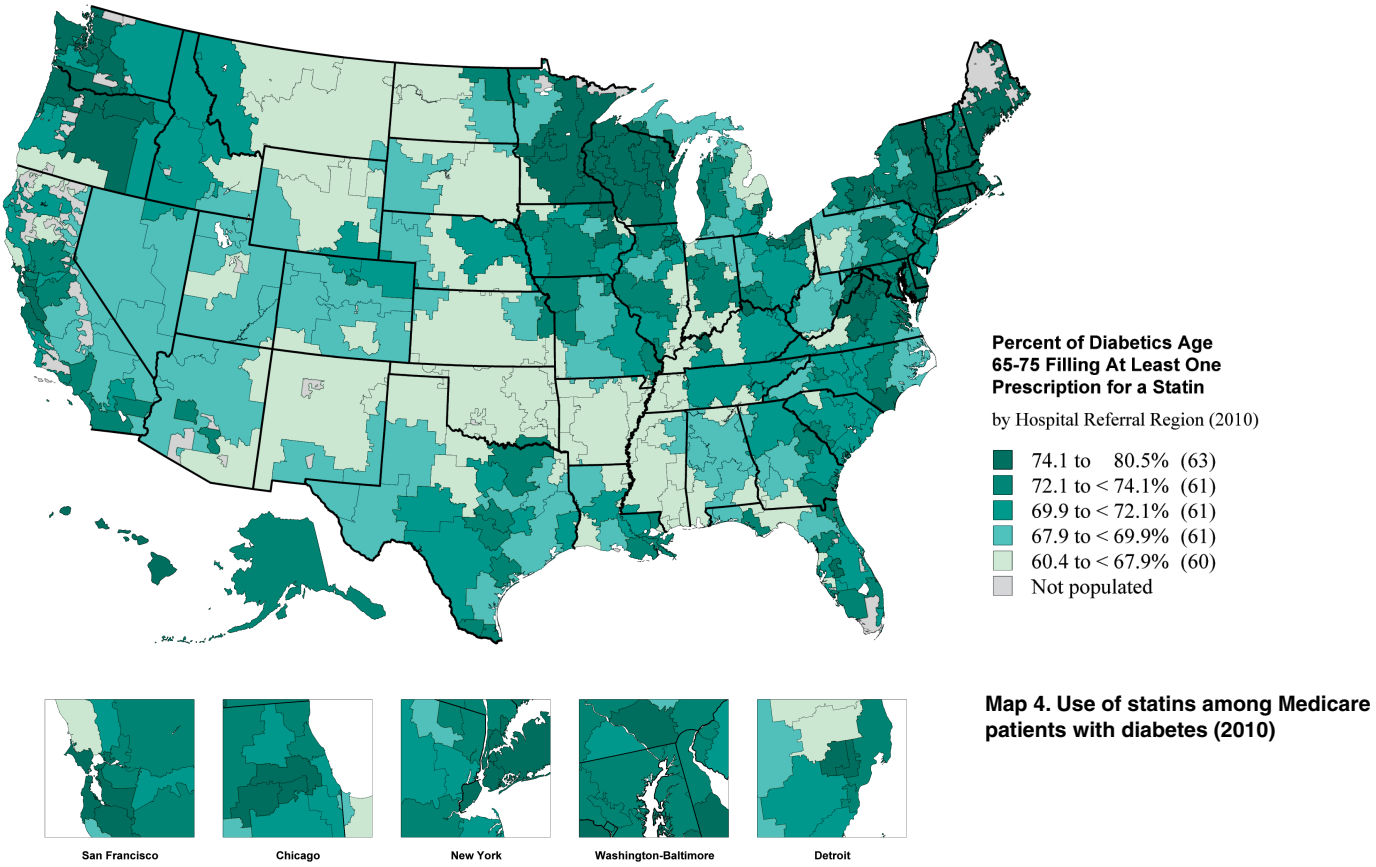
There was less variation in the use of ACE-I and ARBs among diabetics than in either of the effective care metrics for heart attack survivors in 2010 (Figure 4). Among Medicare patients age 65-75 with diabetes in the U.S., 74.6% were treated with an ACE-I or an ARB. Across hospital referral regions, the percent of diabetic patients treated with an ACE-I or ARB ranged from 64.3% of patients in Idaho Falls, Idaho to 81.6% in the Odessa, Texas region. The range across regions at the 10th to 90th percentiles was 71.2% to 77.0%.

*Use of statins among patients with diabetes*

Statin use among patients with diabetes was similar to ACE-I and ARB use. Overall, 71.5% of beneficiaries age 65-75 with diabetes received statins. Both the overall range (60.4% - 80.5%) and the range between regions at the 10th and 90th percentile (66.8% - 76.1%) were slightly larger than the variation observed in the use of ACE-I and ARBs (Map 4).

*Are there regions that excel in providing both statins and ACE-I/ARBs?*

There were regions where diabetic patients received both statins and ACE-I/ARBs at rates that far exceeded national norms in 2010; however, there were also regions with inconsistent performance across these two measures of effective care. As Table 3 shows, 21 regions were in the highest quintile of both statin and ACE-I/ARB use, and an additional 29 were in the highest quintile of one measure and the second highest quintile of the other. At the same time, 13 regions were in the top quintile of one measure and the bottom quintile of the other.

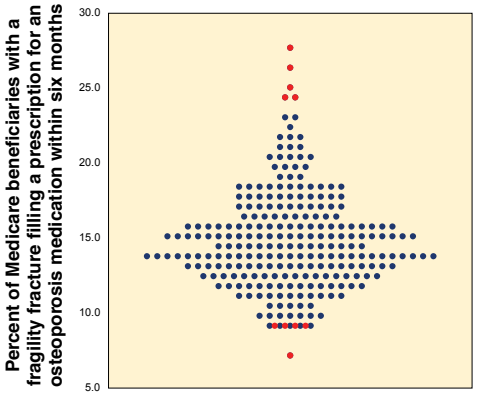



**Map 4. Use of statins among Medicare patients with diabetes (2010)**

The overall correlation between use of statins and use of ACE-I/ARBs among patients with diabetes was weak ($R^2$=0.16) (Figure 6). Some of this is explained by the relatively narrow overall variation across regions for these measures. As Table 3 shows, however, there was a substantial gap between the use of statins and the use of ACE-I/ARBs in several regions. The poor correlation between measures suggests a disconnect in many regions between statin use for prevention of cardiovascular events and the use of ACE-I/ARBs to reduce the risk of progressive kidney disease in the same patient population. It is unclear why physicians do not consistently achieve use of both medications to prevent both outcomes.

**Table 3. Number of regions in each quintile of statin and ACE-I/ARB use among patients with diabetes age 65-75 (2010)**

| Quintile of statin use | Quintile of ACE-I/ARB use (lowest to highest) | | | | |
|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 |
| 1 | 25 | 14 | 10 | 6 | 7 |
| 2 | 20 | 12 | 13 | 7 | 9 |
| 3 | 6 | 14 | 13 | 19 | 9 |
| 4 | 5 | 10 | 16 | 15 | 15 |
| 5 | 6 | 11 | 9 | 14 | 21 |




| | |
|---|---|
| Honolulu, HI | 28.0 |
| Great Falls, MT | 26.2 |
| Sun City, AZ | 25.0 |
| San Luis Obispo, CA | 24.6 |
| Lafayette, IN | 24.1 |
| Huntington, WV | 9.4 |
| Reading, PA | 9.3 |
| Scranton, PA | 9.2 |
| Bangor, ME | 8.9 |
| Newark, NJ | 6.8 |

**Figure 7. Use of drugs to treat osteoporosis following fragility fracture among hospital referral regions (2006-10)**

Each blue dot represents one of 306 hospital referral regions in the U.S. Red dots indicate the five regions with the highest rates and the five with the lowest rates.

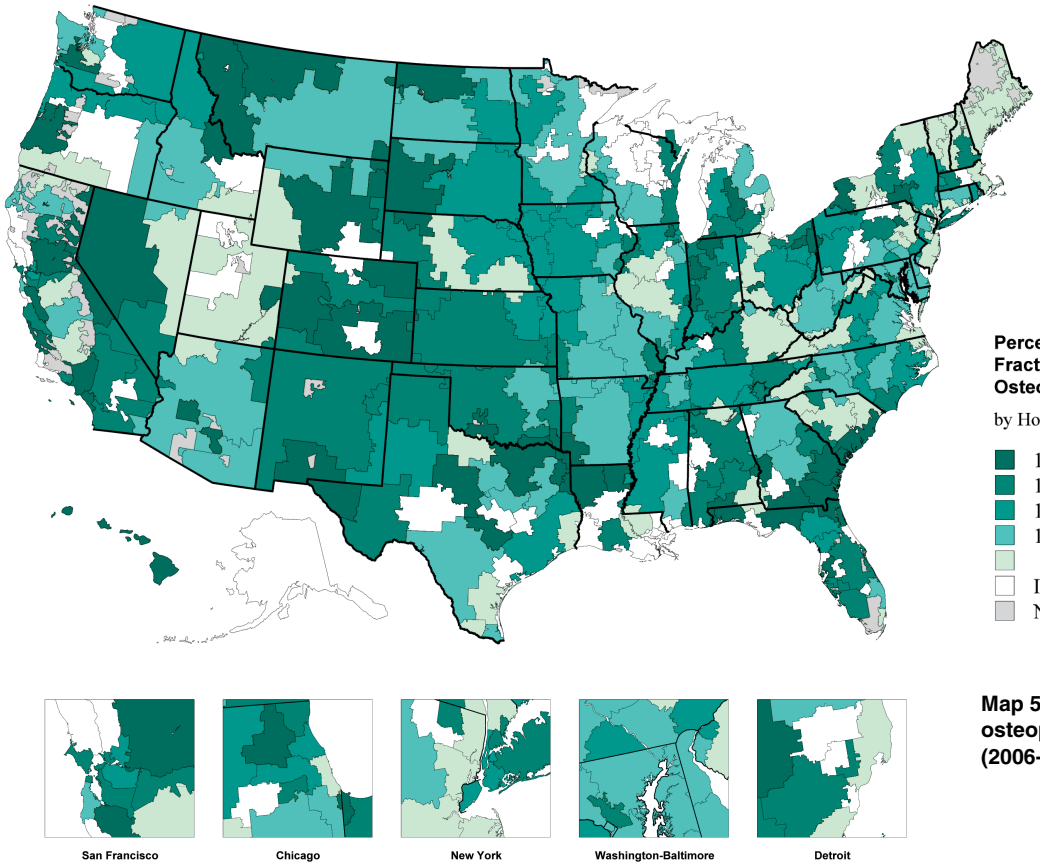
## Effective care of patients after a fragility fracture

Hip fractures caused by osteoporosis are associated with high mortality rates and significant morbidity among survivors.[17] Fractures due to osteoporosis at sites other than the hip, commonly at the wrist and shoulder, are less likely to be life threatening, but can be associated with significant morbidity. Importantly, these fractures also identify patients at increased risk for future hip fractures.[18] In recognition of this, the National Committee for Quality Assurance recommends that survivors of a fragility fracture (a fracture resulting from osteoporosis) should receive drugs that reduce the risk of subsequent fractures within six months of the fracture event.[10]

*Use of drugs to treat osteoporosis among survivors of an osteoporotic fracture*

Only 14.3% of fragility fracture survivors in the U.S. Medicare population enrolled in Part D received a drug to combat osteoporosis within six months of the fracture event. The use of osteoporosis drugs across hospital referral regions ranged from 6.8% of beneficiaries in Newark, New Jersey to 28.0% in Honolulu, Hawaii (Figure 7). These treatment rates are much lower and much more varied than the other measures of effective care presented above. There was almost twofold variation between regions at the 10th percentile and the 90th percentile (11.2% to 19.0%). As with other forms of effective care, some patients may have a contra-indication to treatment, and some may choose not to initiate therapy; these factors will contribute to variation across regions, but they are unlikely to fully explain the magnitude of the observed variation.

It is unclear why the use of drugs to treat osteoporosis is so uncommon compared to the other measures of effective care. It is also unclear why the use of these drugs is not correlated with any other measures of effective care (Table 4). Some may believe that osteoporosis drugs are associated with adverse effects that are both more common and more severe than with beta-blockers, ACE-I/ARBs, or statins. Patients may also opt out of treatment because the beneficial effects of therapy may not be evident for several months to years. Even taking these factors into account, the rates of treatment are lower than expected and suggest the presence of additional obstacles to effective care that do not exist for disease management of diabetes or cardiovascular disease.




**Map 5. Use of medications to treat osteoporosis following fragility fracture (2006-10)**

## Table 4. Relationships between use of drugs to treat osteoporosis and other measures of effective drug therapy

| Measure of effective care | Correlation with the use of drugs to treat osteoporosis (R) |
|---|---|
| Beta-blocker after heart attack | -0.20 |
| Statin after heart attack | -0.06 |
| Statins in patients with diabetes | -0.07 |
| ACE-I/ARB in patients with diabetes | -0.07 |

For more information about the R statistic, please see the section entitled "Utilization, variation, and association – how to interpret the measures."

## Is higher drug spending related to higher rates of effective care?

Higher drug spending is not consistently associated with higher prescribing quality. As Table 5 demonstrates, none of the forms of effective care presented in this report is correlated with total prescription drug spending. Variation in drug spending is therefore unlikely to result from variation in the use of effective medications. This observation is consistent with past Atlas work that has demonstrated no consistent association between higher spending within a region and either markers of care quality or improved patient outcomes.

**Table 5. Relationships between Part D spending per beneficiary and measures of effective drug therapy**

| Measure of effective care | Correlation with total Part D spending (R) |
|---|---|
| Beta-blocker after heart attack | -0.08 |
| Statin after heart attack | -0.16 |
| Statins in patients with diabetes | 0.06 |
| ACE-I/ARB in patients with diabetes | 0.08 |
| Osteoporosis drugs after fragility fracture | -0.01 |

## Summary

Effective prescription drug care fell below optimal levels in most hospital referral regions for survivors of a heart attack and patients with diabetes. High-performing regions can be identified for each effective care measure; these regions achieved treatment rates approaching 90% or more and should serve as a focus of further study. Importantly, however, regions that performed well in delivering one form of effective care did not consistently perform as well in others, even for the same disease population. No region achieved a high rate of effective care following a fragility fracture. Finally, as with many other non-prescription services, higher Part D spending was not associated with improved performance on any of the effective care measures presented in this report.

## References

1. Hoyert D, Xu J. Deaths: Preliminary Data for 2011. Hyattsfille, MD: National Center for Health Statistics; 2012.

2. Third Report of the National Cholesterol Education Program (NCEP) Expert Panel on Detection, Evaluation, and Treatment of High Blood Cholesterol in Adults (Adult Treatment Panel III) final report. *Circulation* 2002;106:3143-421.

3. Sacks FM, Pfeffer MA, Moye LA, et al. The effect of pravastatin on coronary events after myocardial infarction in patients with average cholesterol levels. Cholesterol and Recurrent Events Trial investigators. *N Engl J Med* 1996;335:1001-9.

4. Cannon CP, Braunwald E, McCabe CH, et al. Intensive versus moderate lipid lowering with statins after acute coronary syndromes. *N Engl J Med* 2004;350:1495-504.

5. Freemantle N, Cleland J, Young P, Mason J, Harrison J. beta Blockade after myocardial infarction: systematic review and meta regression analysis. *BMJ* 1999;318:1730-7.

6. Smith SC, Jr., Allen J, Blair SN, et al. AHA/ACC guidelines for secondary prevention for patients with coronary and other atherosclerotic vascular disease: 2006 update: endorsed by the National Heart, Lung, and Blood Institute. *Circulation* 2006;113:2363-72.

7. Smith SC, Benjamin EJ, Bonow RO, et al. AHA/ACCF Secondary Prevention and Risk Reduction Therapy for Patients With Coronary and Other Atherosclerotic Vascular Disease: 2011 Update: A Guideline From the American Heart Association and American College of Cardiology Foundation. *Circulation* 2011;124:2458-73.

8. Lee TH. Eulogy for a quality measure. *N Engl J Med* 2007;357:1175-7.

9. The state of health care quality 2007. National Committee for Quality Assurance, 2007. (Accessed at http://www.ncqa.org/Portals/0/Publications/Resource Library/SOHC/SOHC_07.pdf.)

10. HEDIS 2012 Technical Specifications for Physician Measurement. Washington, DC: National Committee for Quality Assurance; 2011.

11. American Diabetes Association Diabetes Statistics., 2011. (Accessed September 25th, 2013, at http://www.diabetes.org/diabetes-basics/diabetes-statistics/.)

12. United States Renal Data System. 2013. (Accessed September 25th, 2013, at http://www.usrds.org/atlas.aspx.)

13. Brenner BM, Cooper ME, de Zeeuw D, et al. Effects of losartan on renal and cardiovascular outcomes in patients with type 2 diabetes and nephropathy. *N Engl J Med* 2001;345:861-9.

14. Barnett AH, Bain SC, Bouter P, et al. Angiotensin-receptor blockade versus converting-enzyme inhibition in type 2 diabetes and nephropathy. *N Engl J Med* 2004;351:1952-61.

15. Kearney PM, Blackwell L, Collins R, et al. Efficacy of cholesterol-lowering therapy in 18,686 people with diabetes in 14 randomised trials of statins: a meta-analysis. *Lancet* 2008;371:117-25.

16. American Diabetes Association. Standards of Medical Care in Diabetes—2013. *Diabetes Care* 2013; 36:S11-S66.

17. Haentjens P, Magaziner J, Colon-Emeric CS, et al. Meta-analysis: excess mortality after hip fracture among older women and men. *Ann Intern Med* 2010;152:380-90.

18. Colon-Emeric C, Kuchibhatla M, Pieper C, et al. The contribution of hip fracture to risk of subsequent fractures: data from two longitudinal studies. *Osteoporosis International* 2003;14:879-83.

## Does the use of discretionary medications vary?

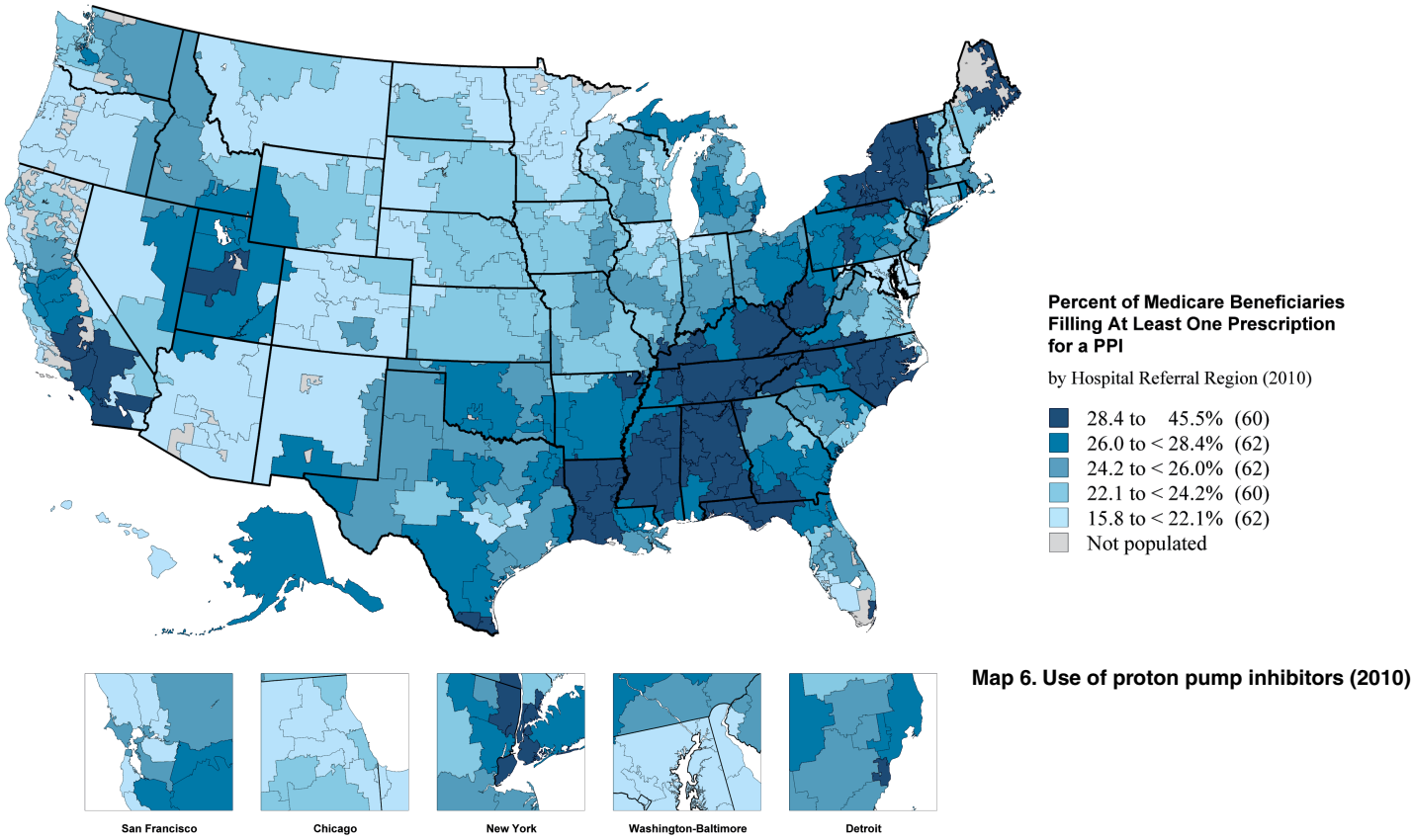
Prior Atlas work has identified a broad category of care that varies across regions as a result of different patient and provider preferences. This section presents an analogous category of prescription drugs: *discretionary medications.* Like preference-sensitive care, medications classified here as discretionary are effective in some patients, but less so in others, and the benefits of treatment for individual patients can be difficult to predict. This uncertainty can stem from the quality of available evidence. For example, many studies of discretionary medications have shown only a small or a variable effect on patient health; some included only a narrowly defined subset of patients with a given disease. For some conditions, studies have not been conducted at all, and evidence must be extrapolated from other, related diseases. Uncertainty can also stem from the complexity of the underlying disease. Many discretionary medications are used to treat heterogeneous conditions defined primarily by symptoms rather than objective tests, or diseases with considerable variability in the severity of the symptoms themselves. As a consequence of this uncertainty, when deciding whether to use a discretionary medication, patients and physicians must consider the tradeoffs between unclear benefits and potential risks (including side effects, drug interactions, and financial costs to the patient). Ideally, these considerations will include evaluation of treatment alternatives. This clinical discussion is called shared decision-making.

This section of the Atlas describes the use of four commonly prescribed drug groups meeting the above definition of discretionary medications.

### Proton pump inhibitors

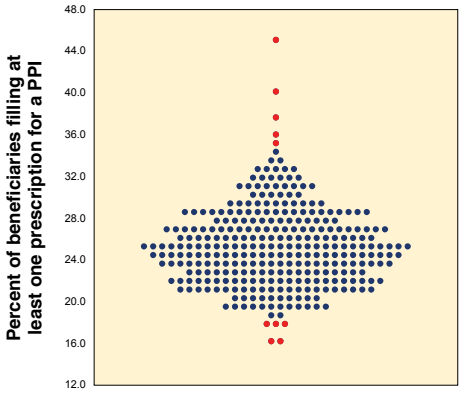
Proton pump inhibitors (PPIs) are commonly prescribed to reduce symptoms of gastroesophageal reflux disease (i.e., heartburn) and gastrointestinal ulcers (ulcers of the stomach or small intestine). PPIs are also prescribed to hospitalized patients to prevent gastric ulcer formation. As with many medications, since entering the market, PPI use has expanded to include patients with less severe forms of the diseases for which they were originally intended. The effectiveness of PPIs in these patients with less severe disease is uncertain. Although many individuals benefit from PPI therapy, others could be managed with alternative treatments or no therapy at all.[1,2] A growing body of evidence suggests that PPIs may also be associated with rare but serious side effects, including fractures and infections.[3-5] Prescribers and patients must therefore consider many factors before initiating or continuing PPI therapy.

Proton pump inhibitor use is common among Medicare beneficiaries. Nationally, one-quarter (25.8%) of patients used a PPI in 2010. There was almost threefold variation in the use of PPIs across hospital referral regions (Figure 8). In Grand Junction, Colorado, 15.8% of beneficiaries filled a prescription for a PPI, while in Miami, Florida, the proportion treated was 45.5% (Map 6).




**Map 6. Use of proton pump inhibitors (2010)**

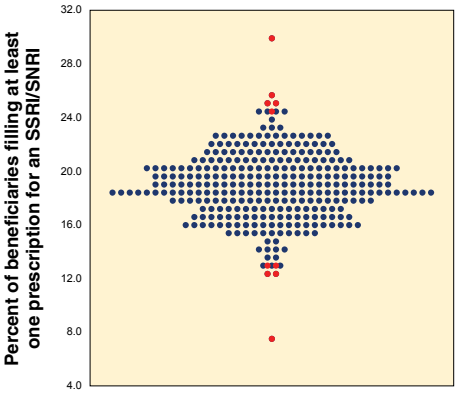
It is unlikely that differences in the number of patients with symptomatic conditions treated most effectively with PPIs or differences in patient preference for PPIs fully explain the threefold variation across regions. Not only would these explanations need to account for the magnitude of the variation in care, but they would also have to explain the marked regional clustering of PPI therapy.




| | |
|---|---|
| Miami, FL | 45.5 |
| McAllen, TX | 39.8 |
| Kingsport, TN | 37.8 |
| Los Angeles, CA | 36.3 |
| Panama City, FL | 35.1 |
| Phoenix, AZ | 18.2 |
| Tucson, AZ | 18.2 |
| San Luis Obispo, CA | 18.2 |
| Boulder, CO | 16.3 |
| Grand Junction, CO | 15.8 |

**Figure 8. Use of proton pump inhibitors among hospital referral regions (2010)**

Each blue dot represents one of 306 hospital referral regions in the U.S. Red dots indicate the five regions with the highest rates and the five with the lowest rates.




| | |
|---|---|
| Miami, FL | 30.2 |
| Alexandria, LA | 25.4 |
| Lafayette, LA | 25.1 |
| Hattiesburg, MS | 24.9 |
| Baton Rouge, LA | 24.5 |
| Alameda County, CA | 13.1 |
| San Francisco, CA | 12.7 |
| San Jose, CA | 12.5 |
| San Mateo County, CA | 12.3 |
| Honolulu, HI | 7.2 |

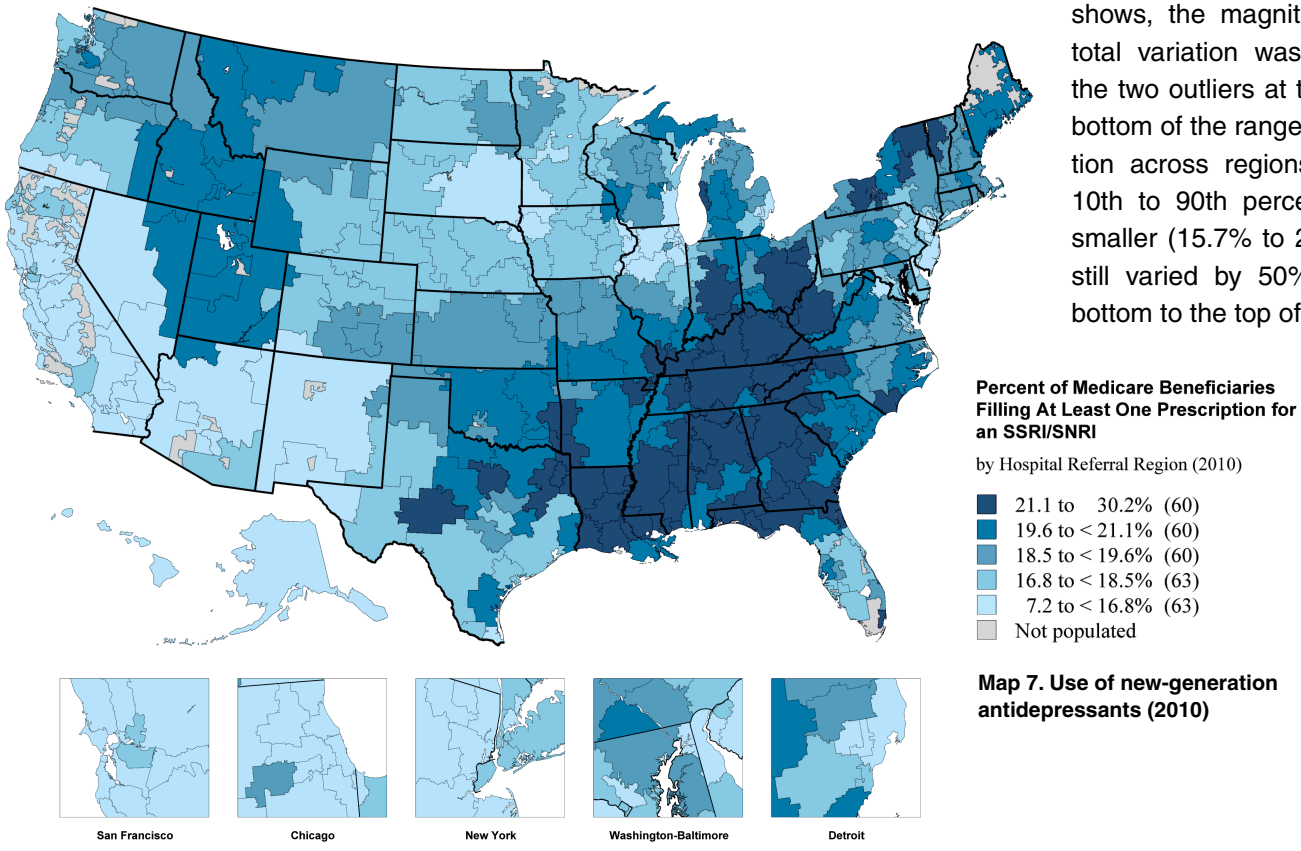
**Figure 9. Use of new-generation antidepressants among hospital referral regions (2010)**

Each blue dot represents one of 306 hospital referral regions in the U.S. Red dots indicate the five regions with the highest rates and the five with the lowest rates.

## Antidepressants

Selective serotonin reuptake inhibitors (SSRIs) and serotonin-norepinephrine reuptake inhibitors (SNRIs) were developed to manage symptoms of depression. Use of these medications has increased dramatically in the past two decades, in part as an alternative to older medications with higher rates of side effects, and in part because of the growing number of conditions for which they are used.[6] Currently, they are prescribed for many mental health disorders, including depression, anxiety, social phobias, and post-traumatic stress disorder (PTSD). They are also used for many non-psychiatric conditions, such as chronic pain and menopausal symptoms. Many of these conditions are characterized by a wide spectrum of symptom severity and are not readily defined by objective medical tests. The effects of treatment in these circumstances can be difficult to predict. As a consequence, the use of SSRIs and SNRIs for these illnesses is likely dependent on the preferences of the physician and the patient.

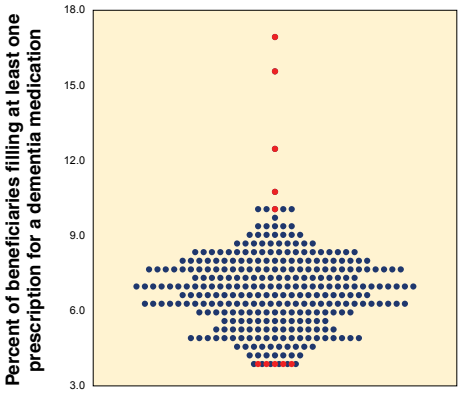
There was more than fourfold variation in the percent of Part D beneficiaries using new-generation antidepressants across hospital referral regions in 2010, ranging from 7.2% in Honolulu, Hawaii to 30.2% in Miami, Florida (Map 7). As Figure 9 shows, the magnitude of the total variation was driven by the two outliers at the top and bottom of the range. The variation across regions from the 10th to 90th percentiles was smaller (15.7% to 22.1%), but still varied by 50% from the bottom to the top of the range.




**Map 7. Use of new-generation antidepressants (2010)**

## Dementia medications

Dementia is characterized by progressive loss of memory and impairment in cognitive function. It is both common among elderly patients and incurable. It also places significant burdens on family members and other caregivers. Effective drugs that halt or reverse the biologic process leading to dementia are urgently needed. Several drugs have been developed to slow the cognitive decline of dementia and to alleviate symptoms; however, these drugs do not alter the underlying disease process. The benefits of existing therapy are often modest or even absent, and side effects are common.[7-10] Given the challenges faced by patients, families, and caregivers when confronted with dementia, many will opt to try drug therapy. It is also reasonable, however, for patients and physicians to agree that the benefits of treatment do not justify the associated risks.

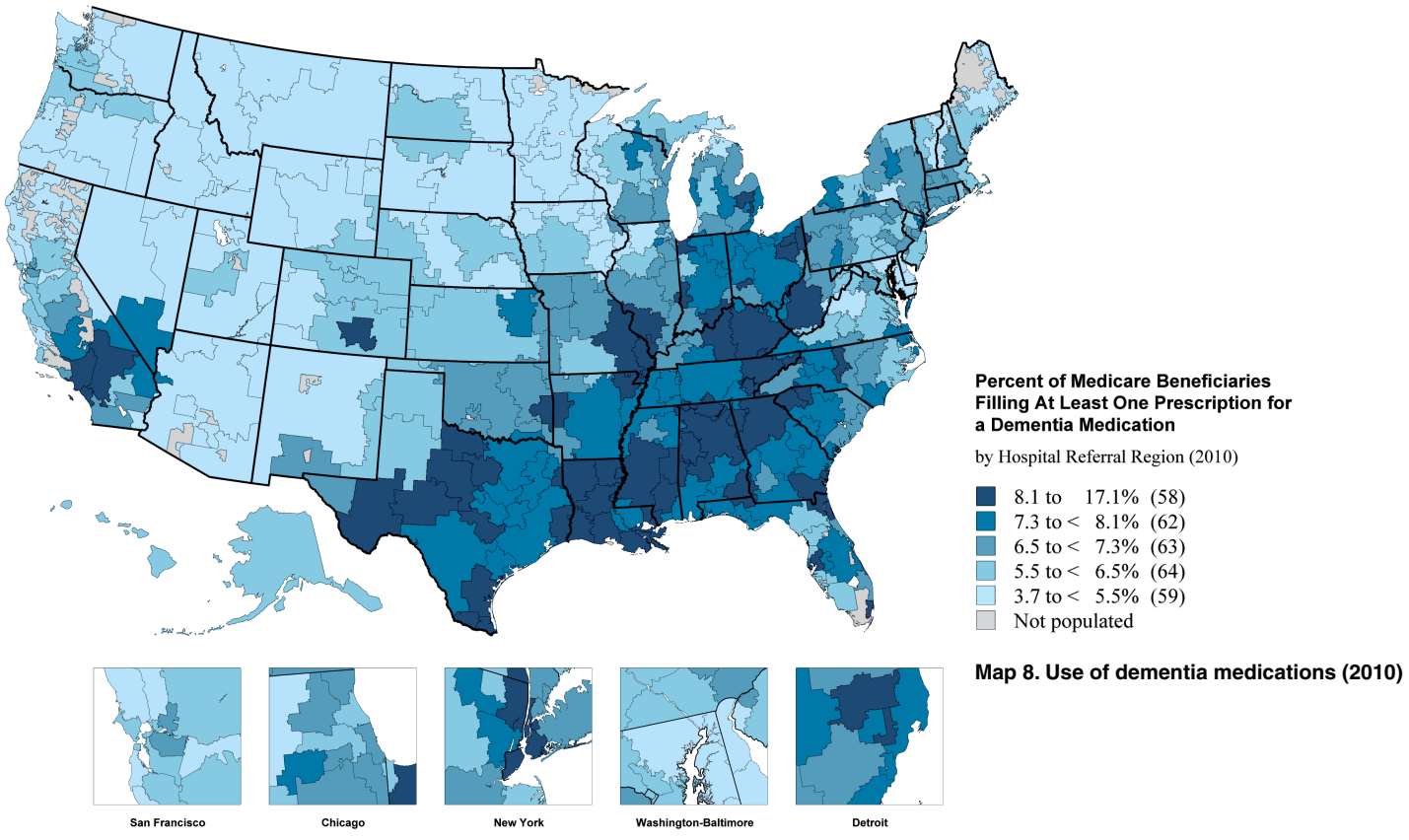



| | |
|---|---|
| Miami, FL | 17.1 |
| McAllen, TX | 15.4 |
| Corpus Christi, TX | 12.4 |
| Los Angeles, CA | 10.7 |
| St. Petersburg, FL | 10.2 |
| St. Cloud, MN | 4.0 |
| Bend, OR | 4.0 |
| Medford, OR | 4.0 |
| Grand Junction, CO | 3.9 |
| Rochester, MN | 3.7 |

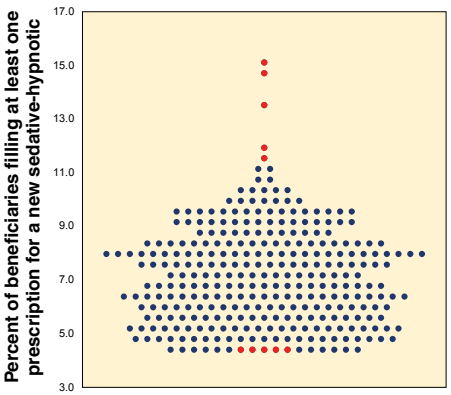
**Figure 10. Use of dementia medications among hospital referral regions (2010)**

Each blue dot represents one of 306 hospital referral regions in the U.S. Red dots indicate the five regions with the highest rates and the five with the lowest rates.

Across the U.S., 7.1% of Part D beneficiaries were treated with a dementia medication in 2010. There was more than fourfold variation across hospital referral regions, ranging from 3.7% of patients to 17.1%. Miami, Florida (17.1%), McAllen, Texas (15.4%), and Corpus Christi, Texas (12.4%) were the three regions with the highest use of dementia medications (Figure 10). Even with these outliers removed, the use of dementia medications in Los Angeles, California (10.7%) was still almost three times higher than in Rochester, Minnesota (3.7%).




**Map 8. Use of dementia medications (2010)**




| | |
|---|---|
| Manhattan, NY | 15.3 |
| Miami, FL | 14.9 |
| Los Angeles, CA | 13.5 |
| Palm Springs/Rancho Mirage, CA | 12.0 |
| Orange County, CA | 11.4 |
| Morgantown, WV | 4.3 |
| Dubuque, IA | 4.2 |
| Erie, PA | 4.2 |
| Appleton, WI | 4.2 |
| La Crosse, WI | 4.2 |

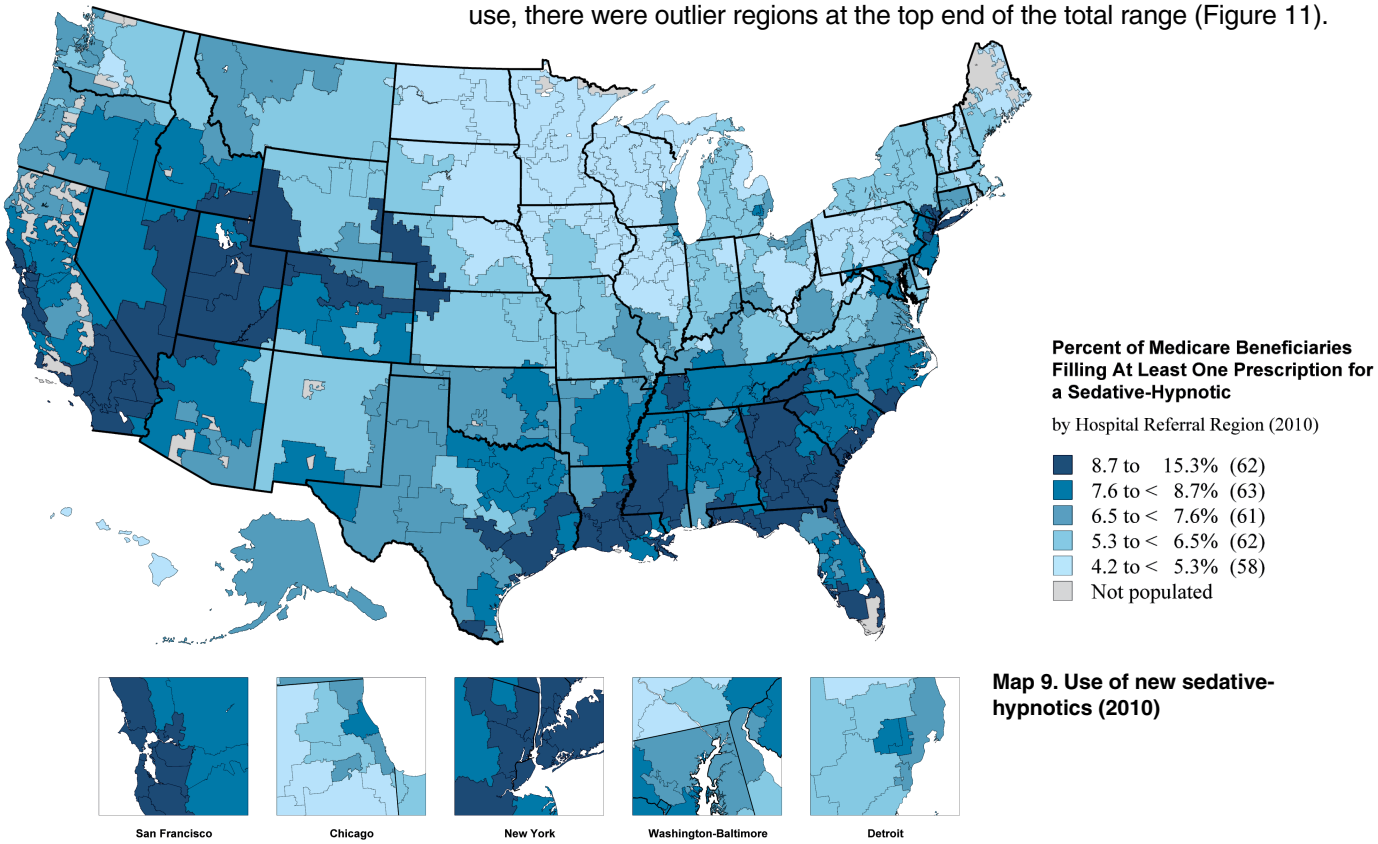
**Figure 11. Use of new sedative-hypnotics among hospital referral regions (2010)**

Each blue dot represents one of 306 hospital referral regions in the U.S. Red dots indicate the five regions with the highest rates and the five with the lowest rates.

## New sedative-hypnotics

Recently, new sedative-hypnotic medications have been developed to treat insomnia. Studies have shown that their effects on sleep are generally small.[11] These drugs are intended for short-term use, and the benefits and harms of long-term treatment have not been consistently evaluated. Initially, this class of medications was considered safe; however, recent data have shown an association with persistent drowsiness that can interfere with driving or other activities requiring attention, particularly at higher daily doses.[12] These effects, as well as additional cognitive and physical side effects, may be more pronounced in the elderly, and use of this drug class for more than 90 days in elderly patients has been specifically discouraged in current specialty society guidelines.[13]

The pattern of sedative-hypnotic use across hospital referral regions was similar to that of other discretionary medications in 2010. On average, 7.6% of Medicare beneficiaries filled at least one prescription for a sedative-hypnotic drug. Once again, there was nearly fourfold variation in the use of these drugs, from 4.2% in four hospital referral regions to 15.3% in Manhattan; and, as with other discretionary medication use, there were outlier regions at the top end of the total range (Figure 11).




**Map 9. Use of new sedative-hypnotics (2010)**

## Use of multiple discretionary medications

The proportion of beneficiaries receiving two or more discretionary medications ranged from 6.4% (in Honolulu) to 31.2% (in Miami) across hospital referral regions; the range among regions at the 10th and 90th percentile was 10.3% to 16.4%. While the medications selected are used to treat distinct and unrelated conditions, their use is often closely correlated. Figures 12 and 13 show the relationships between proton pump inhibitor use and antidepressant use, as well as proton pump inhibitor use and dementia medication use, in 2010. Each correlation was stronger than the correlations between effective care measures presented in the previous section. One result of these close relationships is that regions with the highest use of one discretionary medication were often among the highest ranking in use of other discretionary medications. For example, 31.2% of patients in Miami, Florida, 21.2% of patients in McAllen, Texas, and 20.1% of patients in Alexandria, Louisiana took drugs from more than one category of discretionary medications in 2010.

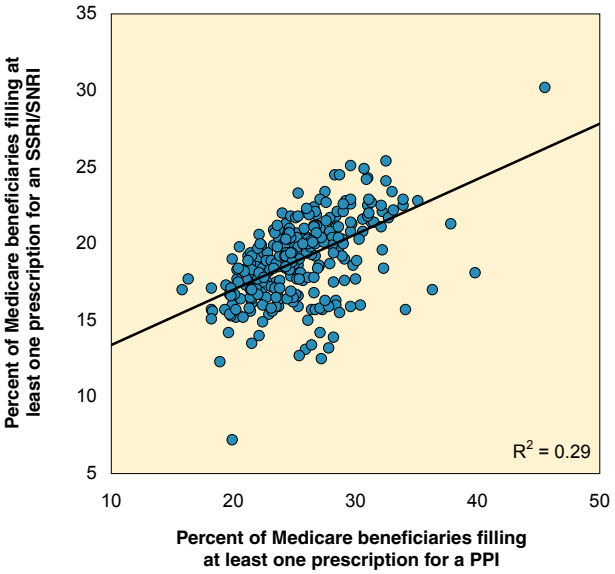



**Figure 12. Relationship between use of PPIs and SSRIs/SNRIs among hospital referral regions (2010)**

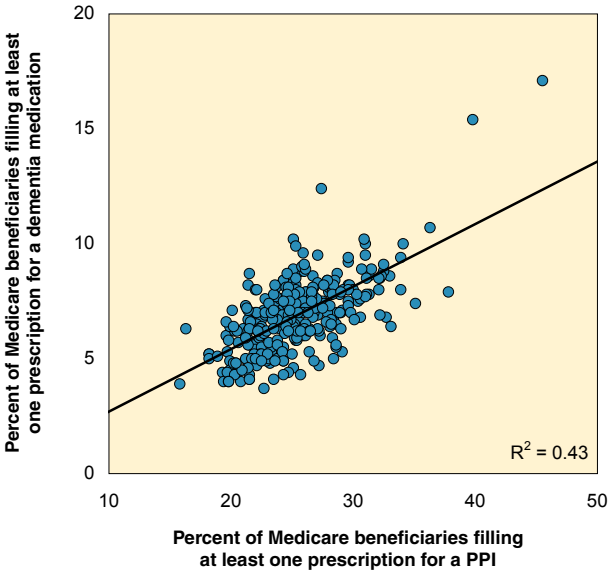



**Figure 13. Relationship between use of PPIs and dementia medications among hospital referral regions (2010)**

## Summary

The use of discretionary medications is common and varies widely among Medicare Part D enrollees living in different regions. The use of distinct drugs targeting clinically unrelated diseases is highly correlated. This suggests that prescribing practices may be influenced by regional factors related generally to the treatment of conditions with high diagnostic and therapeutic uncertainty in addition to the prevalence of specific underlying diseases in the population.

## References

1. Gawron AJ, Rothe J, Fought AJ, et al. Many patients continue using proton pump inhibitors after negative results from tests for reflux disease. *Clin Gastroenterol Hepatol.* Jun 2012;10(6):620-625; quiz e657.

2. Nardino RJ, Vender RJ, Herbert PN. Overuse of acid-suppressive therapy in hospitalized patients. *Am J Gastroenterol.* Nov 2000;95(11):3118-3122.

3. Eom CS, Jeon CY, Lim JW, Cho EG, Park SM, Lee KS. Use of acid-suppressive drugs and risk of pneumonia: a systematic review and meta-analysis. *CMAJ.* Feb 22 2011;183(3):310-319.

4. Kwok CS, Arthur AK, Anibueze CI, Singh S, Cavallazzi R, Loke YK. Risk of Clostridium difficile infection with acid suppressing drugs and antibiotics: meta-analysis. *Am J Gastroenterol.* Jul 2012;107(7):1011-1019.

5. Yang Y-X, Lewis JD, Epstein S, Metz DC. Long-term Proton Pump Inhibitor Therapy and Risk of Hip Fracture. *JAMA.* December 27, 2006 2006;296(24):2947-2953.

6. Pratt L, Brody D, GU Q. A*ntidepressant use in persons aged 12 and over: United States, 2005-2008.* Hyattsville, MD: National Center for Health Statistics;2011.

7. Cummings JL. Use of cholinesterase inhibitors in clinical practice: evidence-based recommendations. *American Journal of Geriatric Psychiatry.* Mar-Apr 2003;11(2):131-145.

8. Howard R, McShane R, Lindesay J, et al. Donepezil and memantine for moderate-to-severe Alzheimer's disease. *N Engl J Med.* Mar 8 2012;366(10):893-903.

9. Qaseem A, Snow V, Cross JT, Jr., et al. Current pharmacologic treatment of dementia: a clinical practice guideline from the American College of Physicians and the American Academy of Family Physicians. *Ann Intern Med.* Mar 4 2008;148(5):370-378.

10. Raina P, Santaguida P, Ismaila A, et al. Effectiveness of cholinesterase inhibitors and memantine for treating dementia: evidence review for a clinical practice guideline. *Ann Intern Med.* Mar 4 2008;148(5):379-397.

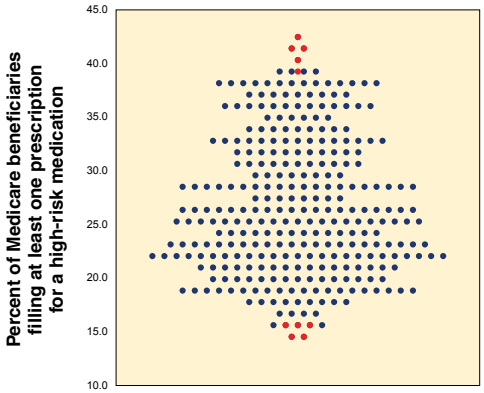
11. Huedo-Medina TB, Kirsch I, Middlemass J, Klonizakis M, Siriwardena AN. Effectiveness of non-benzodiazepine hypnotics in treatment of adult insomnia: meta-analysis of data submitted to the Food and Drug Administration. *BMJ.* 2012;345:e8343.

12. *Risk of next-morning impairment after use of insomnia drugs; FDA requires lower recommended doses for certain drugs containing zolpidem (Ambien, Ambien CR, Edluar, and Zolpimist):* US Food and Drug Administration.;2013. (Accessed September 25, 2013 at http://www.fda.gov/drugs/drugsafety/ucm334033.htm.)

13. American Geriatrics Society updated Beers Criteria for potentially inappropriate medication use in older adults. *J Am Geriatr Soc.* Apr 2012;60(4):616-631.

## How does the use of high-risk medications vary?

The NCQA has included a list of medications to be avoided in the elderly as part of their Healthcare Effectiveness Data and Information Set (HEDIS).[1] These medications have significant rates of adverse effects when used in older patients, and the magnitude of the expected benefit generally does not outweigh these risks. Skeletal muscle relaxants are an example of such potentially hazardous medications. They are sedating, and their use is associated with an increased risk of fractures.[2] Other examples of potentially hazardous medications include long-acting benzodiazepines and highly sedating antihistamines. A complete list is available in the Methods (Table B). Additionally, high-risk medications often have effective alternatives. As a result, overall use of these medications should be be low among older Americans, and variation in utilization across regions is unlikely to reflect differences in the need for treatment.




| | |
|---|---|
| Alexandria, LA | 43.0 |
| Hattiesburg, MS | 41.5 |
| Monroe, LA | 41.2 |
| Dothan, AL | 40.6 |
| Meridian, MS | 39.5 |
| Lebanon, NH | 15.4 |
| St. Cloud, MN | 15.3 |
| La Crosse, WI | 15.2 |
| Mason City, IA | 14.1 |
| Rochester, MN | 14.0 |

**Figure 14. Use of potentially harmful medications among Medicare beneficiaries among hospital referral regions (2010)**

Each blue dot represents one of 306 hospital referral regions in the U.S. Red dots indicate the five regions with the highest rates and the five with the lowest rates.

### The use of high-risk medications

The use of potentially harmful medications is higher than expected and varies widely across regions. More than one quarter (26.6%) of Medicare Part D beneficiaries across the country filled at least one prescription for a high-risk medication in 2010. There was more than a threefold difference between the percent of patients treated with a high-risk medication in Rochester, Minnesota (14.0%) and the percent treated in Alexandria, Louisiana (43.0%) (Figure 14). More than a third (36.6%) of beneficiaries living in regions at the 90th percentile used high-risk medications, while 18.9% of those living in regions at the 10th percentile used these same medications. As Map 10 demonstrates, there is considerable regional clustering of the highest use regions.

**Table 6. Relationships between the use of high-risk medications and measures of effective and discretionary drug therapy**

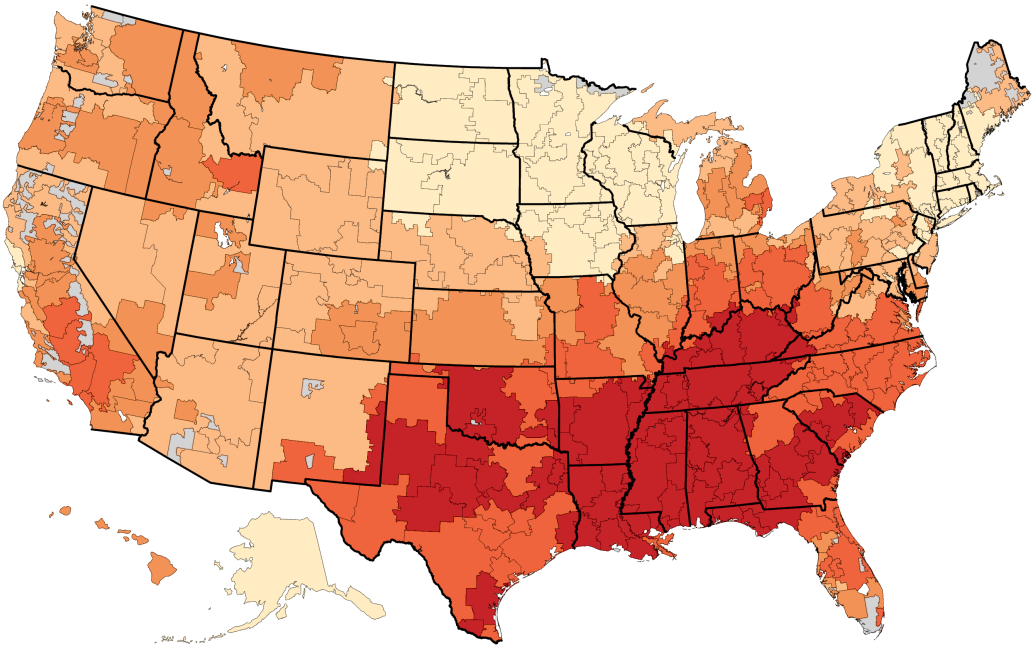
| Measure | Correlation with high-risk medication use (R) |
|---|---|
| Effective care | |
| Beta-blocker after heart attack | -0.35 |
| Statin after heart attack | -0.41 |
| Statins in patients with diabetes | -0.45 |
| ACE-I/ARB in patients with diabetes | -0.04 |
| Osteoporosis drugs after fragility fracture | 0.07 |
| Discretionary medications | |
| Proton pump inhibitors | 0.55 |
| SSRIs/SNRIs | 0.60 |
| Dementia medications | 0.66 |
| New sedative-hypnotics | 0.44 |
| >1 discretionary medication | 0.72 |

### Use of more than one high-risk medication

The use of more than one high-risk medication is less common, but not less varied, than use of a single potentially harmful drug. Across the country, 6.1% of beneficiaries received a prescription for at least two distinct high-risk medications in 2010. There was an almost tenfold variation between the region with the lowest use (Mason City, Iowa at 1.5%) and the highest use (Alexandria, Louisiana at 14.6%) and almost fourfold variation between the regions at the 10th percentile and those at the 90th percentile (2.8% to 11.1%).

### Is high-risk medication use related to other prescribing practices?

The use of potentially harmful medications in Medicare beneficiaries correlates strongly with discretionary medication use but is inversely related to most measures of effective care. As Table 6 demonstrates, increasing use of high-risk medications





**Map 10. Use of potentially harmful medications among Medicare beneficiaries (2010)**

in 2010 was associated with increased use in each category of discretionary medication and with the use of more than one discretionary medication. At the same time, it was inversely related to the use of beta-blockers after a heart attack, statins after a heart attack, and statins among patients with diabetes.

## Summary

The use of high-risk medications in older patients is common overall, and there is considerable variation across regions. The use of these potentially harmful medications appears related to the use of discretionary medications but is inversely related to most measures of effective care. This demonstrates that higher use of potentially harmful medications is not simply a function of more intense medication use overall. Some regions, instead, appear to selectively use high-risk and discretionary medications at high rates while, in relative terms, forgoing effective drug therapy. Such regions seem an appropriate focus of efforts aimed at understanding and improving prescribing quality for Medicare beneficiaries.

## References

1. *HEDIS 2012 Technical Specifications for Physician Measurement.* Washington, DC: National Committee for Quality Assurance; 2011.

2. Golden AG, Ma Q, Nair V, Florez HJ, Roos BA. Risk for fractures with centrally acting muscle relaxants: an analysis of a national Medicare Advantage claims database. *Ann Pharmacother.* Sep;44(9):1369-1375.

## How does total Part D spending vary?

Medicare Part D helps many elderly Americans access prescription drugs. Each year, prescription drugs account for an increasing proportion of total Medicare spending; however, the distribution of this spending across regions of the U.S. and across categories of prescription drugs is not well understood. This section examines regional variation in prescription drug spending and explores factors that may contribute to this variation.

A discussion of Part D spending requires a brief explanation of what higher and lower spending mean for beneficiaries and taxpayers. Part D spending as reported in this section refers to the amount paid at the time prescriptions are filled. The federal government, which pays a fixed monthly premium to private plans on behalf of individual beneficiaries, does not participate directly in the majority of these individual drug transactions. Total spending therefore reflects payments made by the private insurance plans and out-of-pocket payments by patients for each prescription drug dispensed. Spending as it is presented in this section does not translate directly to taxpayer spending in the near term; however, future premiums (which are largely paid by the taxpayer) will be adjusted in response to changing prescription drug expenditures.

### Out-of-Pocket Spending in Medicare Part D Explained

The Medicare Part D benefit design is characterized by a complex patient cost-share structure, which determines out-of-pocket expenses for enrollees. Because this program is administered by private prescription insurers who offer more than 1,000 plans nationally, plans vary considerably in premiums, benefit structure, and patient cost-share. To understand the essentials of patient cost-share, it is useful to focus on the federal minimum standard of coverage, which plans must meet or exceed. For this minimum coverage, the Part D benefit structure includes four different cost-share stages separated by levels of total prescription drug spending. Beneficiaries progress through these stages sequentially as their individual total prescription spending increases, and their spending progress resets annually. The numbers referenced below reflect the standard benefit in 2013.[1]

The first stage of Part D benefit cost-share is the 'deductible'. This amounts to the first $325 in prescription drug spending. The enrollee is responsible for paying this entire amount.

The next benefit stage is the 'initial coverage period'. Enrollees are in this stage when total prescription drug spending falls between $325 and $2,970. During this period, the enrollee is responsible for 25% of the cost of prescription drugs (i.e., 25% co-insurance).

The third and most complex benefit stage is the 'coverage gap' or 'donut hole'. The lower limit of this stage begins when total prescription spending reaches $2,970. Before the implementation of the Affordable Care Act in 2010, which modified the basic Part D plan structure, the enrollee paid for 100% of costs in this stage until the upper limit of $6,734 in total prescription drug spending was reached. This equaled $4,750 in out-of-pocket expenses for the basic plan.

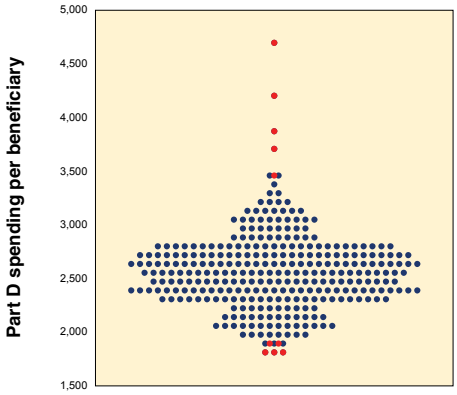
While prescription drug spending is not immediately linked to taxpayers, the relationship between total Part D spending and patient out-of-pocket spending is more direct. Out-of-pocket patient payments vary depending on each individual's prescription drug plan and whether the specific prescription fill occurs within the patient's deductible or is subject to partial co-insurance, a flat co-payment, or full patient payment due to the coverage gap (see box). Although out-of-pocket expenses vary across plans and across individual drug purchases, the general effect of higher observed overall spending is higher out-of-pocket spending for patients. This direct relationship is weaker for patients with a Part D low-income subsidy that greatly reduces cost-share responsibilities; the relationship is also blunted for patients who purchase a high-premium plan that reduces or removes prescription cost-sharing. In the latter example, patients pay higher out-of-pocket premium costs to avoid higher payments at the time of each prescription purchase.

In 2013, for brand-name medications, the enrollee shoulders 47.5% of the cost in this tier. For generic drugs, the enrollee pays 79% of the cost. Coverage in this benefit stage is slated to increase and ultimately match the insurance protection of the 'initial coverage' stage in 2020.[2]

The final benefit stage is labeled 'catastrophic coverage'. This stage begins where the coverage gap ends and has no upper limit. In this stage, the enrollee is responsible for 5% of prescription drug spending.

Importantly, beneficiaries with incomes below 150% of the federal poverty level qualify for Part D low-income subsidy benefits, and through this subsidy, are largely shielded from out-of-pocket spending. Beneficiaries with the subsidy are generally obliged to pay small co-payments for each prescription, ranging from $1.15 to $6.50, depending on income and the specific drug's formulary status in the plan. They are not subject to the full deductible, 25% co-insurance, or the coverage gap.[1]

The complexity surrounding cost-share stages may explain why some beneficiaries, especially those without the low-income subsidy, are willing to pay higher premiums for a comprehensive plan that eliminates uncertainty and covers many out-of-pocket expenses. The complexity may also explain why beneficiaries commonly stay in their chosen plans even when their prescriptions change and new options emerge so that a better match exists for their individual needs.[3,4] Another important implication of the benefit complexity is that prescribing decisions made by physicians can significantly impact the direct costs to patients, but unpredictably, due to the variation across plans and benefit stages.



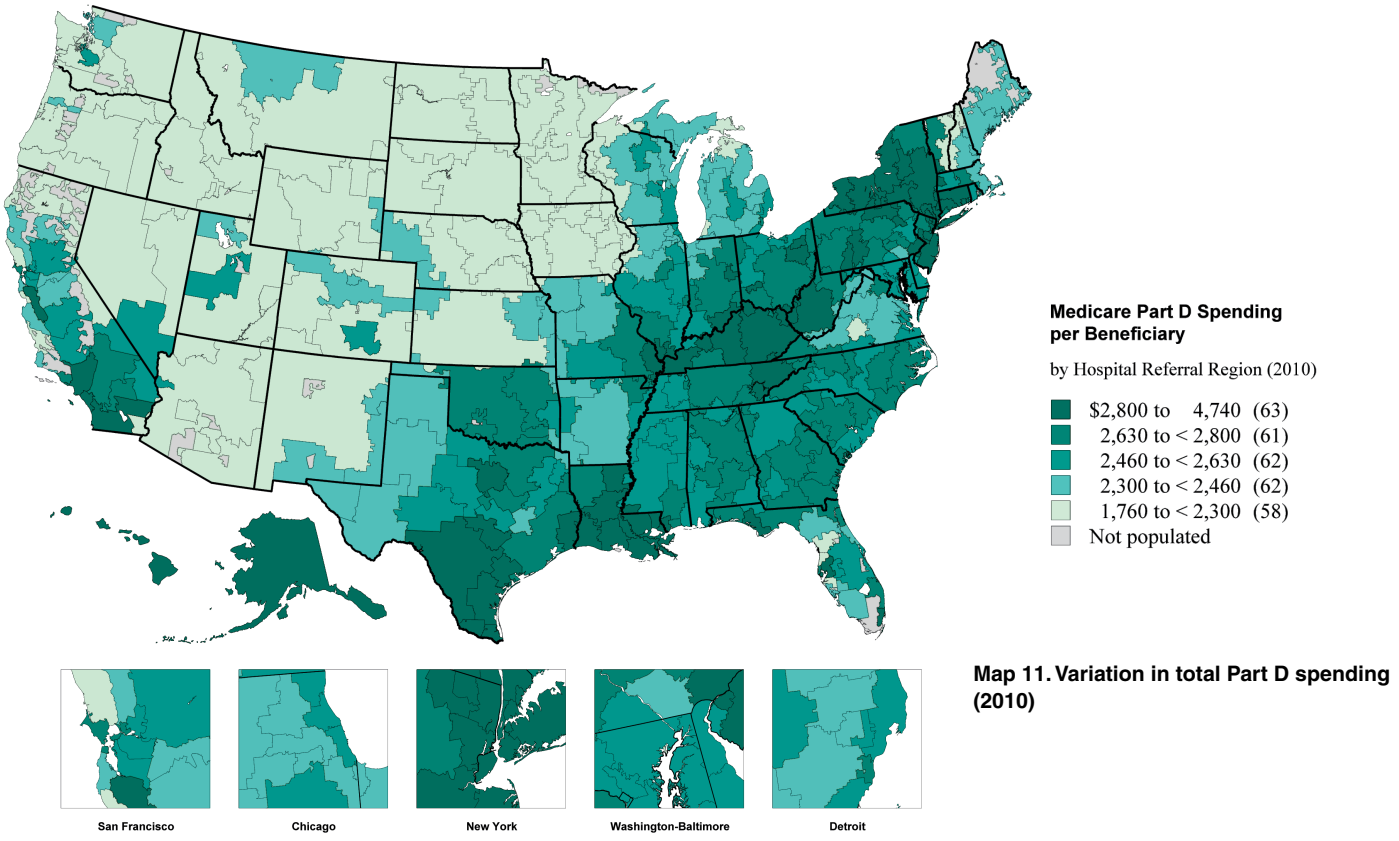

| | |
|---|---|
| Miami, FL | $4,738 |
| Manhattan, NY | $4,200 |
| Los Angeles, CA | $3,863 |
| McAllen, TX | $3,744 |
| Elmira, NY | $3,484 |
| Bend, OR | $1,898 |
| Mason City, IA | $1,858 |
| Rochester, MN | $1,844 |
| Grand Junction, CO | $1,826 |
| St. Cloud, MN | $1,770 |

**Figure 15. Variation in total Part D spending among hospital referral regions (2010)**

Each blue dot represents one of 306 hospital referral regions in the U.S. Red dots indicate the five regions with the highest rates and the five with the lowest rates.

## Total Part D spending

Total prescription drug spending per beneficiary varied by a factor of more than 2.5 across hospital referral regions in 2010 (Figure 15). This translated to a difference of $2,968 per beneficiary when the lowest spending region—St. Cloud, Minnesota, where the mean per beneficiary spending was $1,770—is compared to the highest, Miami, Florida, where the mean per beneficiary spending was $4,738 (Map 11). The national average for prescription spending was $2,670 per beneficiary. Spending in HRRs from the 10th to the 90th percentile differed by $876 per beneficiary.




**Map 11. Variation in total Part D spending (2010)**

## How are total prescription spending and prescription use related?

The first section of this report described the regional variation in prescription volume, measured as the number of 30-day prescriptions filled by each beneficiary. Because total spending is made up of spending on individual prescriptions, regions with the highest prescription drug volume would be expected to have the highest total Part D expenditures. Figure 16 demonstrates this relationship.

The significance of the relationship between prescription drug volume and Part D spending depends in part on whether the variation in spending is due to differences in effective medication use, discretionary medication use, or high-risk medication use. Increases in total spending that result from improved access to effective prescription drugs are appropriate, and even desirable. On the other hand, spending that results from increased use of discretionary or high-risk medications warrants further scrutiny.

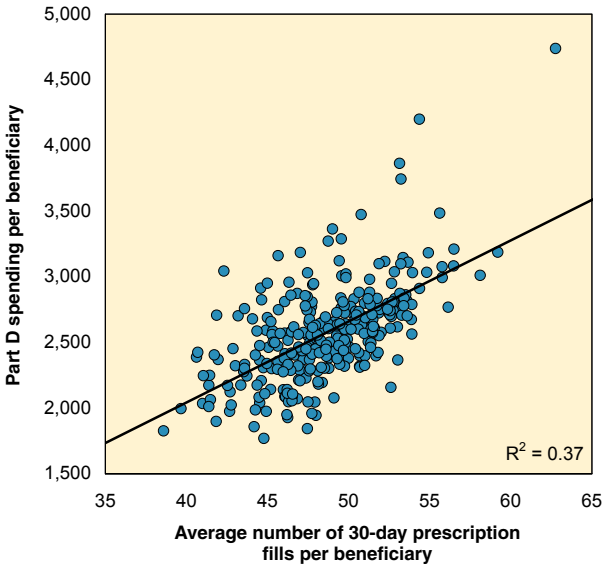



**Figure 16. Relationship between prescription drug use and Part D spending (2010)**

## How does total Part D spending relate to the use of effective drugs?

No clear relationship exists between the five measures of effective care described in this report and either total Part D spending or total prescription drug volume. Table 7 presents the correlations between each measure of effective prescribing and 1) total Part D spending and 2) the number of 30-day prescription fills.

**Table 7. Relationships between Part D spending, total prescription volume and measures of effective drug therapy**

| Measure of effective care | Relationship with spending (R) | Relationship with drug volume (R) |
|---|---|---|
| Beta-blocker after heart attack | -0.08 | 0.10 |
| Statin after heart attack | -0.16 | -0.20 |
| Statins in patients with diabetes | 0.06 | -0.05 |
| ACE-I/ARB in patients with diabetes | 0.08 | -0.10 |
| Osteoporosis drugs after fragility fracture | -0.01 | -0.07 |

When individual effective care measures are aggregated to a summary performance score (defined for each hospital referral region as the sum of quintile ranks for each individual measure), there is no difference in prescription drug spending between regions where clinicians consistently provide effective care and regions where they do not. Figure 17 presents Part D spending across quintiles of effective prescribing performance scores. Regions at the left of the figure were, on average, in the bottom two quintiles for each of the five effective care measures, while regions at the right of the figure were, on average, in the top two quintiles for all effective care measures. These results suggest that spending more on prescription drugs does not lead to more consistent use of effective care, while spending less does not create barriers to the use of effective drugs.

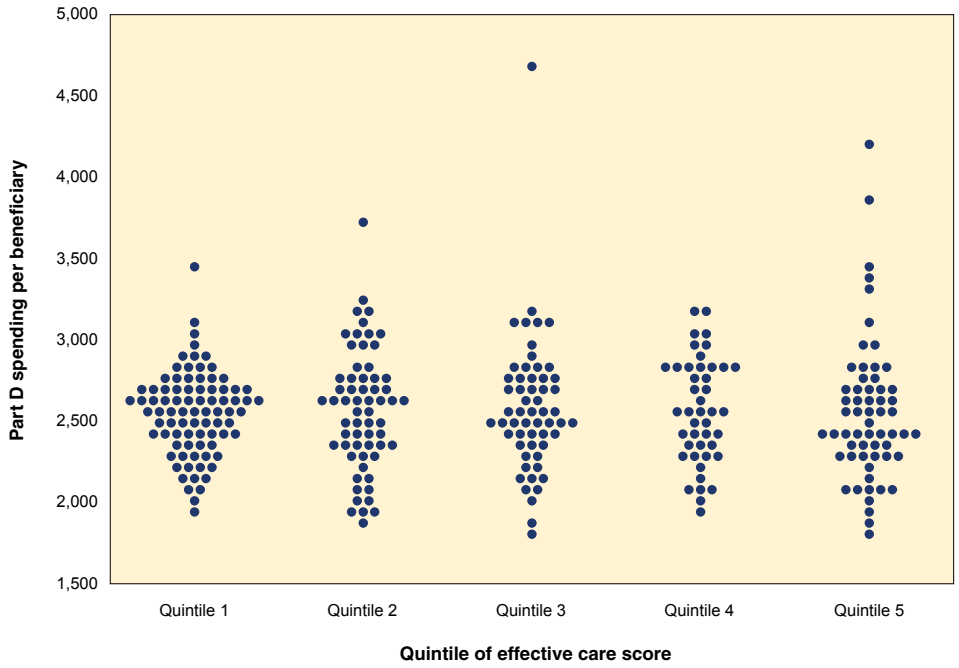



**Figure 17. Variation in total Part D spending by quintile of effective drug care (2010)**

The effective care score represents an aggregate of each region's performance across all effective care measures. It is calculated as the sum of quintile ranks for each individual measure.

## How does total Part D spending relate to the use of discretionary medications?

Higher discretionary medication use is associated with higher total prescription drug spending. As Figures 18-21 show, there is a positive correlation between each of the four examples of discretionary medication use examined and total prescription drug spending. This relationship is strongest for proton pump inhibitors and dementia medications; however, the association between total spending and the use of each discretionary medication is stronger than that observed for any of the effective care measures.

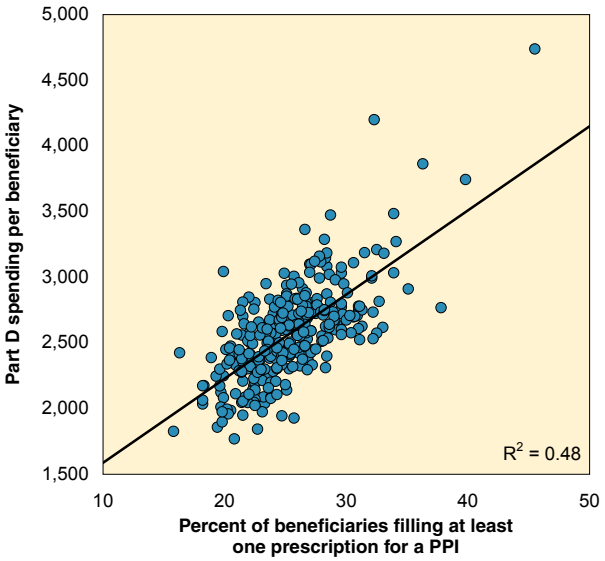



**Figure 18. Relationship between the use of proton pump inhibitors and Part D spending (2010)**

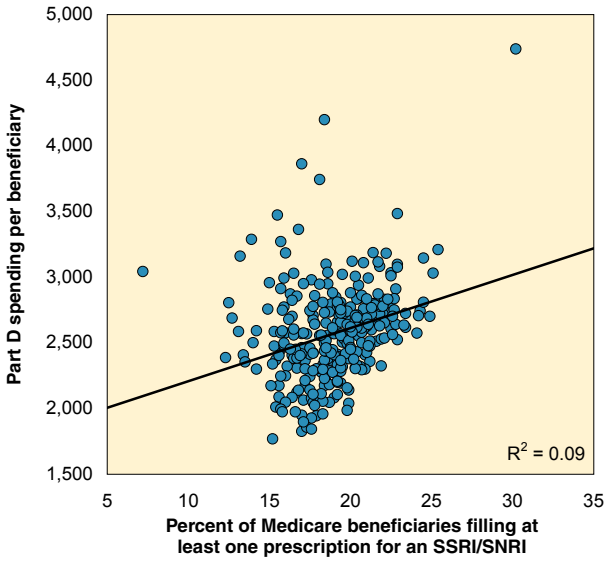



**Figure 19. Relationship between the use of new-generation antidepressants and Part D spending (2010)**

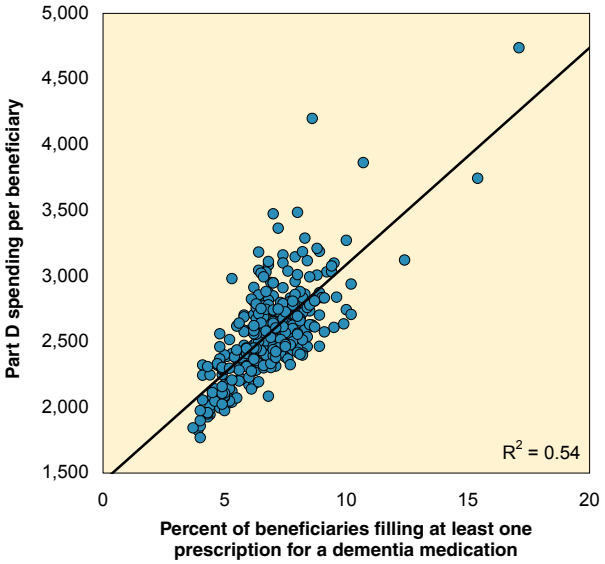



**Figure 20. Relationship between the use of dementia medications and Part D spending (2010)**

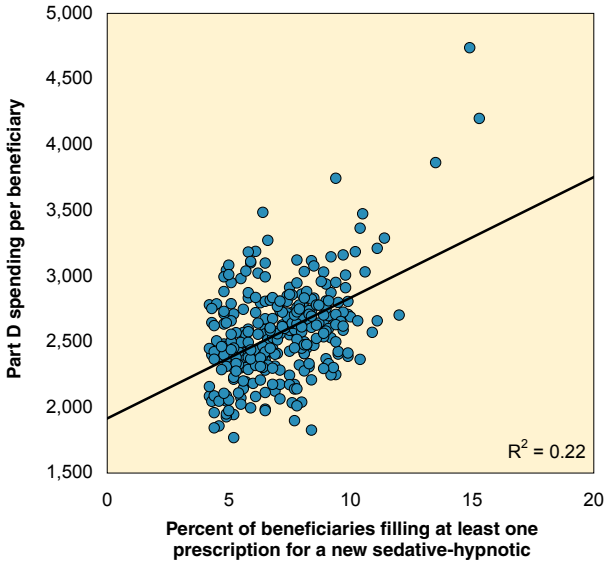



**Figure 21. Relationship between the use of new sedative-hypnotics and Part D spending (2010)**

## How does total Part D spending relate to high-risk medication use?

A positive relationship was observed between the use of high-risk medications and total Part D spending. This relationship is not as strong as that shown earlier for proton pump inhibitors and dementia medications, but it is stronger than that observed for any effective care measures (Figure 22).

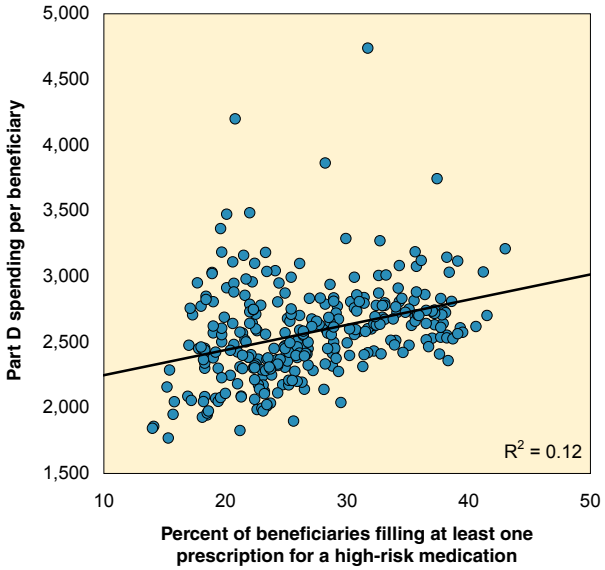



**Figure 22. Relationship between the use of high-risk medications and Part D spending (2010)**

## Is higher total Part D spending related to the selection of more expensive drugs?

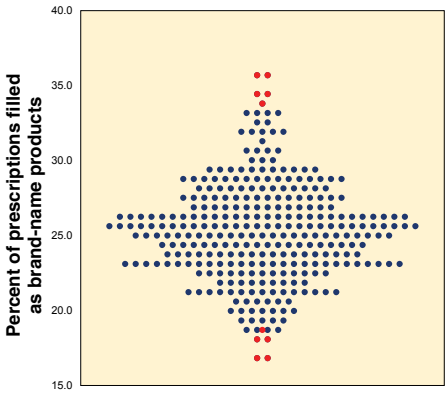
Physicians often choose between several available drugs or drug classes when writing a prescription. In some instances, the options include both brand-name and generic drugs. Not all prescription drugs have an available generic equivalent or substitute, but, when available, generic medications are generally equally effective and less costly than their brand-name counterparts. The ratio of brand-name fills to total prescription fills in each region therefore provides an estimate of regional prescribing efficiency. This section presents regional variation in the use of brand-name drugs and examines the correlation between this use and total Part D spending per beneficiary.

## The Invisibility of Price

The complex Medicare Part D benefit structure leaves patients responsible for a significant portion of prescription drug costs. This cost-share structure is intended to encourage the use of lower cost options when available. One such option is the use of generic drugs instead of more expensive branded products. Generic and branded drugs are generally therapeutically equivalent, though they occasionally differ in dosing convenience. While branded drugs are more expensive than their generic alternatives, the magnitude of the difference in cost varies for specific drugs, drug classes, and across Part D plans.

Insurance companies offering Part D plans negotiate prescription drug prices with the drug manufacturers. Within drug groups, branded products are often organized into cost-share tiers reflecting the relative price paid by the Part D plan to the manufacturer; however, the actual price paid by the plan is not disclosed. The cost to the patient then varies according to these tiers, which are not uniform across plans.

For patient cost-sharing strategies to be effective at reducing total prescription drug spending, patients and physicians must be able to compare the relative costs of prescription drugs at the time they are prescribed. Currently, the differences in cost between branded drugs and generic alternatives, as well as the prices of different branded products, are largely invisible to the patient and prescribing physician. This is because it is unusual for the physician to know which cost-share tier a particular drug falls into for a particular plan at the time a prescription is written. Often the relative cost is only known when the pharmacist requests payment for the filled prescription. Without easy access to information about the real and relative cost of drugs, discussions involving cost-value tradeoffs are limited. The result may be higher spending for patients and, eventually, taxpayers funding the Medicare program.




| | |
|---|---|
| Manhattan, NY | 36.0 |
| Miami, FL | 35.5 |
| Newark, NJ | 34.4 |
| Hackensack, NJ | 34.4 |
| Los Angeles, CA | 34.0 |
| Iowa City, IA | 18.4 |
| Cedar Rapids, IA | 18.1 |
| St. Cloud, MN | 18.1 |
| Rochester, MN | 16.8 |
| La Crosse, WI | 16.5 |

**Figure 23. Variation in the use of brand-name medications among hospital referral regions (2010)**

Each blue dot represents one of 306 hospital referral regions in the U.S. Red dots indicate the five regions with the highest rates and the five with the lowest rates.

There was more than twofold variation across regions in the proportion of prescriptions filled with brand-name products in 2010. Nationally, 26.3% of prescriptions were filled as a brand-name product. This proportion varied from 16.5% in La Crosse, Wisconsin to 36% in Manhattan, with a range between the 10th and 90th percentiles of 21.3% to 29.4% (Figure 23, Map 12). As Figure 24 shows, brand-name drug use was highly correlated with total Part D spending. This relationship suggests that some higher drug spending is caused by greater use of brand-name drugs that in some cases may not provide significant additional benefits to patients.

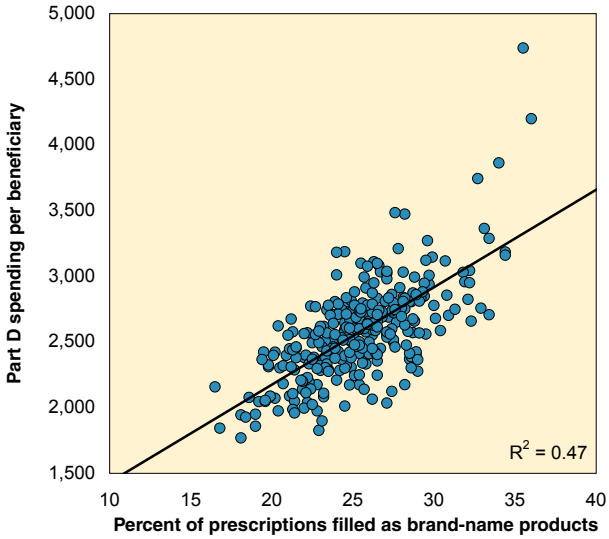
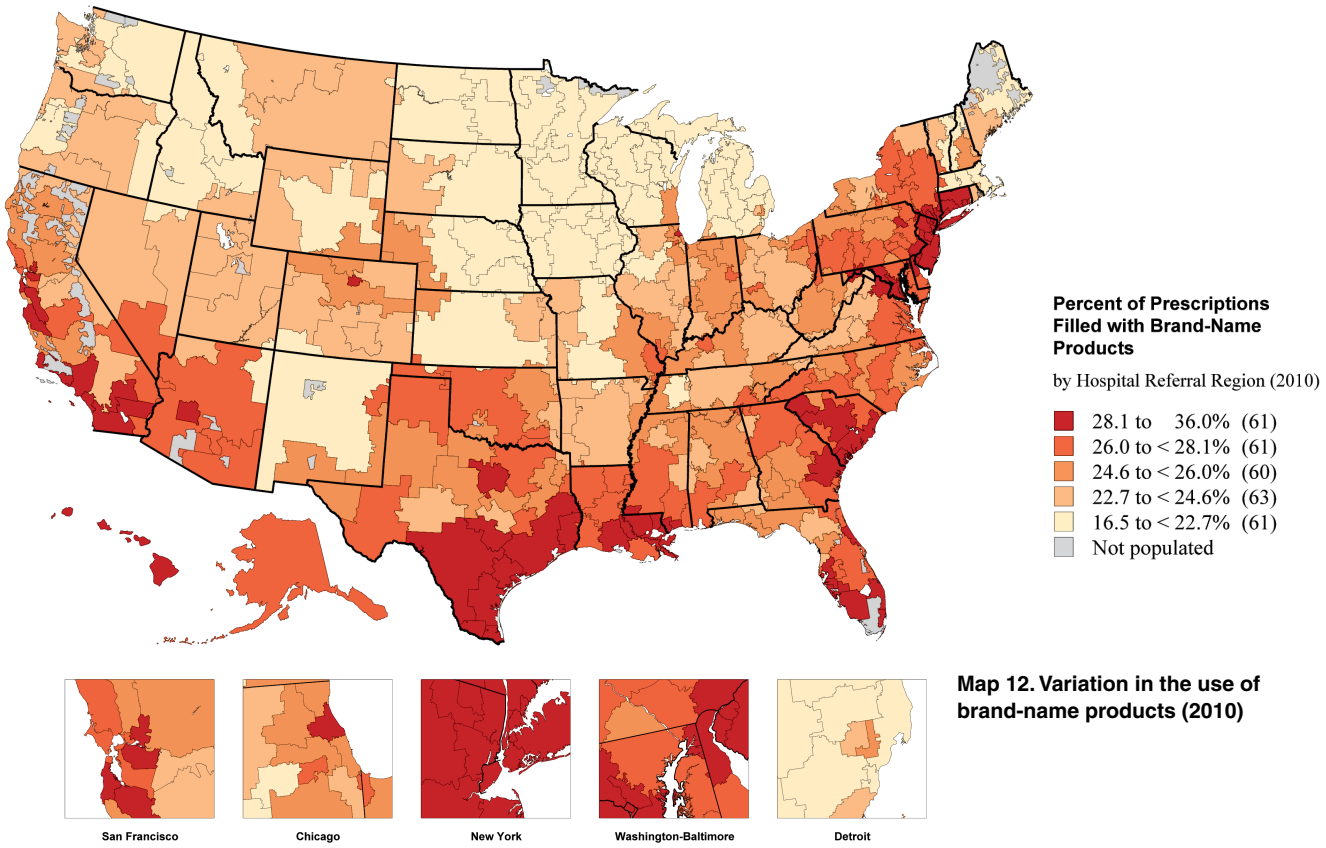



**Figure 24. Relationship between the use of brand-name medications and total Part D spending (2010)**




**Map 12. Variation in the use of brand-name products (2010)**

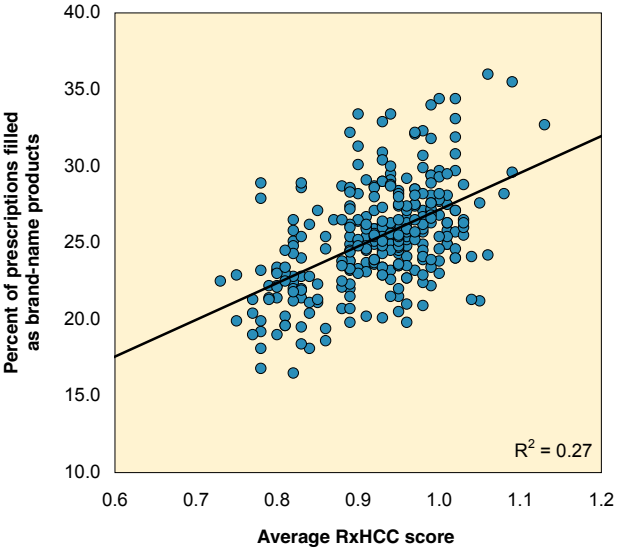



**Figure 25. Relationship between average disease severity and the use of brand-name medications (2010)**

Some might expect that higher brand-name drug use within a region results from higher levels of disease burden because newer treatments without generic alternatives may be used more commonly for "sicker" patients. A comparison of brand-name use with each region's average disease burden (measured by the drug hierarchical condition categories (RxHCC) used by CMS to risk adjust payments to plans) does in fact show a moderate correlation between these factors (Figure 25). When regions are stratified on average RxHCC score, however, it becomes clear that disease burden is not the entire explanation for these differences in the use of brand-name products. As Figure 26 shows, within each quintile of average RxHCC score, there is wide variation in the use of brand-name products similar in magnitude to that observed across all regions. Furthermore, there is significant overlap in the use of brand-name products across regions with different average measures of illness burden. The considerable variation in brand-name drug use even among regions with very comparable population-level measures of illness suggests that the relationship between brand-name use and total prescription spending cannot be the result of disease burden alone.

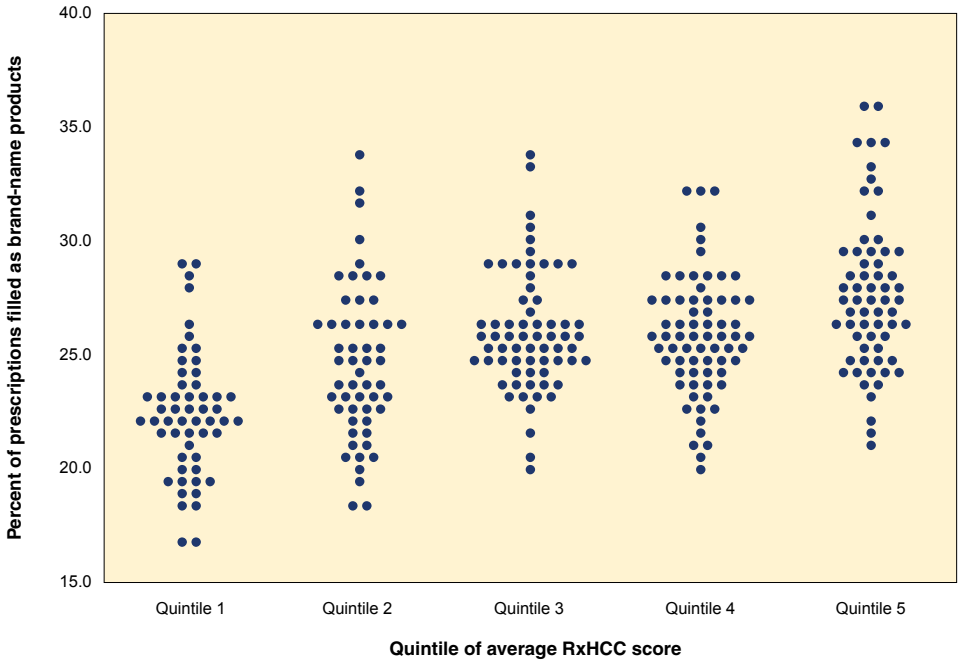



**Figure 26. Brand-name drug use by quintile of RxHCC score (2010)**

## How does total Part D spending relate to other Medicare spending?

Regions with higher Part D prescription drug spending generally also have higher spending on health care services covered by Medicare Parts A and B. Figure 27 illustrates the relationship between Medicare spending on inpatient and outpatient services covered by Medicare Parts A and B and spending for prescription drugs across hospital referral regions.

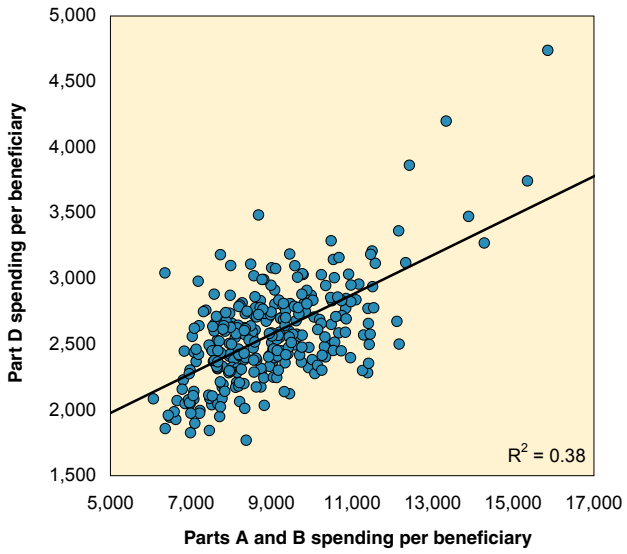



**Figure 27. Relationship between Medicare Parts A/B and Part D spending (2010)**

The relationship between prescription and non-prescription expenditures is not constant across all levels of Parts A and B spending. Figures 28-32 present the relationship between Parts A and B spending and Part D spending for each quintile of non-drug spending. As these figures show, regions with both the highest and the lowest spending on Parts A and B had moderately positive relationships between drug and non-drug spending in 2010. At the same time, there was no correlation between drug and non-drug expenditures in two of the three quintiles with intermediate A and B spending; in the third intermediate quintile, the relationship was positive but weak.

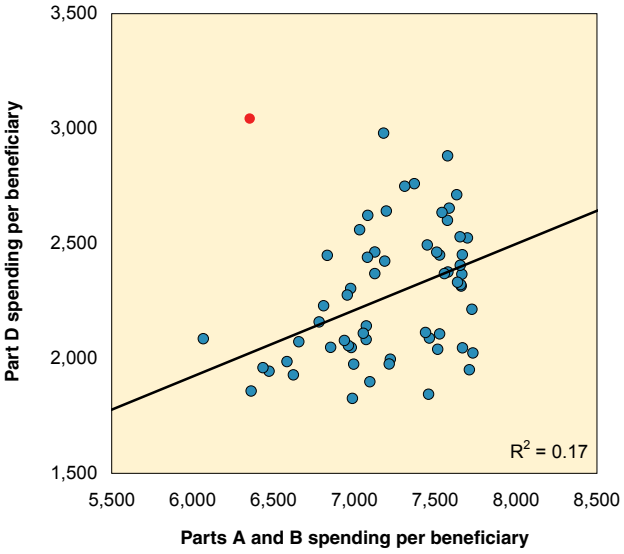



**Figure 28. Relationship between Medicare Parts A/B and Part D spending in quintile 1 (lowest) of Part A/B spending (2010)**

The red dot in the figure represents an extreme outlier region. This region was not included in the calculation of the $R^2$ statistic.

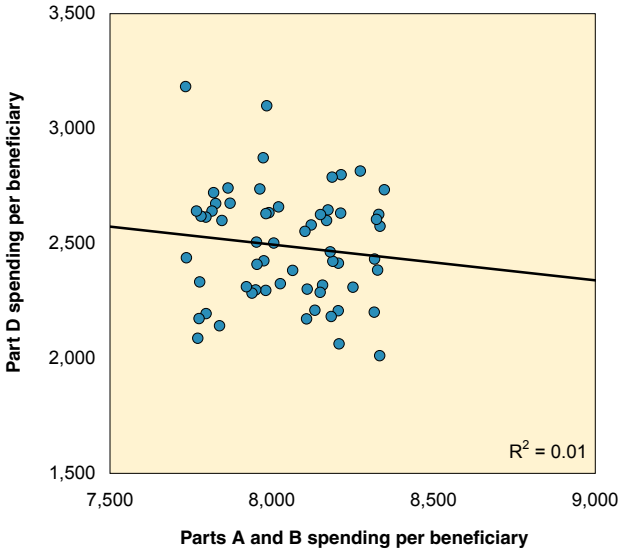



**Figure 29. Relationship between Medicare Parts A/B and Part D spending in quintile 2 of Part A/B spending (2010)**

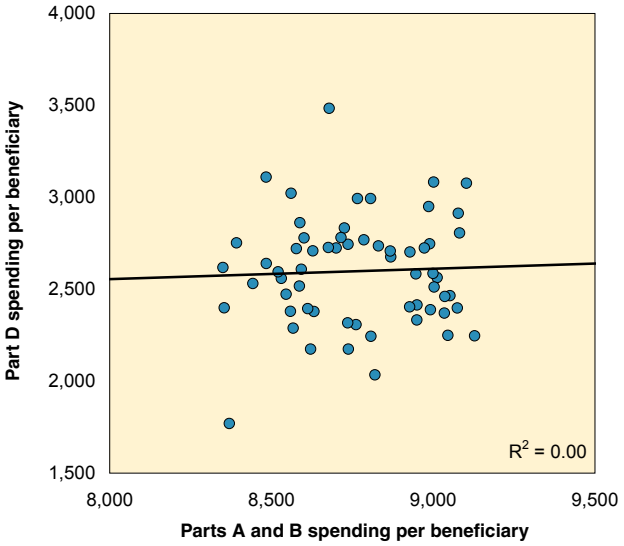



**Figure 30. Relationship between Medicare Parts A/B and Part D spending in quintile 3 of Part A/B spending (2010)**

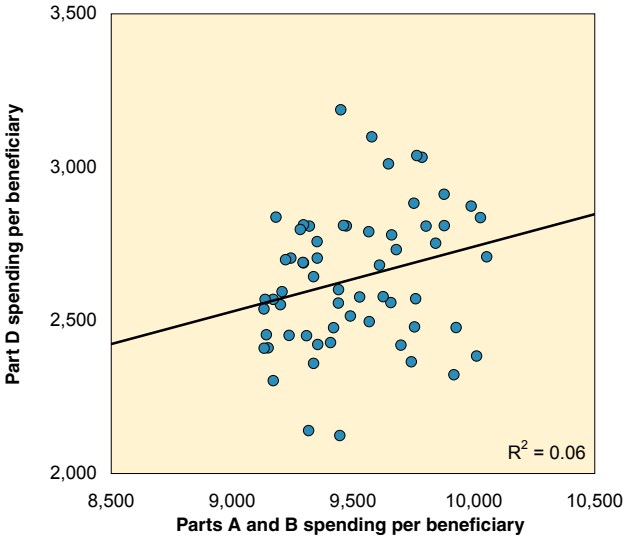



**Figure 31. Relationship between Medicare Parts A/B and Part D spending in quintile 4 of Part A/B spending (2010)**

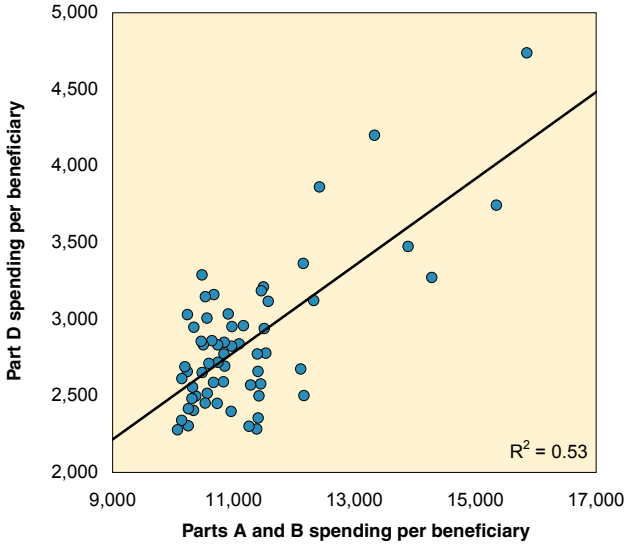



**Figure 32. Relationship between Medicare Parts A/B and Part D spending in quintile 5 (highest) of Part A/B spending (2010)**

The positive relationship between prescription drug expenditures and other Medicare expenditures at the extremes of spending is highlighted by comparing the ten regions with the highest Part D spending per beneficiary with those with the highest non-Part D spending per beneficiary (Table 8). Seven regions are present in the top ten of both lists. A similar pattern, but at the opposite end of the spectrum, is observed when the ten regions with the lowest prescription drug spending are examined. As Table 9 demonstrates, four of these regions are also in the bottom ten regions for Parts A and B spending, and two additional regions are in the bottom twenty. None of these regions is in the top half of non-prescription spending.

**Table 8. Highest 10 ranked regions for Part D spending and their rank in total Parts A and B spending (2010)**

| Region | Rank - Part D spending | Rank - Parts A and B spending |
|---|---|---|
| Miami, FL | 1 | 1 |
| Manhattan, NY | 2 | 5 |
| Los Angeles, CA | 3 | 6 |
| McAllen, TX | 4 | 2 |
| Elmira, NY | 5 | 160 |
| Bronx, NY | 6 | 4 |
| East Long Island, NY | 7 | 9 |
| Orange County, CA | 8 | 47 |
| Harlingen, TX | 9 | 3 |
| Alexandria, LA | 10 | 14 |

**Table 9. Lowest 10 ranked regions for Part D spending and their rank in total Parts A and B spending (2010)**

| Region | Rank - Part D spending | Rank - Parts A and B spending |
|---|---|---|
| Sioux Falls, SD | 297 | 288 |
| Minot, ND | 298 | 303 |
| Minneapolis, MN | 299 | 247 |
| Cedar Rapids, IA | 300 | 302 |
| Iowa City, IA | 301 | 300 |
| Bend, OR | 302 | 281 |
| Mason City, IA | 303 | 304 |
| Rochester, MN | 304 | 269 |
| Grand Junction, CO | 305 | 289 |
| St. Cloud, MN | 306 | 181 |

Average Part D expenditures per beneficiary do not always track with Parts A and B expenditures, even in higher spending regions. For instance, Elmira, New York ranks 5th in Part D spending but 160th in Parts A and B spending; Lexington, Kentucky ranks 11th in Part D spending but 92nd in non-Part D spending; and Rochester, New York, which ranks 13th in overall Part D spending, is 244th in total non-Part D spending. Regions with high Parts A and B spending but very low Part D spending can also be identified: Chicago, Illinois ranks 8th in non-drug spending, but 172nd in Part D spending; Las Vegas, Nevada ranks 17th in Parts A and B spending, but 173rd in Part D spending; and Munster, Indiana ranks 18th in non-prescription spending, but 230th in prescription drug spending.

## How does disease burden influence the relationship between Part D spending and other Medicare spending?

Some suggest that prescription drug spending is closely related to other Medicare spending because both reflect the chronic disease burden of the population. Certainly, regions with sicker patients are expected to have higher spending resulting from necessary treatments. This is demonstrated by the strong correlation ($R^2$=0.55) between overall Medicare drug spending and the prescription drug hierarchical condition categories (RxHCC) used by CMS to adjust payments to regions based on documented diseases.

Three observations suggest that the positive relationship between drug and non-drug spending is not entirely explained by differences in quintile of disease burden. First, as illustrated by Figures 33 and 34, considerable variation in both drug and non-drug spending remains even when regions are stratified by the average RxHCC score of their population. Second, these figures also show considerable overlap in spending across regions with very different average RxHCC scores. Finally, even after stratifying regions on quintile of disease burden, drug and non-drug spending are still correlated for regions in the highest and lowest quintiles (Table 10). This means that, at one extreme of disease burden, regions that spend the most on Parts A and B also spend the most on Part D even when compared only to regions with a similar burden of disease. Likewise, at the other extreme of disease burden, regions that spend the least on Medicare Parts A and B spend the least on Part D compared to other regions with the same average disease burden.

**Table 10. Relationships between total Part D spending and Parts A and B spending among quintiles of RxHCC score (2010)**

| Quintile of disease burden (lowest to highest) | Correlation between drug and non-drug spending (R) |
|---|---|
| 1 | 0.39 |
| 2 | 0.13 |
| 3 | -0.19 |
| 4 | 0.17 |
| 5 | 0.37 |

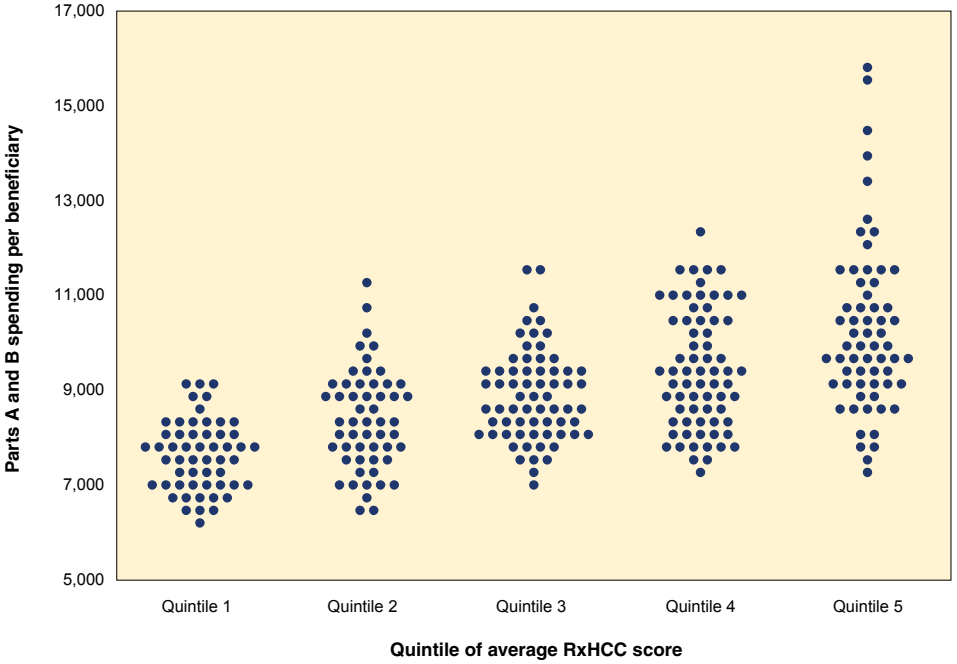



**Figure 33. Medicare Parts A and B spending by quintile of RxHCC score (2010)**

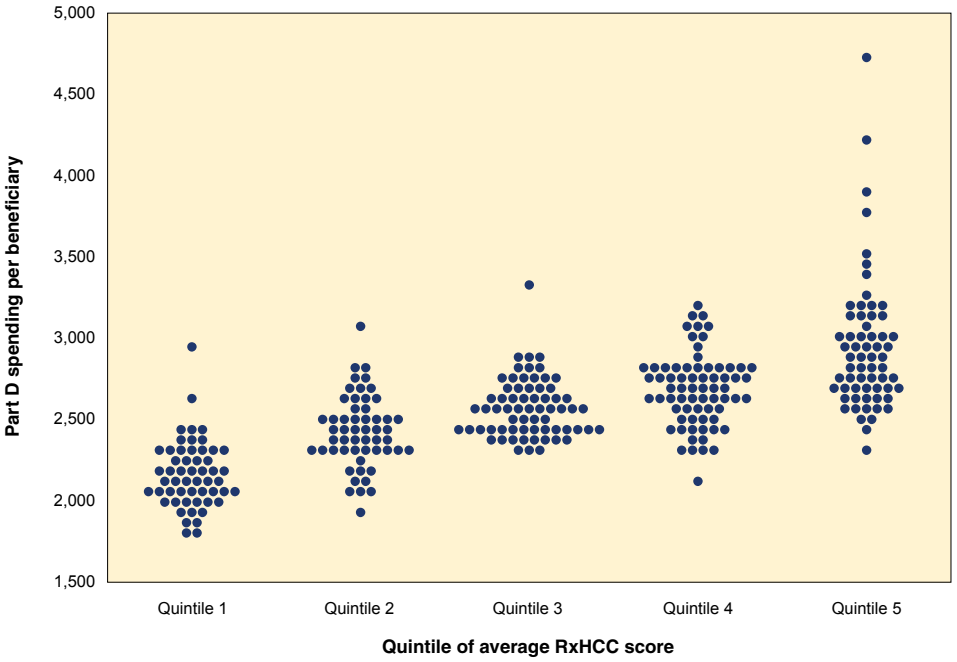



**Figure 34. Medicare Part D spending by quintile of RxHCC score (2010)**

## Summary

Considerable variation exists in overall prescription spending across hospital referral regions in the U.S. This variation is not related to differences in the use of any of the effective care measures presented in this report, but it is strongly related to two forms of discretionary medication use, and somewhat correlated with the use of high-risk medications. Both the overall volume of drugs prescribed and the decision to use brand-name products contribute to the variation in total Part D spending.

The relationship of prescription spending to non-prescription spending is complex and heterogeneous. At the extremes, regions where Medicare spending is highest for non-prescription care are also regions where prescription spending is also relatively high. Regions where spending is lowest for Medicare Parts A and B are regions where Part D spending is lowest. At the same time, there are high- and low-spending regions where Part D expenditures are uncoupled from Parts A and B expenditures. Furthermore, across regions with intermediate expenditures for non-prescription services, there is no clear correlation between drug and non-drug spending.

The complexity of the relationship between Part D spending and Parts A and B spending is likely the result of many factors. The correlations observed at the high and low end of total spending cannot be attributed solely to differences in measured disease burden among the population; however, measured disease burden has been shown to be an imperfect indicator of health.[5,6] The heterogeneity in the relationship between spending measures may reflect heterogeneity in the role of prescription drugs themselves. Some prescription drugs can serve as a substitute for other services and thereby reduce non-drug spending. This is especially true of effective drugs. Other drugs—those with more uncertain benefits—may serve as a complement to other health care services, adding cost with no offset of other care needs. At the extreme, high-risk drugs may lead to additional non-prescription care, thus actually inducing additional spending for other services. The regional variation observed across drug categories suggests varying combinations of these effects are likely contributing to the complex and inconsistent relationship observed between prescription and non-prescription spending. Notwithstanding this complexity, the findings overall suggest greater prescription efficiency is achievable, even if efforts are limited to improving the consistent use of effective care and reducing the use of high-risk medications.

## References

1. Centers for Medicare & Medicaid Services. Part D Benefit Parameters. http://www.cms.gov/Outreach-and-Education/Training/CMSNationalTrainingProgram/Downloads/2013-Part-D-Benefits-Parameters-Job-Aid.pdf. Accessed September 18, 2013.

2. The Boards of Trustees FHIaFSMITF. The 2013 Annual Report of the Boards of Trustees of the Federal Hospital Insurance and Federal Supplementary Medical Insurance Trust Funds. http://downloads.cms.gov/files/TR2013.pdf.

3. Zhou C, Zhang Y. The vast majority of Medicare Part D beneficiaries still don't choose the cheapest plans that meet their medication needs. *Health Aff (Millwood)*. Oct 2012;31(10):2259-2265.

4. Abaluck J, Gruber J. Choice Inconsistencies Among the Elderly: Evidence from Plan Choice in the Medicare Part D Program. *Am Econ Rev.* Jun 1 2011;101(4):1180-1210.

5. Welch HG, Sharp SM, Gottlieb DJ, Skinner JS, Wennberg JE. Geographic variation in diagnosis frequency and risk of death among Medicare beneficiaries. *JAMA*. Mar 16;305(11):1113-1118.

6. Wennberg JE, Staiger DO, Sharp SM, et al. Observational intensity bias associated with illness adjustment: cross sectional analysis of insurance claims. *BMJ*.346:f549.

## What can we learn from regional variation in prescription use?

This Dartmouth Atlas report has described clinically significant regional variation in the use of all three prescription drug categories—effective, discretionary, and high-risk drugs. At one end of this spectrum, variation means that some patients are not receiving drugs known to be effective, apparently as a result of where they live. At the other end, elderly patients in some regions are being given drugs known to be risky, while physicians in other regions have learned to practice without using these products. In the middle—for the use of discretionary drugs, where uncertainty is the greatest—regional variation highlights the absence of a "best practice" consensus. For this category, the value of fully informed, shared decision-making cannot be overstated.

Observed variation in the use of the individual drug categories provides insights into broader patterns of prescription drug care. The correlation between multiple unrelated discretionary medications in broad geographic clusters hints at regional influences on prescribing that are independent of disease prevalence or severity. The fact that higher use of these discretionary medications does not correlate with higher use of effective medications suggests that these regional influences are complex, and do not simply represent more frequent prescribing for all categories of prescription drug care. Finally, variation in individual drug categories ultimately adds up to variation in total prescription drug volume and spending, both of which may have important implications for patients faced with increasingly complex drug combinations and high out-of-pocket drug spending.

### What can patients learn?

Regional variation in the use of prescription medications has important implications for patients. The findings presented in this report suggest that region of residence influences the quality of prescription care received, as demonstrated by variation in both effective and potentially harmful medication use. Additionally, region of residence appears to be strongly associated with the use of a diverse set of unrelated discretionary medications that are widely prescribed but have uncertain benefits for many patients. The decision to use these drugs should involve informed discussions between physicians and patients about the tradeoffs of treatment. These conversations should truly clarify the likely benefits of a drug as well as the risks, costs, and alternatives.

## What can clinicians learn?

This portrayal of prescription drug use provides clinicians and administrators with a view of their regional prescribing practices as well as national benchmarks for prescribing quality. This report reveals that local patterns of care do not necessarily represent national norms or optimal treatment. At the same time, the geographic clusters of prescribing behavior suggest the presence of large, self-reinforcing regional influences on prescribing practice. Achieving improved clinical outcomes may therefore require physicians and administrators to look well beyond neighboring communities for improved practice solutions.

## What can researchers learn?

The causes and consequences of the regional variations described in this Atlas report are largely unknown. These findings can serve as a starting point for investigating both the upstream causes and downstream effects of the observed variation. Identifying regional factors that are associated with differences in prescribing quality and discretionary medication use is a critical step toward improving prescribing behavior. Understanding how clusters of prescribing behavior arise, how they persist, and why they affect distinct forms of care differently is also key to achieving lasting improvements in prescribing quality. Answers to many other questions are also needed in order to optimize prescribing practice and efficiency, including: Why are many regions with high prescription volumes and costs unable to achieve greater use of effective drug therapy for heart attack survivors and patients with diabetes? Why do some regions excel in one form of effective care but not others? It is also important to understand the consequences of observed variation in prescription drug use more clearly. For instance, the clinical risks associated with combining multiple medications are often not clear. Similarly, the impact of high regional utilization of prescription drugs on patient out-of-pocket expenses and adherence to effective medications is poorly understood.

## What are the implications for medical educators?

To develop physicians adept at effective and efficient prescribing, specific skills must be taught to medical trainees and practicing physicians. Prescribers should be able to engage effectively in the process of shared decision-making around prescription drug therapy. This includes an ability to review medical literature critically, apply the results of studies to diverse patient populations, and understand clearly the degree of uncertainty surrounding distinct treatment decisions. It also means they must develop skills in effectively communicating the likely benefits of specific drugs, as well as the potential harms and costs compared to available alternatives. Most importantly, physicians must be able to elicit the preferences of patients in the process of developing a shared treatment plan. Finally, the next generation of physicians will need a more sophisticated understanding of health policy and insurance coverage. Prescribing decisions have important financial ramifications for patients, and these are often poorly or incompletely understood by clinicians.

## What are the implications for policymakers?

Medicare Part D poses complex policy challenges. Unlike other services covered by Medicare in fee-for-service models, prescription drugs are paid for by private insurance plans that compete with one another in an open market and receive a subsidy from the federal government. Regional variation in prescription drug therapy raises several questions about this model: Why do plans receiving the same capitated premium subsidy from the government encounter such different patterns of prescription drug utilization and costs? What does that mean for individual patient costs? How can CMS ensure that prescription insurance plans align incentives to encourage and achieve near-universal access to effective treatment? How do formulary designs and cost-share models influence the use of effective and discretionary medications? How can diverse plans in a single region hold individual physicians or physician groups accountable for their prescribing decisions? Perhaps most importantly, what policy levers will be effective in improving overall prescribing quality and ensuring that receipt of effective—or harmful—care is not a function of a patient's ZIP code? Regional variation of the magnitude presented in this report requires consideration of these and other challenging questions, but it also presents an opportunity for policymakers to study successful regions that provide effective care efficiently, determine what factors lead to this success, and disseminate these systems more broadly.

# Utilization, variation, and association — how to interpret the measures

## What is a rate?

A rate measures how often something happens in a defined population. In health care, a rate is usually expressed as the number of events (prescription fills, procedures, tests, etc.) that occur in a given group of people over a given period of time (the numerator), divided by the total number of members of the group (the denominator) during that period. For example, if there are 100 people in a group, and 15 of them fill a prescription for an antibiotic in one year, the rate of antibiotic use is 15 per 100 for that year. This can also be expressed as a rate of 15%. In this report, the rates reported represent the number Medicare beneficiaries receiving a drug of interest divided by the total number of Medicare Part D enrollees living in a given geographic area. The rates are expressed as the number of people with one or more fills for a specific type of drug per 100 beneficiaries.

These rates (with the exception of those for effective prescription care) have been adjusted for age, sex, and race. This means that patient characteristics that might affect how common a health condition is have been taken into account. For example, in communities where a greater proportion of Medicare Part D enrollees are women, there may be a higher incidence of clinical depression because this condition is more common in women than men. That could affect the rate of observed antidepressant use. Adjusting reported rates for sex makes it unlikely that the variation we see in rates of antidepressant use in different communities is due to differences in the sex composition of the population, and thus to different rates of depression itself. Adjusting for age and race similarly make it unlikely that observed differences in prescription use across regions is explained by illness differences. In essence, these adjustments make the results what they would be if there were no age, sex, or race differences between areas.

Knowing the rate at which a particular prescription drug or drug group is received in communities is a way to compare the average chance of receiving that treatment, depending on where one lives. For example, in 2010, the average rate of receiving one or more high-risk medications was 41.2 per 100 Part D enrollees in Monroe Louisiana, one of the highest rates in the nation. The rate in La Crosse, Wisconsin was 15.2 per 100, less than half that of Monroe. That means that a resident in Monroe was more than twice as likely to get a high-risk medication than a resident of La Crosse. Another way to judge the chance of receiving a medication is to compare the rate in a given community against the U.S. average. The rate of high-risk medication use in Monroe was nearly twice the U.S. average.

## Measures of variation and association

*The distribution graph*

The distribution graphs used in the Atlas provide a simple way to show the dispersion in particular rates of health care, or in this case, prescription drug utilization across the 306 hospital referral regions. For example, Figure 14 shows the distribution of potentially hazardous medication use across the 306 hospital referral regions. The vertical axis shows the rates of hazardous medication use per 100 Part D enrolled residents. Alexandria, Louisiana, which had the highest rate of use, is represented by the highest point on the graph. Rochester, Minnesota, which had a rate of 14.0, and Mason City, Iowa, which had a rate of 14.1, are represented by two points side-by-side on the graph. Areas with very similar rates are arrayed on a single line because their rates fall into a "bin" between two values.

This chart summarizes two features of the data. The first is a measure of dispersion; if the rate of potentially hazardous medication use per 100 enrolled residents (or whatever measure is on the vertical axis) for the highest hospital referral region is two or three times higher than the rate per 100 enrolled residents in the lowest hospital referral region, it suggests substantial variation in prescribing quality. Second, the distribution graph shows whether the variation is caused by just a few outliers—hospital referral regions that, for various reasons, are very different from the rest of the country—or whether the variation is pervasive and widespread across the country. In the above example, there is widespread dispersion across the country; no one area stands apart from all other areas, as displayed in Figure 14.

*$R^2$ and regression lines*

In this Atlas, we often suggest that some factors may be related in a systematic way to other factors. For example, in section 2 we hypothesize that regions with high use rates of one effective medication—angiotensin active drugs—in diabetics might also have high rates of use of another effective medication, statins. To capture the degree and extent of the association between angiotensin active drug use and statin use, in Figure 6, we plotted angiotensin active drug use per 100 resident diabetics on the horizontal axis and statin use per 100 resident diabetics on the vertical axis, and placed a point on the graph for each of the 306 hospital referral regions. If angiotensin active drug use and statin use rates were negatively correlated, so that regions with higher angiotensin active drug use per 100 patients had lower statin use per 100 patients, then we would see a cloud of points tilted downward, running from northwest to southeast. Conversely, if they were positively correlated—as they in fact are—the cloud of points runs from southwest to northeast on the graph, as seen in Figure 6.

It is sometimes difficult to discern from a cloud of points in a figure the strength of the relationship between two variables. A linear regression line estimates the best fit of the data and summarizes the relationships between them. A measure of the "goodness of fit," or the extent to which angiotensin active drug use predicts statin

use, is the $R^2$ (from Pearson's correlation), which is defined as the proportion of total variation in the vertical axis (statin use) that is explained by variation in the horizontal axis (angiotensin active drug use). It ranges from 0 to 1, where 1 is perfect correlation and 0 means that the two variables are completely unrelated. In Figure 6, the $R^2$ for the relationship between angiotensin active drug use and statin use is 0.16, which means that the two are weakly related; only 16% of the variation in statin use per 100 residents is related to angiotensin active drug use. In contrast, Figure 13 shows that use of proton pump inhibitors is strongly related to use of dementia medications. In this case, the $R^2$ value is 0.43, which means 43% of the variation in the use of dementia medications is related to variation in proton pump inhibitor use.

*R values*

While the $R^2$ value is informative and lets readers understand how much use of one medication is related to use of another medication as a percent (see example above), we also present R values (not squared) from Spearman correlation tests. The R values presented in tables are similar to the $R^2$ values; they tell readers how one measure relates to another measure. The value of the R falls between +1 and –1. An R value of +1 represents a perfect positive correlation; as one measure increases, the other measure increases (or moves in the same direction) a predictable amount. An R value of zero means there is no correlation; the measures move independently, and change in one measure results in no predictable change in the other measure. An R value of –1 is a perfect negative correlation; as one measure increases, the other decreases (or moves in the opposite direction) a predictable amount. The R value lets readers assess how two measures relate. Table 7 shows a weak negative relationship between the use of statins among heart attack patients in a region and average total Part D spending in that same region. The R value is -0.16. This means regions with higher rates of use of this effective therapy tend to have modestly lower total spending. A similar relationship is seen between this effective care measure and average total prescription use (volume): the R value is -0.20, meaning regions with higher use of this effective care tend to be regions with lower overall prescription drug use.

## Methods

**Data:** We began with a 40% Medicare random-sample denominator file for each year from 2006 to 2010. For patients in this sample, we used claims records from the Medicare Denominator, Medicare Provider Analysis and Review (MedPAR), Outpatient, Hospice, Carrier, and Part D Event (PDE) files to create one enrollment cohort and three disease-specific cohorts for the study of prescription drug use measures. Cohorts were defined as follows:

**(A) 2010 Part D enrollment cohort:** Patients were included if they (1) were age 65 or older as of 1/1/2010, (2) were alive and continuously enrolled in a stand-alone Medicare Part D plan for all 12 months of 2010, and (3) were not enrolled in hospice or a managed Medicare plan (Medicare Advantage) at any time during 2010.

**(B) Diabetes cohort:** Patients were included if they (1) were age 65 to 75 as of 1/1/2009, (2) met the HEDIS definition of diabetes mellitus in 2009[1], (3) were enrolled in a stand-alone Medicare Part D plan for at least 6 months of 2009 and at least 6 months of 2010, (4) filled at least one prescription for a insulin or an oral diabetes medication recorded in the 2009 PDE file, and (5) were not enrolled in hospice or a managed Medicare plan at any time during 2009 and 2010.

**(C) Acute myocardial infarction (AMI) cohort:** Patients were included if they (1) were admitted to an acute care hospital with a principal discharge diagnosis of AMI following a stay longer than one day between 1/1/2008 and 12/31/2009, (2) were age 65 or older as of the index discharge date, (3) were alive and enrolled in a stand-alone Medicare Part D plan for 12 consecutive months following their index AMI discharge, and (4) had no hospice or managed Medicare plan enrollment in the 12 months following index AMI discharge.

**(D) Fragility fracture cohort:** Patients were included if they (1) experienced a fracture of the hip, distal forearm or humerus between 5/1/2006 and 12/31/2009, (2) were continuously enrolled in fee-for-service Medicare Parts A and B for at least 36 months preceding the index fracture and at least 12 months following the fracture, (3) were alive and continuously enrolled in and used (one or more fill record) a stand-alone Medicare Part D plan for at least 6 months following the fracture, (4) did not have an identically-defined fragility fracture in the 36 months preceding the index fracture, (5) were predominantly community dwelling (not hospitalized for more than 90 days and had no prescriptions filled by a long-term care pharmacy type) in the first 6 months following index fracture, (6) had no cancer diagnosis (other than non-melanoma skin cancer), hospice enrollment, or managed Medicare enrollment at any time in claims records analyzed.[2]

In the development of each cohort, we restricted inclusion to beneficiaries with continuous enrollment for the duration of the observation period (12 full months for the enrollment cohort and 6 to 12 months for the disease-specific cohorts depending on the target time frame for achieving the prescription fill measure of interest). By intention, this restriction results in a biased patient sample in several regards. Prescription fill patterns may vary toward the end of life or as one approaches disenrollment from an insurance plan. The exclusion of beneficiaries in such transitions is intended to help assure that observed prescription fills capture average patterns. In our disease-specific cohorts, restricting inclusion to beneficiaries with continuous enrollment creates the important additional requirement of survival. This results in cohorts most likely to be appropriate for the effective care measures assessed and excludes beneficiaries who properly may not be treated with the target pharmacotherapy because they are understood to be near death and thus unlikely to benefit from treatments that confer benefit over relatively long time frames (years rather than weeks or months).

**Prescription outcomes measured:** To assess overall prescription utilization, we used Part D event records to calculate individual-level total Part D prescription spending, prescription volume (prescription fills standardized to 30-day supplies), and the proportion of prescription fills dispensed as branded (vs. generic) products. For context and comparison, total non-prescription (Parts A and B) spending was also calculated from inpatient and outpatient claims records.

Additionally, specific prescription use measures were developed to permit study of three main categories of prescription care: (1) treatments that are widely viewed as *effective*, (2) treatments that may involve a high degree of prescriber or patient *discretion* due to diagnostic and therapeutic uncertainty, and (3) treatments with good evidence of potential *harm* in specific populations. Specific prescription measures assessed in this Atlas are outlined in Table A. Effective care was measured in the AMI, diabetes, and fragility fracture cohorts. Each of these disease states has broadly accepted, evidenced-based pharmacotherapy recommendations for secondary prevention (AMI and fragility fracture) or for reduction of disease-associated end-organ damage (diabetes).[3-6] Measures of relative discretionary drug use were developed to assess the use of common products often employed to treat medical conditions with higher potential for diagnostic uncertainty, conditions that encompass a broad range of severity and thus a broad range of pharmacotherapy effectiveness, or conditions characterized exclusively or largely by subjective experience (symptoms) rather than objective measures (medical tests). These discretionary drug use measures were assessed in the 2010 enrollment cohort. Measures of potentially harmful drug use relied on the HEDIS potentially harmful drugs list, which identifies drugs of high risk to people over 65 years of age; use of these medications was studied in 2010 enrollees.[7] These measures are listed in Table B.

All medication use measures were based on Part D event fill records for the time frame specific to each cohort's observation. The Lexi-Data Basic database (Lexicomp) was used to obtain the drug name, dose, brand or generic status, and active ingredient according to the National Drug Code (NDC).[8]

**Table A. Prescription Care Category, Cohort & Measure Definitions**

| Measure Type | Cohort(s) | Measures |
|---|---|---|
| **Overall Prescription Use** | 2010 enrollment cohort | Total prescription volume (30-day supplies)<br>Total prescription spending<br>Ratio of brand-name to total prescription fills |
| **Effective** | Myocardial infarction patients | Beta-blocker and statin for secondary prevention within 12 months |
| | Fragility fracture patients | Osteoporosis pharmacotherapy for secondary prevention within 6 months |
| | Diabetic patients | Angiotensin active agents and statins for prevention of end-organ damage, any use |
| **Discretionary** | 2010 enrollment cohort | Dementia medications: any use<br>Proton pump inhibitors: any use<br>New-generation antidepressants: any use<br>New-generation sedative-hypnotics: any use<br>Overall discretionary medication: more than one of above categories |
| **High-Risk** | 2010 enrollment cohort | HEDIS high-risk medications:<br>Any in a year<br>More than one high-risk medication type in year |

**Covariates:** Covariates obtained from the Denominator file included race/ethnicity (categorized as black or other), age at the time of cohort entry, and sex. Using the residential ZIP code, each patient was assigned to one of 306 Dartmouth Atlas hospital referral regions (HRRs).[9] We calculated prescription hierarchical condition category (RxHCC) scores using diagnoses from inpatient and outpatient claims occurring during each cohort's observation time.[10] The RxHCC classification system is used by the Centers for Medicare and Medicaid Services to adjust Part D plan payments according to health status.[11]

**Analysis:** Each cohort-specific pharmacotherapy outcome was measured without adjustment for beneficiary population characteristics. We also calculated age, sex, and race-adjusted rates of each pharmacotherapy measure by the indirect population standardization method, using the measure-specific cohort for the population standardization. In general, the rates of each pharmacotherapy measure calculated with and without adjustment were very similar. Outcomes are presented as the mean for each HRR. For the effective care measures, unadjusted values are presented because, theoretically, race, sex, and age should not affect receipt of evidence-based care shown to prevent or delay negative health outcomes. In contrast, measures of overall prescription use and prescription spending, as well as discretionary medication use and potentially harmful medication use, are presented as age, sex, and race adjusted HRR-level mean values. This approach adjusts for population characteristics that might reasonably influence medication use according to disease epidemiology: for example, higher rates of depression among women, or optimally lower use of sedative-hypnotics among older patients. The data released on our web site (www.dartmouthatlas.org) include those presented in this report, adjusted for most measures, but not adjusted for the effective care measures.

For each measure, we categorized HRRs into quintiles of the measure's values. Pearson's and Spearman's coefficients were used to test correlation between pairs of measures across HRRs. In this way we tested relationships between diverse prescription use measures as well as non-prescription service use measures.

**Table B. HEDIS Measures of Potentially Harmful Drug Use in Patients Over Age 65**

| Description | Prescription | | |
|---|---|---|---|
| **Antianxiety (includes combination drugs)** | • Aspirin-meprobamate | • Meprobamate | |
| **Antiemetics** | • Scopolamine | • Trimethobenzamide | |
| **Analgesics (includes combination drugs)** | • Ketorolac | | |
| **Antihistamines (includes combination drugs)** | • APAP/dextromethorphan/diphenhydramine<br>• APAP/diphenhydramine/phenylephrine<br>• APAP/diphenhydramine/pseudoephedrine<br>• Acetaminophen-diphenhydramine<br>• Carbetapentane/diphenhydramine/phenylephrine<br>• Codeine/phenylephrine/promethazine<br>• Codeine-promethazine<br>• Cyproheptadine | • Dexchlorpheniramine<br>• Dexchlorpheniramine/dextromethorphan/PSE<br>• Dexchlorpheniramine/guaifenesin/PSE<br>• Dexchlorpheniramine/hydrocodone/phenylephrine<br>• Dexchlorpheniramine/methscopolamine/PSE<br>• Dexchlorpheniramine-pseudoephedrine<br>• Dextromethorphan-promethazine<br>• Diphenhydramine | • Diphenhydramine/hydrocodone/phenylephrine<br>• Diphenhydramine-magnesium salicylate<br>• Diphenhydramine-phenylephrine<br>• Diphenhydramine-pseudoephedrine<br>• Hydroxyzine hydrochloride<br>• Hydroxyzine pamoate<br>• Phenylephrine-promethazine<br>• Promethazine |
| **Antipsychotic, typical** | • Thioridazine | | |
| **Amphetamines** | • Amphetamine-dextroamphetamine<br>• Benzphetamine<br>• Dexmethylphenidate | • Dextroamphetamine<br>• Diethylpropion<br>• Methamphetamine | • Methylphenidate<br>• Phendimetrazine<br>• Phentermine |
| **Barbiturates** | • Butabarbital<br>• Mephobarbital | • Pentobarbital<br>• Phenobarbital | • Secobarbital |
| **Long-acting benzodiazepines (includes combination drugs)** | • Amitriptyline-chlordiazepoxide<br>• Chlordiazepoxide | • Chlordiazepoxide-clidinium<br>• Diazepam | • Flurazepam |
| **Calcium channel blockers** | • Nifedipine—short-acting only | | |
| **Gastrointestinal anti-spasmodics** | • Dicyclomine | • Propantheline | |
| **Belladonna alkaloids (includes combination drugs)** | • Atropine<br>• Atropine/CPM/hyoscyamine/PE/scopolamine<br>• Atropine/hyoscyamine/PB/scopolamine<br>• Atropine-difenoxin | • Atropine-diphenoxylate<br>• Atropine-edrophonium<br>• Belladonna<br>• Belladonna/ergotamine/phenobarbital | • Butabarbital/hyoscyamine/phenazopyridine<br>• Hyoscyamine<br>• Hyoscyamine/methenam/M-blue/phenyl salicyl |
| **Skeletal muscle relaxants (includes combination drugs)** | • ASA/caffeine/orphenadrine<br>• ASA/carisoprodol/codeine<br>• Aspirin-carisoprodol<br>• Aspirin-methocarbamol | • Carisoprodol<br>• Chlorzoxazone<br>• Cyclobenzaprine | • Metaxalone<br>• Methocarbamol<br>• Orphenadrine |
| **Oral estrogens (includes combination drugs)** | • Conjugated estrogen<br>• Conjugated estrogen-medroxyprogesterone | • Esterified estrogen<br>• Esterified estrogen-methyltestosterone | • Estropipate |
| **Oral hypoglycemics** | • Chlorpropamide | | |
| **Narcotics (includes combination drugs)** | • ASA/caffeine/propoxyphene<br>• Acetaminophen-pentazocine<br>• Acetaminophen-propoxyphene<br>• Belladonna-opium | • Meperidine<br>• Meperidine-promethazine<br>• Naloxone-pentazocine | • Pentazocine<br>• Propoxyphene hydrochloride<br>• Propoxyphene napsylate |
| **Vasodilators** | • Dipyridamole—short-acting only | • Ergot mesyloid | • Isoxsuprine |
| **Others (including androgens and anabolic steroids, thyroid drugs, urinary anti-infectives)** | • Methyltestosterone<br>• Nitrofurantoin | • Nitrofurantoin macrocrystals<br>• Nitrofurantoin macrocrystals-monohydrate | • Thyroid desiccated |

Source: HEDIS 2012 Technical Specifications for Physician Measurement. National Committee for Quality Assurance, 2011.

## References

1. HEDIS 2009 Measures. National Committee for Quality Assurance, 2008. (Accessed December 15, 2008, at http://www.ncqa.org/Portals/0/HEDISQM/HEDIS2009/2009_Measures.pdf.)

2. Liu Stephen K, Munson Jeffrey C, Bell J-E, et al. Quality of Osteoporosis Care of Older Medicare Recipientswith Fragility Fractures: 2006 to 2010. *JAGS* 2013;Forthcoming.

3. Krumholz HM, Radford MJ, Wang Y, Chen J, Heiat A, Marciniak TA. National use and effectiveness of beta-blockers for the treatment of elderly patients after acute myocardial infarction: National Cooperative Cardiovascular Project. *JAMA* 1998;280:623-9.

4. Smith SC, Jr., Allen J, Blair SN, et al. AHA/ACC guidelines for secondary prevention for patients with coronary and other atherosclerotic vascular disease: 2006 update: endorsed by the National Heart, Lung, and Blood Institute. *Circulation* 2006;113:2363-72.

5. Haffner SM, Lehto S, Ronnemaa T, Pyorala K, Laakso M. Mortality from coronary heart disease in subjects with type 2 diabetes and in nondiabetic subjects with and without prior myocardial infarction. *N Engl J Med* 1998;339:229-34.

6. Strippoli GF, Bonifati C, Craig M, Navaneethan SD, Craig JC. Angiotensin converting enzyme inhibitors and angiotensin II receptor antagonists for preventing the progression of diabetic kidney disease. *Cochrane Database Syst Rev* 2006:CD006257.

7. HEDIS and Quality Compass, 2011 Measures. 2011. (Accessed January 18, 2012, at http://www.ncqa.org/tabid/187/default.aspx.)

8. LexiComp Basic database (Lexicomp). Denver: Cerner Multum. 2013. (Accessed April 5, 2013, at http://www.lexi.com/businesses/solutions/clinical-decision-support.)

9. The Dartmouth Atlas of Health Care. The Dartmouth Institute for Health Policy and Clinical Practice, Center for Health Policy Research, 2013. (Accessed January 4, 2013, at http://www.dartmouthatlas.org/.)

10. 2008 RxHCC Model Software. 2012. (Accessed November 4, 2012, at https://http://www.cms.gov/Medicare/Health-Plans/MedicareAdvtgSpecRateStats/Risk-Adjustors.html.)

11. Robst J, Levy JM, Ingber MJ. Diagnosis-based risk adjustment for medicare prescription drug plan payments. *Health Care Financ Rev* 2007;28:15-30.

**The Dartmouth Atlas Project** works to accurately describe how medical resources are distributed and used in the United States. The project offers comprehensive information and analysis about national, regional, and local markets, as well as individual hospitals and their affiliated physicians, in order to provide a basis for improving health and health systems. Through this analysis, the project has demonstrated glaring variations in how health care is delivered across the United States.

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