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Racial Disparities in Adherence to Cardiovascular Medications among the Elderly in Medicare: Three Empirical Essays

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Abstract

This dissertation sought to explore the relatively understudied area of racial disparities in adherence to cardiovascular medication regimens among the elderly. Black and Hispanic seniors are well documented to have lower rates of adherence to their prescribed cardiovascular medications, relative to their white counterparts. This disproportionately lower adherence places these minority groups at higher risk for worse cardiovascular prognosis and premature cardiovascular death. The Medicare Program, which covers healthcare predominantly for elderly Americans, offers an interesting laboratory to study these disparities and their response to policy changes. Using nationally representative data from the Medical Expenditure Panel Survey on white, black, and Hispanic Medicare seniors, this dissertation was an endeavor to: 1) evaluate the impact on these disparities of the introduction of Medicare Part D, the prescription drug benefit, in 2006, 2) explore the heterogeneity of these disparities at various locations in the adherence distribution, signifying population subgroups with potentially distinct behavioral patterns, and 3) systematically estimate the extent to which the inequality in the determinants of adherence, such as socioeconomic status, insurance coverage, access to care, and experience with providers, contributes to the particularly significant and consequential black-white adherence differential. To pursue these aims, this dissertation used some of the recent advances in econometric techniques for the study of inequality, including the rank-and-replace procedure to adjust for health status in non-linear models, unconditional quantile regression, and distribution-wide Oaxaca-Blinder decomposition, respectively. The Institute of Medicine's framework on racial healthcare disparities constituted the primary basis for defining and empirically estimating adherence disparities. These investigations contribute threefold to the literature: substantively, conceptually, and empirically. The substantive findings can improve our understanding of what works and what does not work for disparity reduction, bring our attention to disparities among subpopulations potentially deserving priority intervention, and systematically quantify the roles of clinical, social, and health-system factors in perpetuating adherence disparities. The various conceptualizations of adherence disparities employed in this dissertation, along with the state-ofthe-art empirical approaches to implement them offer much needed examples to guide future research on disparities in general and medication-related disparities in particular.

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Racial Disparities in Adherence to Cardiovascular Medications among the Elderly in Medicare: Three Empirical Essays

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Presented for
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Health Science Center

In Partial Fulfillment
Of the Requirements for the Degree
Doctor of Philosophy
From The University of Tennessee

By
Mustafa Hussein Muhammad Hussein
May 2014

DEDICATION

To the soul of my father…

To my family…

To those who fight for their freedom and dignity…

To those who struggle to make their ends meet…

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I am eternally thankful to Allah, the most Gracious, the most Merciful, for endowing me with the aptitude, tenacity, and great mentors to pursue the path of life-long learning and scholarship, and I ask Him for the strength to stand to His expectations.

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ABSTRACT

This dissertation sought to explore the relatively understudied area of racial disparities in adherence to cardiovascular medication regimens among the elderly. Black and Hispanic seniors are well documented to have lower rates of adherence to their prescribed cardiovascular medications, relative to their white counterparts. This disproportionately lower adherence places these minority groups at higher risk for worse cardiovascular prognosis and premature cardiovascular death. The Medicare Program, which covers healthcare predominantly for elderly Americans, offers an interesting laboratory to study these disparities and their response to policy changes. Using nationally representative data from the Medical Expenditure Panel Survey on white, black, and Hispanic Medicare seniors, this dissertation was an endeavor to: 1) evaluate the impact on these disparities of the introduction of Medicare Part D, the prescription drug benefit, in 2006, 2) explore the heterogeneity of these disparities at various locations in the adherence distribution, signifying population subgroups with potentially distinct behavioral patterns, and 3) systematically estimate the extent to which the inequality in the determinants of adherence, such as socioeconomic status, insurance coverage, access to care, and experience with providers, contributes to the particularly significant and consequential black-white adherence differential. To pursue these aims, this dissertation used some of the recent advances in econometric techniques for the study of inequality, including the rank-and-replace procedure to adjust for health status in non-linear models, unconditional quantile regression, and distribution-wide Oaxaca-Blinder decomposition, respectively. The Institute of Medicine's framework on racial healthcare disparities constituted the primary basis for defining and empirically estimating adherence disparities. These investigations contribute threefold to the literature: substantively, conceptually, and empirically. The substantive findings can improve our understanding of what works and what does not work for disparity reduction, bring our attention to disparities among subpopulations potentially deserving priority intervention, and systematically quantify the roles of clinical, social, and health-system factors in perpetuating adherence disparities. The various conceptualizations of adherence disparities employed in this dissertation, along with the state-of-the-art empirical approaches to implement them offer much needed examples to guide future research on disparities in general and medication-related disparities in particular.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER 1. INTRODUCTION

"*Ill fares the land, to hastening ills a prey*,
Where wealth accumulates, and men decay"

Oliver Goldsmith,
Anglo-Irish writer (1730-1774)

Racial Disparities in Cardiovascular Disease

Cardiovascular diseases are the leading cause of death.[1] They are also the most costly conditions.[2] Black Americans have 2-3 times higher likelihood of death due to cardiovascular disease at any given age.[3,4] This disparity in cardiovascular death accounts for the largest share (34%) of the racial all-cause mortality differential in the United States, with the disparity in death due to uncontrolled hypertension making up most of that share.[5] In the CARDIA study, Bibbins-Domingo et al found adult blacks to be 20 times more likely than their white counterparts to develop heart failure before the age of 50, pursuant to a striking disparity in uncontrolled blood pressure that persisted over more than 10 years of follow-up.[6] Based on an analysis of the National Health and Nutrition Examination Survey, Fiscella et al estimated that bringing the blood pressure level among blacks to that among whites could save more than 7,000 lives annually from death due to heart disease or stroke.[7] Hispanics as well are more likely to fall short of treatment goals, including having persistently elevated blood pressure[8,9] and cholesterol levels.[10,11] Among the social and behavioral factors that might explain the racial disparities in cardiovascular disease,[8,12-14] the lower levels of adherence to cardiovascular medications among minorities is a repeatedly identified suspect that is amenable to intervention.[7,8,12,15]

Medication Adherence

Medication adherence is "the extent to which a patient's behavior, relevant to medication and lifestyle recommendations, coincides with medical or health advice."[16,17] Adherence as a process encompasses three components: initiation, implementation, and persistence.[18] Regimen initiation refers to patients filling their newly prescribed medications,[19,20] thereby initiating the adherence process. If the patient starts taking his/her medications but to varying degrees (in terms of the amount or frequency), then this is a problem with the implementation phase of the process or the actual "execution" of the regimen relative to what has been prescribed.[21] The third phase of the adherence process, persistence, describes the degree of conformity of the actual duration to the recommended duration of therapy.[16,22] Patient adherence to prescribed medications, that are indicated, safe, and effective, plays a key role in the realization of therapeutic goals, such as healthier blood pressure, blood glucose, and cholesterol, and positive overall health outcomes, such as reduction in morbidity, and mortality.[23] In 2005, the cost of

poor medication adherence in the United States was estimated to be $500 billion in medication-related hospitalizations.[24] In cardiovascular diseases, 40% of patients are estimated to be poorly adherent (having less than 80% medication possession) to their cardiovascular medications.[25] Poor adherence to cardiovascular medications is associated with 25% higher risk for cardiovascular events, including coronary heart disease (CHD), stroke, and sudden cardiac death, and 60% higher risk for all-cause mortality.[25] Poor adherence to beta-blockers, angiotensin-converting enzyme (ACE) inhibitors and statins among CHD patients is associated with 10-40% higher odds of hospitalization and 15-32% higher odds of coronary revascularization. Overall, 9% of the risk for major cardiovascular events is directly attributable to poor adherence.[25] Elderly patients, given their multiple chronic conditions, polypharmacy, and functional decline, are at especially high risk for the adverse effects of poor adherence.[26,27]

Racial Disparities in Adherence among the Elderly

Among the elderly, blacks and Hispanics with uncomplicated hypertension were about 45% less likely to be adherent to their antihypertensive medications, including alpha- and beta-blockers, ACE inhibitors, angiotensin II receptor blockers (ARBs), Calcium channel blockers (CCBs), diuretics and vasodilators.[28] Zhang et al examined adherence to ACE inhibitors/ARBs and diuretics among seniors with heart failure, and found blacks, Hispanics, and Native Americans to be about 40% less likely to achieve adherence than whites.[29] Zhang et al also reported that black and Hispanic seniors surviving acute myocardial infarction (AMI) were 20-30% less likely to adhere to beta-blocker, ACE inhibitor, or statin therapy for 6 months or a year post-infarction.[30] In an analysis across race and gender of AMI survivors, Lauffenburger et al reported that black and Hispanic women were least likely (having about 30-36% lower odds), compared with white men, to be adherent to these post-AMI preventive therapies.[31] In a meta-analysis of published studies, Lewey et al estimated that generally patients of non-white race were at about 50% higher odds of non-adherence to statins than whites.[32] Racial disparities in adherence persist even in settings with equal access to prescription drugs.[11,33] Despite their significant role in placing minorities at a higher risk for adverse cardiovascular outcomes, adherence disparities have received very little attention in the literature.

Medicare: the Policy Context

The Medicare program offers an interesting laboratory to study adherence disparities among the elderly and how these disparities respond to policy changes. Medicare covers the cost of healthcare for more than 50 million elderly and disabled Americans, with the elderly population (65 years and older) accounting for about 85% of the Medicare population.[34] Medicare is the largest single payer for healthcare in the United States and spending on Medicare makes up about 16% of the federal budget, making it a very rich policy arena.[34] One major policy change in Medicare, perhaps the largest since inception in 1965, was the introduction of the Medicare prescription drug benefit, Part D by the Medicare Modernization Act of 2003.[35] Prior to 2003, a

"conspicuous failure in the US health policy"[36] was the lack of a prescription drug benefit for Medicare seniors, making the United States the only industrialized country to have such a deficiency.[36] Before Part D, 90% of Medicare elderly beneficiaries were taking prescription medications for their conditions, and 27% of them had no source of prescription drug coverage.[37] Prevalence of drug uninsurance reached 34% among poor seniors.[37] Rates of foregoing prescription drugs because of cost, i.e. cost-related non-adherence (CRN), was about 26% in the overall Medicare population, 37% among those with no coverage, 35% among the low-income, and 35% among those with complex chronic diseases.[37] Seniors with multiple chronic conditions had a striking 52% likelihood of CRN, with similar rates among patients with congestive heart failure and diabetes.[37] Except for individuals with Medicaid and other public coverage (e.g. Veteran Affairs and Indian Health Services), covered beneficiaries had patchy, discontinuous and variable levels of drug coverage (through previous employers, HMOs, Medigap and other private plans, and States' Pharmaceutical Assistance Programs) with various caps and deductibles that made beneficiaries, especially those who were sicker, seek to change plans during the year after reaching their catastrophic limits.[36,37] Studies that examined the effect of the lack or restriction of drug coverage on seniors have shown detrimental effects of these limits on their health, especially among the low-income and those in poor health and multiple comorbidity (to the extent that limits and caps placed in some drug plans may have resulted in irreversible health problems that led to nursing home admissions).[36]

The introduction of Part D aimed to expand access to prescription drugs by reducing the financial out-of-pocket burden associated with them and to improve the quality of medication use by requiring drug plans to offer medication therapy management (MTM) services to their eligible Medicare enrollees.[38,39] Rates of CRN, which motivated the introduction of Part D,[36,40] decreased among Medicare enrollees following Part D implementation in 2006.[41-43] Part D also increased drug use and reduced out-of-pocket expenditure.[44,45] Among patients with cardiovascular diseases, Part D improved medication adherence in hypertension, hyperlipidemias, and heart failure.[46] Some have suggested that this improvement has led to a significant (about 4%) reduction in hospitalizations for acute myocardial infarction (MI), angina, and congestive heart failure (CHF).[47] The Part D coverage gap, the "donut hole", however, was associated with some reduction in adherence to cardiovascular medications.[48-51] While optimal design and delivery of MTM services and the eligibility threshold are still active areas of research,[52] early evaluations of MTM among beneficiaries in 2010 show the versatility of MTM for improving the quality of medication use process and its outcomes, including medication adherence in clinically complex patients.[53]

In addition to its general goals and provisions, Medicare Part D also further supported the low-income population, among whom racial/ethnic minorities are overrepresented, by creating the low-income subsidy (LIS). The LIS effectively eliminated cost-sharing for beneficiaries with limited assets and income below 150% of the federal poverty line (assets < $25,010 and income <$21,855 for a couple in 2010).[54] Dually eligible beneficiaries and those receiving Supplemental Security Income were automatically signed up for the LIS.[55] Recent evidence suggests that the LIS brought

medication-related metrics, including adherence, duration of therapy, and overall exposure to prescription drugs, among LIS-recipients closer to those among the more advantaged non-LIS beneficiaries.[56-58]

Although the goals and effects of Part D introduction underscore a potential for reduction of medication-related disparities, studies of minority experience with Part D raise some alarming signs. In comparison with whites, minorities have had greater difficulty navigating the Part D program, due in part to health literacy and socioeconomic disadvantage,[59] and were more unaware of and confused by their Part D benefits.[60] Very scant literature has formally examined the impact of Part D on drug-related disparities. In one pre-post study of elderly beneficiaries,[61] Part D was associated with a larger decrease in out-of-pocket expenditure and unmet drug needs among black non-dually eligible beneficiaries, and a larger decrease in unmet drug needs only among Hispanic dual-eligibles, relative to their white counterparts. In a difference-in-differences evaluation,[62] Part D was associated with a reduction of white-Hispanic disparities in expenditure and use of prescription drugs, but an increase in the white-black disparity in total drug expenditure. Minorities were also less likely to meet Part D utilization-based eligibility criteria for MTM services,[63,64] depriving scores of minority patients from a benefit that is well-equipped to help them with their complex medication-related issues, including adherence behavior.

Research Aims

This dissertation sought to examine the racial disparities in adherence to cardiovascular medications in the Medicare elderly population. Using nationally representative data from the Medical Expenditure Panel Survey (MEPS), the following three aims were pursued:

Aim 1: To estimate the impact of Part D introduction on the racial disparities in adherence to cardiovascular medications

By investigating the impact of Part D, we sought to answer two interrelated questions: 1) whether adherence behavior among blacks and Hispanics was further increased or reduced as a result of Part D coverage, and 2) to what extent the potential of Part D to reduce adherence disparities has been realized. Such an impact evaluation can inform future policy endeavors, by reinforcing our knowledge of what works and what does not work for disparities reduction, including further recognition of the potential of a policy change to exert unintended effects on both the absolute outcomes, adherence among minorities in this dissertation, as well as, from a social justice perspective, the state of adherence disparities among seniors.

***Aim 2*: To identify population subgroups along the distribution of adherence where disparities were most amplified**

Although the traditional approach to studying adherence disparities at the mean probability of achieving 80% medication possession is informative, it risks overlooking significant disparities that might exist at other locations in the distribution. These locations signify population subgroups with potentially distinct patterns of adherence behavior, and they get indiscriminately lumped together when adherence is measured as a binary classification of patients above and below 80% medication possession. Investigating the extent of disparities along the distribution of adherence can thus bring to our attention disparities that might be deserving of tailored, and potentially priority, interventions.

***Aim 3*: To identify the potential drivers of the black-white disparity in adherence**

After quantifying the extent of disparities across the distribution of adherence, identifying where they were most significant, and after evaluating how Part D changed the policy and coverage landscape for Medicare seniors, this dissertation turned to the question of what might be driving those persistent disparities. As it unfolded in studies for the first two aims, the black-white disparity in cardiovascular medication adherence was the largest and potentially the most consequential, given the higher burden of cardiovascular disease among blacks and their persistent social disadvantage.[65] Despite a large literature on adherence behavior among blacks, conducting a systematic, comparative analysis of how the determinants of adherence disparately work to produce the observed patterns of adherence among blacks and whites remains a critical gap in the literature. For Aim 3, this dissertation built on the methods and findings under Aim 2 to investigate the potential sources of black-white differences in adherence across the distribution, in an attempt to reveal the determinants of adherence most responsible for the observed black-white differential, as well as the population subgroups among whom these determinants were significant.

In the course of investigating these research questions, which were previously unstudied, disparities were conceptually defined according to the Institute of Medicine's framework on studying racial healthcare disparities.[66,67] Extending this framework to the study of disparities in adherence behavior is a much needed theoretical contribution. This dissertation also makes use of recent advances in state-of-the-art econometric methods to study inequality, including the rank-and-replace procedure to adjust for health status in non-linear models,[68,69] unconditional quantiles regression,[70] and Oaxaca-Blinder decomposition across outcome quantiles.[71] Further, this dissertation introduces specific methodology with validation to measure adherence in MEPS, filling an important gap in the literature on prescription drug research. Finally, the substantive findings from this dissertation regarding adherence disparities carry implications for disparity reduction efforts under Medicare Part D.

CHAPTER 2. IMPACT OF MEDICARE PART D ON RACIAL DISPARITIES IN ADHERENCE TO CARDIOVASCULAR MEDICATIONS AMONG THE ELDERLY

Background

Patient adherence to evidence-based cardiovascular medications is imperative for attaining intermediate therapeutic goals, such as blood pressure and low-density lipoprotein levels, and for the subsequent realization of favorable health outcomes.[23,72-74] Poor adherence can have especially detrimental consequences among older adults, given their multiple comorbidities, polypharmacy, and declining cognitive function.[75-77] Further, across racial/ethnic groups, differentially worse adherence to cardiovascular medications, such as angiotensin-converting enzyme (ACE) inhibitors, beta-blockers, and statins, have been repeatedly observed, even after adjustment for socioeconomic status and insurance coverage.[28-32,78-85] Worse adherence among blacks and Hispanics, is a key predisposing factor for falling short of treatment goals, including having persistently elevated blood pressure[8,9] and cholesterol levels.[10,11] In the landmark CARDIA study, blacks were 20 times more likely to develop heart failure before the age of 50, than whites, with a persistent disparity in uncontrolled blood pressure as a key antecedent.[6] Not surprisingly, the disparity in cardiovascular mortality is the major contributor to the disparity in life expectancy in the United States,[86] with blacks 2-3 times more likely than whites to die from heart diseases at any given age.[4]

Medicare Part D, signed into law in 2003 and implemented in 2006, aimed to 1) expand access to prescription drugs by reducing the financial out-of-pocket burden associated with them, and 2) improve the quality of medication use by requiring drug plans to offer medication therapy management (MTM) services to their eligible Medicare enrollees.[38,39] Cost-related non-adherence, which motivated the introduction of Part D,[36,40] decreased among Medicare enrollees following Part D implementation in 2006, though not among the most vulnerable, e.g. those with low-income or poor health.[41-43] Part D also increased drug use and reduced out-of-pocket expenditure.[44,45] Among patients with cardiovascular diseases, Part D improved medication adherence in hypertension, hyperlipidemias, and heart failure.[46] Some have suggested that this improvement has led to a significant (about 4%) reduction in hospitalizations for acute myocardial infarction (MI), angina, and congestive heart failure (CHF).[47] The Part D coverage gap, the "donut hole", however, was associated with some reduction in adherence to cardiovascular medications.[48-51] While optimal design and delivery of MTM services and the eligibility threshold are still active areas of research,[52] early evaluations of MTM among beneficiaries in 2010 show the versatility of MTM for improving the quality of medication use process and its outcomes, including medication adherence in clinically complex patients.[53]

In addition to its general goals and provisions, Medicare Part D also aimed to further support the low-income population, among whom racial/ethnic minorities are overrepresented, by creating the low-income subsidy (LIS). The LIS effectively

eliminated cost-sharing for beneficiaries below 150% of the federal poverty line, automatically including those who are dually eligible for Medicare and Medicaid as well as those receiving Supplemental Security Income.[55] Recent evidence indicates that LIS recipients are doing better on medication use quality metrics, including medication adherence in a number of chronic conditions.[56-58]

Taken together, the goals and impact of Part D coverage on the general Medicare and LIS populations suggest that it may have reduced the racial/ethnic disparities in medication adherence. Testing this hypothesis in a formal impact evaluation is still an open empirical question. This evaluation is further motivated by the increasing vulnerability among minorities who may not be receiving as much benefit from Part D as their white majority counterparts. This concern is supported by studies showing that, compared to whites, minorities have had more difficulties navigating the Part D program, due in part to health literacy and socioeconomic disadvantage,[59] and have been more unaware of and confused by their Part D benefits.[60] Further, given the greater burden of cardiovascular diseases among minorities, particularly blacks, any potential unintended consequences of Part D benefit designs and delivery structure may have especially negative consequences for these already burdened minority beneficiaries. Very scant literature has formally examined the impact of Part D on drug-related disparities, generally, and to the best of our knowledge, none has focused specifically on the impact of Part D on adherence disparities. In one pre-post study of elderly beneficiaries,[61] Part D was associated with a larger decrease in out-of-pocket expenditure and unmet drug needs among black non-dually eligible beneficiaries, and a larger decrease in unmet drug needs only among Hispanic dual-eligibles, relative to their white counterparts. In a difference-in-difference evaluation by Mahmoudi and Jensen,[62] Part D was associated with a reduction of white-Hispanic disparities in expenditure and use of prescription drugs, but increased white-black disparity in total drug expenditure.

The goal of this study was to investigate, using nationally representative data, how Part D introduction affected the time course of adherence disparities in the Medicare population, controlling for the secular trends that would have prevailed in the absence of Part D. By investigating the impact of Part D, we sought to answer two interrelated questions: 1) whether adherence behavior among blacks and Hispanics was further increased or reduced as a result of Part D coverage, and 2) to what extent the potential of Part D to reduce adherence disparities has been realized. Such an impact evaluation can inform future policy endeavors, by reinforcing our knowledge of what works and what does not work for disparities reduction, including further recognition of the potential of a policy change to exert unintended effects on both the absolute outcomes, adherence among minorities in our case, as well as, from a social justice perspective, the state of disparities.

Methods

Data and Population

We analyzed the annual data files, linked to the Medical Conditions files and Prescribed Medicines event files, of the Household Component of the Medical Expenditure Panel Survey (MEPS-HC; MEPS for short) from 2002 to 2010. MEPS is an annual, nationally representative survey of healthcare access, use, and expenditure by the US civilian non-institutionalized population, with oversampling of minorities, administered by the US Agency for Healthcare Research and Quality (AHRQ). Each year MEPS panel participants are sampled from the previous year's respondents to the National Health Interview Survey. Each panel is then interviewed for five rounds over two and a half years, providing data for two calendar years. MEPS annual files (known as Full Year Consolidated Data Files) combine data from the two panels that overlap in the particular year a file covers: rounds 3, 4, and 5 of the previous year's panel and rounds 1, 2, and 3 of the current year's panel. By combining data from the overlapping panels, these annual files provide nearly double the sample size of individual panels and cover the entire calendar year for each respondent. Although all MEPS data are reported by respondents during computer-assisted personal interviewing, further detailed health service use data, including on prescription drugs, are collected from a sample of providers with respondents' permission. Specifically of relevance to this study, the quality of MEPS prescription drug data, as well as Medicare Part D enrollment has been shown to be comparable to that of claims data.[87,88] Additionally, MEPS provides very rich data on respondents' sociodemographics, health and chronic conditions, as well as experience with providers and the healthcare system, allowing a thorough study of adherence as shaped by these determinants.

The study sample included respondents who were: **1)** continuously included in all MEPS survey rounds for a calendar year. This excludes respondents who went "out of scope" because of death, institutionalization, or other reasons. **2)** Medicare beneficiaries 65 years and older (the "treated" group) as of January 1st of survey year, and non-Medicare but otherwise insured individuals 60-64 years old (near-elderly, the control group) as of December 31st of survey year. This latter date serves to exclude individuals who may become eligible for Medicare during survey year. The near-elderly were used as the control group, since they are presumably closest in characteristics to the elderly and, for the most part, have seen minimal policy changes in their drug coverage in the study period.[47] **3)** Self-reported being non-Hispanic white (henceforth "white"), non-Hispanic black (henceforth "black"), or Hispanic. We could not include other racial/ethnic groups or further distinguish Hispanic subgroups due to their small sample sizes. **4)** Had at least one of the following six conditions: hypertension, hyperlipidemia, angina, congestive heart failure, myocardial infarction, and stroke. Clinical Classification Codes and 3-digit ICD-9 codes in MEPS were used to identify respondents with these conditions in MEPS Medical Conditions Files. **Appendix Table A-1** lists all the conditions and their associated codes. **5)** Had at least one refill during the survey year of a maintenance cardiovascular drug of the following therapeutic classes: ACE Inhibitors, Angiotensin II Receptor Blockers (ARBs), HMG-CoA Reductase Inhibitors (Statins), Beta-blockers,

Calcium Channel Blockers, Diuretics, or combination products of these medications. **Appendix Table A-2** lists the specific medications included and their Multum Lexicon® class information.

Since the study population represents only a small portion of MEPS respondents each year, it was necessary to pool the annual files to ensure adequate sample size for the analyses we conducted. Survey design variables in annual files 2002 and following years provide a correctly specified common variance structure to calculate the appropriate standard errors with pooling.[89] For our impact evaluation, we considered MEPS years from 2002-2005 to cover the pre-Part D period, whereas data from 2007-2010 covered the post period. We excluded 2006 from the post period since it was a transition year for both individuals and health plans under Part D, and thus, if used in the post-Part D period, it is likely that Part D effects might be under-estimated.[39,47] We test this hypothesis in a sensitivity analysis.

Measurement of Adherence

Using drug refill records for each included respondent, we measured adherence to each medication class as the proportion of days covered (PDC) by refills for any medication from that class, expressed as a percentage and capped at 100%. ACE inhibitors and ARBs were considered a single class for this purpose. Also, component medications of combination products were counted towards their respective classes. A follow-up period specific to each drug class was calculated for each respondent, starting from an index date corresponding to the first day of the interview round in which the first refill (of that class) occurred. The end date was the last day of survey year, December 31st. While the majority of index refills (60-65%) for any class occurred in rounds 3/1 (resulting in January 1 as the index date), some respondents did not have refills for one or more classes until rounds 4/2 or 5/3; in this case, the index date was set to the start date of the specific round in which the refill occurred. More than 91% of index refills had occurred in the first two rounds of a calendar year. In addition to calculating class-specific PDCs, we calculated an average PDC to summarize adherence to all drug classes an individual was taking. We then classified respondents as adherent if they had PDC of at least 80% over the follow-up period. The main outcome variable was the overall binary adherence classification. Class-specific adherence classifications were examined in secondary analyses.

Although all MEPS years in our analysis have extensive data on prescription refills, including dispensed quantity, strength, dosage form, and therapeutic class/subclass, data on days of supply were not available in years prior to 2010. We used 2010 data to characterize the patterns of observed days' supply as they relate to dispensed quantities of drug refills. In so doing, we identified the most frequent number of supply days furnished by each level of dispensed quantity. Next, we derived a scheme to smoothly approximate the distribution of refill supply days for use in prior years of MEPS (where actual days of supply data are not available). For comparison, we also more coarsely approximated days of supply by discretizing the distribution of dispensed

quantities on the basis of some rough "rules of thumb" (e.g. dispensed quantities ≤ 45 pills give 30 days of supply, quantities >45 but ≤ 75 pills cover 60 days, and quantities >75 provide 90 days of supply). Then, in 2010 data, we measured adherence, both as a continuous PDC and as a dichotomous classification as explained above, using the actual and the approximated days' supply distributions.

To assess the validity of our derivations, we used Lin's concordance coefficient[90,91] to compare the approximate continuous distributions of supply days and estimated PDC to their actual counterparts. We also used Kappa and C-statistics to compare dichotomous adherence classifications produced using approximate PDC distributions against those produced using the actual PDC distribution. Finally, using the most valid method for approximating refill days of supply from dispensed quantities, we calculated days of supply for refills in years prior to 2010. The validity of computing refill days of supply in earlier years using the pattern of days' supply vis-à-vis dispensed quantities in 2010 hinges on the potentially plausible assumption (based on discussions with two cardiologists with more than 20 years of practice experience) that the dosing frequency of a given strength of a specific cardiovascular drug has been stable over 2002-2010 in a specific patient population (for example: for the same patient population, if a 30-pill refill of 40-mg simvastatin covers 30 days in 2010, on average, this would have also been true in 2002).

Conceptualizing Adherence Disparities

In most empirical research on healthcare disparities, authors have typically estimated the disparity as the difference in outcome levels across racial/ethnic groups, after adjusting for the entire set of covariates, including socioeconomic status (SES) and other measures of race-related disadvantage.[67] Typically, the magnitude of disparity is viewed as the coefficient of the race indicator variable in a multivariable linear model or the odds ratio in a logistic regression. Although not expressly stated, the normative judgment underlying this approach to estimating disparities posits that racial disparities are the differences due to race-related factors other than the control variables already accounted for. This is because, in a multivariable model that adjusts for measured racial disadvantage, such as income and education, the race variable only captures variation in the remaining manifestations of racism that are not accounted for, such as discrimination.[69] McGuire and colleagues termed this disparity the residual direct effect (RDE) of race.[92] This traditional approach to estimating disparities ignores the contributions of other inextricable features of racial disadvantage, such as low SES, potentially leading to false conclusions regarding the existence of disparities.[67,92] When race is viewed as a complex, multidimensional lived experience involving both material and psychosocial disadvantage, racial disparities in health outcomes must include all differences due to every relevant dimension of racial inequality.[65,93] This argument also applies to ethnic disparities. In the interest of parsimony, and since race captures most aspects of ethnicity and the two categorizations are not meaningful to disentangle in a society with inequitable race relations,[65,94] we use the term "race" here to refer to race and ethnicity together.

In its 2002 landmark report, "*Unequal Treatment*," the Institute of Medicine (IOM) provided a framework to define racial disparities in healthcare, distinguishing *disparities*, which insinuate inequity and injustice, from benign *differences* in healthcare that might be more legitimate.[66,92] According to the IOM, racial healthcare disparities correspond to the racial differences in healthcare that are justified neither by the clinical appropriateness and health status needs, nor by the preferences and attitudes towards medical care, assuming that those preferences were formulated under "full and accurate understanding of treatment options."[66] Healthcare disparities arise through two broad mechanisms:[66] 1) The operative legal, and regulatory environment in which healthcare systems function, including policies and practice patterns, insurance coverage, SES, and other differential factors that constrain healthcare use disproportionately for minorities,[92] and 2) discrimination at the patient-provider level, which may take the form of prejudice, stereotyping, or statistical discrimination under clinical uncertainty.[95]

To illustrate differences vs. disparities: if, for instance, Hispanics are on average younger and thus healthier, the age-related difference in healthcare use between them and whites should not be counted towards a disparity. On the other hand, if the health status among blacks is worse than whites, but they are not receiving healthcare commensurate with their health needs because of inequitable factors, then this difference in healthcare use is indeed a disparity. In essence, the IOM framework attempts to isolate the contributions of the current structural and fundamental impediments to achieving equity in the health system, which are extrinsic to individuals and potentially ameliorable through appropriate interventions. While it is true that the differentials in health status and chronic disease burden have been shaped by historical racism, selectively adjusting for health status allows examining differences between two clinically comparable groups that, in the absence of racialized social factors such as poverty, stress, and limited access to resources, would have exhibited similar rates of healthcare utilization and health-related behaviors. Not only does the IOM framing of disparities and their potential sources provide an organizing heuristic to guide empirical research on disparities, particularly by being explicit about value judgments, it also acknowledges the contributions of multiple relevant dimensions of racial disadvantage to healthcare disparities

In this study, we applied the IOM framework to examine disparities in medication adherence and the impact of Medicare Part D on these disparities. Adherence behavior is shaped by complex interactions of multiple factors, pertinent to the patient, the condition, the drug regimen, the provider and the health system, as well as the social and economic environments.[17,77] MEPS offers a wide array of variables that we used to characterize these determinants. We made *a priori* classifications for each predictor/determinant of adherence as potentially contributing to disparities, on the basis of how it correlates with race and socioeconomic disadvantage. Specifically, as we show in **Figure 2-1**, which is similar in spirit to the IOM framework,[66] the racial difference in adherence can be decomposed into disparities and "non-disparities."

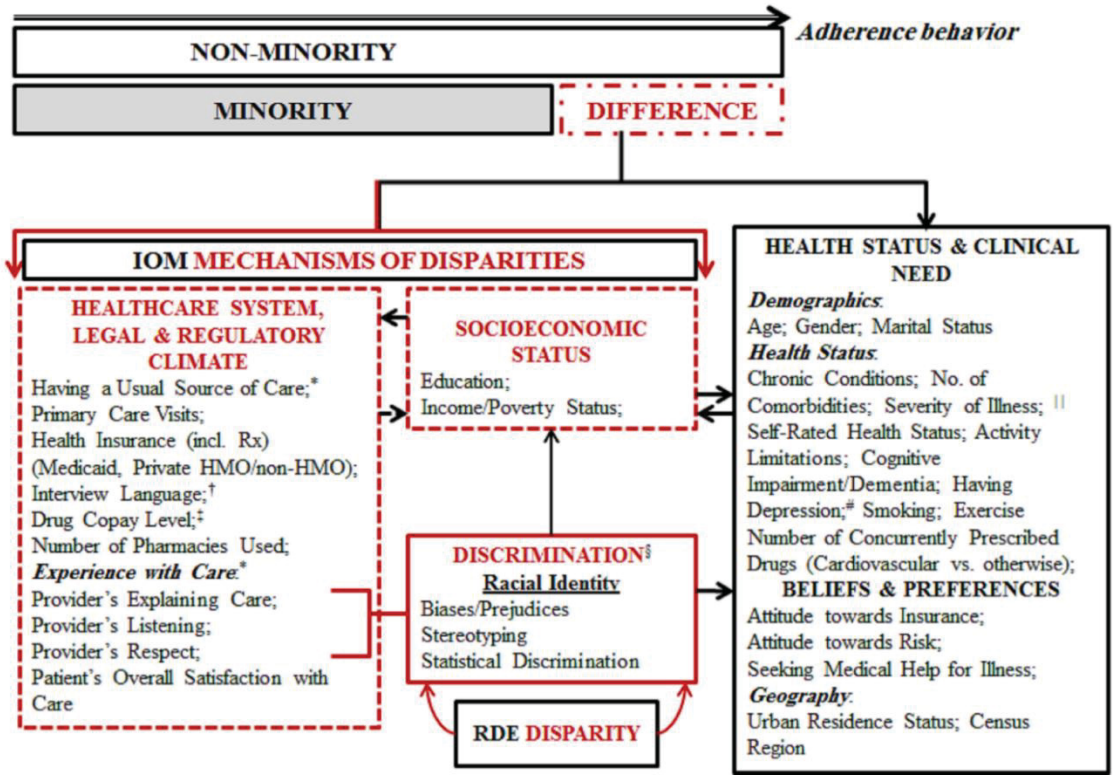

Figure 2-1. Conceptualizing adherence disparities in the light of the IOM framework

* Measured in MEPS Self-Administered Questionnaire (SAQ)

† Proxy for language in clinical encounter

‡ We do not adjust for drug copay since it is on the causal pathway between Part D and adherence. Adjusting for copay biases down Part D effects.

§ Discrimination in the clinical encounter is roughly captured by the experience with provider variables, to the left.

| | Measured by the D'Hoore's version of the Charlson comorbidity index[96] using MEPS 3-digit ICD-9 codes, excluding respondent-specific cardiovascular conditions. Conditions included in the index are not further adjusted for.

Defined using depression ICD-9 codes 296 and 311.

HMO: Health Maintenance Organization; IOM: Institute of Medicine; RDE: Residual Direct Effect.

Adherence disparities arise due to disparate SES across racial groups, racial discrimination, as well as racial differences in the experience with the healthcare system, including having a usual source of care, health/drug insurance, language in the clinical encounter (proxied by the interview language), satisfaction with care, and the quality of patient-provider relationship. Differences in adherence that arose due to differences in health status were not counted towards the disparity. As explained above, although health differentials have been shaped by historical disadvantage, our goal was to compare adherence behavior across racial groups of comparable health status so as to produce disparity estimates that incorporate how the social and health-system factors *in their current form* perpetuate these disparities. Following the IOM, we also do not count differences in adherence due to preferences/beliefs, instantiated in MEPS by respondents' attitudes towards risk, insurance, and medical care, towards disparities.

We discuss below the statistical details of how we empirically implemented our **Figure 2-1**-conceptualization of disparities. Each of the conceptual stipulations we make as to what constitutes a disparity in adherence and what does not is a hypothesis that can be formally tested. To evaluate how our conclusions about disparities might change depending on classification of particular factors, we conducted a series of sensitivity analyses that ranged from counting only demographic differences towards disparities, to fully adjusting disparity estimates for all covariates in hand (i.e. estimating RDE disparities).

Statistical Analysis

We used a difference-in-differences (DID) design (**Figure 2-2**) to evaluate the impact of Part D introduction on the racial disparities in adherence to cardiovascular medications. DID is a quasi-experimental evaluation strategy that uses the mean outcome in the control group observed after the treatment as an estimate of the counterfactual outcome that would have been observed in the treated group, in the absence of treatment.

The key identifying assumption for a valid DID analysis is that the treated and control groups exhibit parallel trends in the mean outcome in the absence of treatment (policy implementation). With such a valid control group, the DID estimate of the treatment effect thus equals what's left after taking the difference across time and across groups in the mean outcome, which serves to eliminate the secular time trend that is common to both groups and unrelated to the treatment, as well as the systematic differences due to time-invariant group characteristics (e.g. adherence is systematically higher among the near-elderly than among the elderly), respectively.[97] In regression analysis, DID estimation is done using a set of binary indicator variables for groups, time period, and their interaction term. To estimate the impact on disparities, we added race indicator variables and their interaction terms with group and time indicators to the basic DID setup, as shown in **Equation 2-1**. We apply the DID framework to pooled cross-sectional MEPS data on Medicare seniors and the near-elderly before and after Part D.

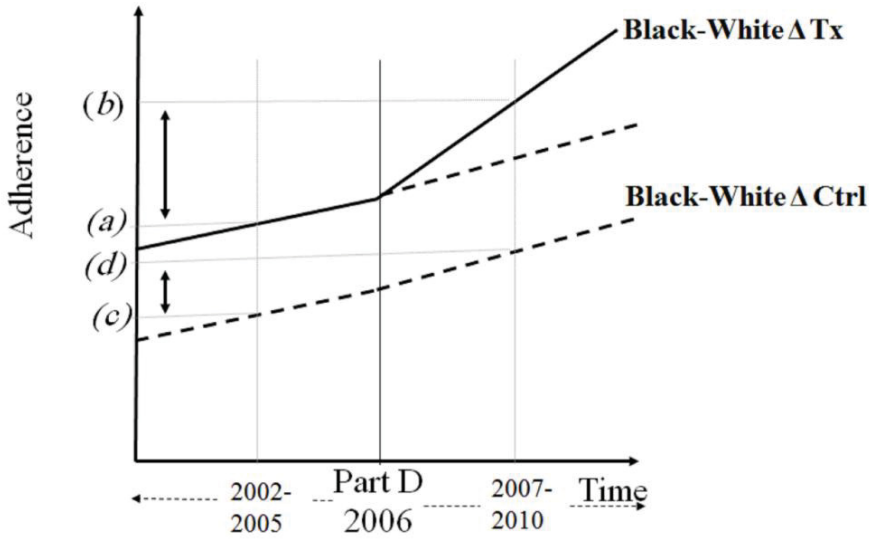

Figure 2-2. Difference-in-Difference (DID) evaluation of Part D effect on racial disparities in adherence

Change in Disparities in Medicare (Tx Group) $= \Delta_b - \Delta_a$
Change in Disparities in the near-elderly (Ctrl Group) $= \Delta_d - \Delta_c$
DID Effect of Part D on Disparities $= (\Delta_b - \Delta_a) - (\Delta_d - \Delta_c)$.

Using logistic regression, we model adherence, as a dichotomous outcome variables (at or above 80% PDC cutoff) as a function of the DID setup as well as the aforementioned predictors of adherence. In notation,

$$Pr[\text{PDC}\geq 80\%|x] = g^{-1}(\hat{\alpha} + \sum_{k=1}^{K} X_k.\widehat{\beta_k} + \widehat{\gamma_1}.Post + \widehat{\gamma_2}.Medicare + \widehat{\gamma_{12}}.Medicare \times Post$$
$$+ \widehat{\gamma_3}.Black + \widehat{\gamma_4}.Hispanic + \widehat{\gamma_{13}}.Black \times Post + \widehat{\gamma_{14}}.Hispanic \times Post$$
$$+ \widehat{\gamma_{23}}.Black \times Medicare + \widehat{\gamma_{24}}.Hispanic \times Medicare$$
$$+ \widehat{\boldsymbol{\gamma_{123}}}.Black \times Medicare \times Post + \widehat{\boldsymbol{\gamma_{124}}}.Hispanic \times Medicare \times Post) \quad \textbf{(Eq. 2-1)}$$

Where, g^{-1} is the inverse of the logistic function that relates that the outcome (on the probability scale) to the covariates. *Pr[]* is the population average probability of adherence, conditional on covariates. *X* represents the individual characteristics that predict adherence behavior, including demographics, health, SES, insurance, and experience with the healthcare system, as listed in **Figure 2-1**. We also included the interactions of SES and race indicators. *Post*, *Medicare*, *Black*, and *Hispanic*, are binary indicator variables, each equals one for the post-Part D period (2007-2010), being a Medicare senior, self-identifying as black, or Hispanic, respectively, and zero otherwise. The interaction terms serve to capture the heterogeneity of average adherence across the three dimensions of comparison: time, treated/control groups, and race. The coefficients of the two triple interaction terms, $\widehat{\boldsymbol{\gamma_{123}}}$ and $\widehat{\boldsymbol{\gamma_{124}}}$, provide an estimate of the effect of Part D on adherence, comparing minorities to whites, i.e. the effects of Part D on the racial disparities in adherence.

To implement our IOM conceptualization of adherence disparities within this DID framework, we defined adherence disparities as the differences in mean adherence across clinically comparable racial groups that arise due to inequitable social and health-system factors, including SES, insurance coverage, access to primary care, and discrimination in the clinical encounter (**Figure 2-1)**. To make racial groups clinically comparable, we selectively adjusted our race-specific outcomes predictions for perceived health status, comorbidity, and clinical need (including the use of other prescription drugs). We also adjusted for beliefs/preferences (including geographic location), per the IOM definition. For brevity, we collectively label the factors that are potential sources of disparities (the left two thirds of **Figure 2-1**) by the letter ***S***, for SES and denote factors we adjust for by ***H***, for health (right side of **Figure 2-1**), reflecting that SES and health are at the heart of the two groups of factors we conceptually distinguish.[68]

For empirical implementation, we followed Cook, McGuire, and colleagues[68,69,92] in using a rank-and-replace procedure to estimate disparities. Briefly, we first estimated our multivariable logistic DID model as above (**Equation 2-1**), controlling for all the aforementioned covariates. The adequacy of model fit was tested using a modified Hosmer-Lemeshow test for complex survey data.[98] Next, we generated a composite score of ***H*** factors for each individual in the dataset by calculating the linear combination of each individuals' observed value of each ***H*** variable multiplied by the pertinent coefficient in the multivariable model, i.e. the ***H***-score $= \sum_{k=1}^{K} X_{ik}^{H} \beta_{ik}^{H}$; simply, it is the

sum of the $\boldsymbol{X\beta}$ products for all K $\boldsymbol{H}$ variables, for each individual i. Next, we ranked individuals in each racial group by their $\boldsymbol{H}$-score, generating a percentile rank for each individual within their race-specific $\boldsymbol{H}$ distribution. Then, to match minority and white distributions of $\boldsymbol{H}$ variables, we replaced the value of each $\boldsymbol{H}$ variable for each minority individual by the value of that variable in the white individual with the corresponding $\boldsymbol{H}$-based percentile rank. Replacing minority with white distributions this way preserves the joint associations among $\boldsymbol{H}$ variables and is superior to other methods for ranking and replacement.[69] This replacement creates a counterfactual minority group that still preserves its observed distributions of social and health-system exposures (the $\boldsymbol{S}$ variables), while now possessing the white distributions of health, clinical need, and preferences ($\boldsymbol{H}$ variables). Then, we predicted average marginal adherence levels in counterfactual minority and factual white groups using our estimated DID model (**Equation 2-2**). Finally, we computed racial disparities as the differences in predicted average adherence between each counterfactual minority group (blacks, Hispanics) and the reference (factual) white group. In simple notation, the disparity $\boldsymbol{\Delta}$ is given by

$$\Delta = Adherence_{Factual\ Whites} - Adherence_{Counterfactual\ Minority}$$
$$\Delta = Pr(\text{PDC} \geq 80\% \mid \boldsymbol{R}=W, \boldsymbol{S}=W, \boldsymbol{H}=W)$$
$$- Pr(\text{PDC} \geq 80\% \mid \boldsymbol{R}=M, \boldsymbol{S}=M, \boldsymbol{H}=W) \qquad \textbf{(Eq. 2-2)}$$

Where, $\boldsymbol{R}$ is race, M minority, W white, and $\boldsymbol{S}$ and $\boldsymbol{H}$ take on the same designation as above. To calculate the DID effect of Part D on the disparities, we used predictive margins[99] to compute $\boldsymbol{\Delta}$ before and after Part D in the treated and control groups and took the double difference across time and groups (see notes of **Figure 2-2**).

Finally, since there were high rates of missing data for the (categorical) variables on beliefs and experience with providers (highest rate 4.4%, leading to up to 25% sample reduction if only complete cases were included), we used multiple imputation using chained equations (MICE) to impute the missing data for each of these variables.[100] Following recent recommendations in the imputation literature,[100,101] we imputed the variables with missing data in 5 imputation datasets, adjusting for survey design in the imputation model. Using Stata –MI- set of commands, we carried out our analyses, including ranking-and-replacement and estimating predictive margins, across all imputation datasets and produced a single set of point estimates and standard errors that took into account the uncertainty due to imputation. All analyses accounted for MEPS complex survey design using Taylor series linearization in STATA® 13 (StataCorp; College Station, TX).

Analogous to the main analysis, we also conducted a series of sensitivity and subgroup analyses to assess robustness of our findings to the conceptual and empirical decisions made, and to assess potential heterogeneity of Part D effects across policy-relevant groups. First, we assessed the robustness of our DID-based predictions to a series of empirical adjustments, using the rank-and-replace procedure, for demographics, health, concurrent drug therapy, and beliefs/preferences. These various adjustments reflect different value judgments regarding how differences in each of these factors originated and how they contribute to producing adherence disparities. We also estimated

Part D impact on RDE disparities directly from our multivariable DID model. Second, we graphically assessed the plausibility of the parallel trend assumption necessary for the validity of DID estimation. We further considered how our DID estimates would change if we included 2006 data in post-Part D year, and if we restricted the treated group to a population more comparable to the near-elderly controls (i.e. Medicare elderly 65-70 years old).[102] Third, we analyzed the effect of Part D on disparities in adherence to each of the five cardiovascular medication classes we considered, in addition to evaluating effects by gender and dual-eligibility status.

Results

Sample Characteristics

The main study sample included 14,221 and 3,456 MEPS respondents, nationally representative of 19.7 and 5.3 million Medicare seniors and non-Medicare near-elderly individuals, respectively. Thus, our total sample size was 17,677 respondents, representing a total of 25 million individuals nationwide. As shown in **Table 2-1**, over the entire study period (2002-05, 2007-2010), Medicare seniors and the near-elderly had comparable adherence behaviors, with overall adherence rates hovering around 40%. Black seniors in Medicare had the lowest overall adherence rate (36.59%). In comparison with the near-elderly controls, Medicare seniors were more likely to be females and less likely to be married. They also had worse health status, more physical/cognitive limitations and comorbidities, and a higher burden of cardiovascular disease, particularly the advanced stages of coronary heart disease, congestive heart failure, myocardial infarction, and stroke. They were also less likely to be current smokers, obese, or to exercise. Seniors were also more likely to be poor or low-income, and less likely to have completed high school or college education. As expected, seniors were less likely to have private or employer-sponsored insurance coverage, but concurrently used more medications, visited physicians more often, and were more likely to have had hospitalizations during survey year. Seniors' experience with providers was comparable to that of their near-elderly counterparts, but they tended to more positively rate their satisfaction with the healthcare system.

In both treated and control groups, blacks and Hispanics were more likely than whites to have no spouse/significant other, and to live in urban areas. Across regions, blacks were heavily concentrated in the South while Hispanics also concentrated in the West. Both groups were less likely to live in the Midwest. Minorities had worse health status and comorbidity, as well as a higher burden of hypertension and diabetes. However, they had either lower or comparable prevalence rates of other conditions, such as hyperlipidemia, cardiovascular complications (CHD and AMI), and depression. Minorities were also less likely to exercise and to be obese. Relative to whites, smoking was higher among blacks while lower among Hispanics. Invariably, minorities had lower education and income, and expectedly were more likely to receive Medicaid coverage and less likely to have private or employer-sponsored insurance. Blacks were more likely

Table 2-1. Characteristics of treated and control groups by race

Characteristics	Medicare Elderly (65 years or older)				Near-Elderly Controls			
	White	Black	Hispanic	Overall	White	Black	Hispanic	Overall
Sample Size	10,311	2,300	1,610	14,221	2,519	547	390	3,456
Weighted Population	16,722,679	1,767,117	1,164,105	19,653,901	4,469,185	498,497	284,937	5,252,619
	% (unless otherwise noted)							
Adherence to CV Medications								
Overall	39.93	**36.59**	38.51	39.54	40.61	41.13	41.53	40.71
ACEIs/ARBs	47.02	43.55	47.81	46.75	47.67	47.78	49.17	47.78
Statins	44.08	45	43.49	44.11	43.74	41.15	48.74	43.8
Beta-Blockers	48.42	**43.58**	48.8	48.04	47.34	45.35	45.68	47.02
Ca Channel Blockers	41.36	40.68	37.53	41	41.07	48.78	**56.84**	43.24
Diuretics	48.01	43.92	43.52	47.32	49.82	46.05	53.09	49.51
Demographics								
Age (Mean±SD)	74.69 ±6.36	73.54 ±6.25	73.63 ±5.91	74.53 ±6.34	61.97 ±1.38	62.05 ±1.42	61.74 ±1.35	61.96 ±1.38
Female Gender	57.85	**63.37**	60.8	**58.52**	51.17	53.67	57.98	51.78
Married	57.38	**34.05**	**46.84**	**54.66**	77.25	**47.35**	**62.34**	73.6
Urban Residence	77.67	**86.25**	**92.73**	79.33	78.33	**91.55**	**92.47**	80.36
Census Region								
Northeast	21.05	18.73	**14.89**	20.47	20.2	21.16	23.04	20.45
Midwest	25.42	**17.25**	**6.02**	23.54	26.65	**17.44**	**9.48**	24.84
South	35.21	**56.75**	**43.35**	37.63	35.51	**53.47**	31.2	36.98

Table 2-1. (Continued)

Characteristics	Medicare Elderly (65 years or older)				Near-Elderly Controls			
	White	Black	Hispanic	Overall	White	Black	Hispanic	Overall
West	18.32	**7.28**	**35.75**	18.36	17.64	**7.93**	**36.28**	17.73
Self-Reported Health								
Excellent	14.54	**9.23**	**7.54**	13.65	16.6	**6.34**	**7.49**	15.13
Very Good	29.52	**21.82**	**16.83**	**28.08**	35.79	**26.08**	**18.07**	33.9
Good	33.41	33.66	31.96	33.35	31.26	34.55	31.89	31.61
Fair	16.62	**26.66**	**32.69**	**18.48**	11.31	**24.64**	**27.85**	13.47
Poor	5.9	**8.63**	**10.99**	6.45	5.04	**8.39**	**14.7**	5.88
Any Physical Limitation *	62.19	63.61	65.45	**62.51**	39.09	**48.87**	43.07	40.23
Any Cognitive Limitation *	9.05	**14.86**	**15.15**	**9.93**	3.6	**6.41**	**10.21**	4.22
Conditions (over survey year)								
Charlson Comorbidity Score								
1st/2nd Quartiles	57.06	**47.07**	**44.27**	**55.41**	64.63	**54.1**	**45.52**	62.6
3rd Quartile	31.91	**38.25**	**40.96**	**33.02**	28.56	33.49	**43.66**	29.85
4th Quartile	11.02	**14.68**	**14.77**	**11.57**	6.81	**12.41**	**10.82**	7.56
Comorbidity Count, † Median(IQR)	6(3,8)	4(2,6)	5(3,7)	5(3,8)	4(3,7)	4(2,6)	4(2,6)	4(2,7)
Hypertension	81.96	**92.89**	**90.23**	**83.43**	77.13	**94.55**	**91.38**	79.55
Hyperlipidemia	59.82	**48.15**	**51.53**	**58.28**	64.34	**47.45**	**56.64**	62.32
Angina/CHD	17.25	**11.71**	16.09	**16.68**	9.54	7.36	8.53	9.27
CHF	4.66	5.12	2.89	**4.59**	1.86	2.14	**0.41**	1.81

Table 2-1. (Continued)

Characteristics	Medicare Elderly (65 years or older)				Near-Elderly Controls			
	White	Black	Hispanic	Overall	White	Black	Hispanic	Overall
AMI	6.88	**5.12**	5.15	**6.62**	3.96	4.17	3.39	3.95
Stroke	5.49	5.94	5.3	**5.51**	2.28	2.62	4.75	2.45
Depression	11.78	**5.61**	11.87	11.23	13.02	**7.11**	13.49	12.48
Diabetes	22.08	**35.49**	**40.7**	24.39	20.89	**32.38**	**39.58**	22.99
Asthma	9.03	**11.03**	10.53	**9.3**	11.79	14.06	12.4	12.04
Emphysema	7.27	**3.95**	**3.07**	**6.72**	4.08	2.79	1.39	3.81
Arthritis	61.04	63.98	58.83	**61.17**	48.99	55.6	47.72	49.55
Beliefs & Behaviors								
More likely to take risks	14.44	14.27	16.39	14.54	16.04	12.6	18.6	15.85
Can overcome illness without medical care	9.89	**8.26**	**7.56**	**9.61**	12.68	**7.94**	8.89	12.03
Does not need health insurance	3.65	3.92	**6.4**	**3.84**	2.59	1.77	**7.07**	2.75
Behaviors								
Current Smoker	8.35	**10.52**	**5.6**	**8.38**	14.49	**19.76**	9.72	14.73
Moderate/ Vigorous Exercise	46.85	**38.56**	**40.62**	**45.74**	57.07	**43.59**	**45.14**	55.14
Obese (BMI≥30)	27.86	**40.26**	**32.69**	**29.26**	39.85	**50.07**	44.38	41.06

Table 2-1. (Continued)

Characteristics	Medicare Elderly (65 years or older)				Near-Elderly Controls			
	White	Black	Hispanic	Overall	White	Black	Hispanic	Overall
Socioeconomic Status								
Income: ‡ Poor/Near-Poor	13.39	**31.57**	**32.54**	**16.16**	6.83	**20.94**	**25.88**	9.2
Low-Income	18.34	**26.36**	**24.75**	**19.44**	6	**14.6**	**13.89**	7.24
Middle-Income	31.4	**25.8**	**27.52**	**30.67**	26.33	27.45	28.13	26.54
Education: Less than High School	22.5	**47.94**	**67.62**	**27.46**	10.77	**32.33**	**55.23**	15.23
High School Diploma	50.8	**38.02**	**22.2**	**47.95**	43.19	44.63	**29.76**	42.6
Language: Interview Not in English	0.28	**0.06**	**51.21**	**3.28**	0.22	**0.59**	**41.25**	2.48
No English at Home	1.18	1.01	**57.81**	4.52	1.02	1.32	**52.12**	3.82
Insurance (over survey year)								
Employer-Sponsored	34.48	**28.06**	**16.14**	**32.82**	82.77	**68.48**	**54.76**	79.9
Medicaid	5.47	**25.44**	**37.36**	**9.16**	3.89	**20.92**	**31.64**	7.01
Private- Non HMO	42.73	**24.22**	**14.14**	**39.37**	62.28	**44.09**	**25.39**	58.55
Private- HMO	9.29	9.13	**6.87**	**9.13**	31.2	31.18	36.32	31.47
Healthcare Use (over survey year)								
No. of concurrent CV Medications §								
0-1	39.63	**36.28**	40.02	**39.35**	47.74	**35.19**	42.14	46.24

Table 2-1. (Continued)

Characteristics	Medicare Elderly (65 years or older)				Near-Elderly Controls			
	White	Black	Hispanic	Overall	White	Black	Hispanic	Overall
2-3	53.74	54.51	54.25	**53.84**	46.97	**56.37**	49.91	48.02
≥4	6.63	**9.21**	5.74	6.81	5.29	8.44	7.95	5.74
No. of other concurrent medications								
0-1	11.49	**14.94**	13.62	**11.92**	15.31	15.83	18.72	15.54
2-4	48.13	47.02	49.89	**48.14**	53.96	49.22	**46.09**	53.08
≥5	40.38	38.04	36.49	**39.94**	30.73	34.95	35.2	31.38
No. of Pharmacies Used, Median(IQR)	1(1,2)	1(1,1)	1(1,1)	1(1,2)	1(1,2)	1(1,1)	1(1,1)	1(1,2)
Average Copay for CV Drugs ($2010), Median(IQR)	19.92 (8.60,43.41)	13.36 (4.00,31.48)	9.62 (2.67,27.66)	18.59 (7.63,41.72)	17.07 (9.62,32.69)	13.93 (6.27,25.58)	12.18 (3.32,25.45)	16.53 (9.01,31.81)
Had a Usual Source of Care	97.59	**96.4**	96.55	**97.42**	96.79	96.99	**92.71**	96.59
Had ≥1 Any Inpatient Stay	19.78	20.88	**16.45**	**19.68**	12.91	15.78	12.75	13.17
Quintiles of ambulatory physician visits (range)								
Q 1 (0-2)	15.35	**22.59**	**20.4**	**16.3**	23.78	27.85	27.79	24.38
Q 2 (3-4)	17.78	**21.75**	19.19	**18.22**	23.44	23.92	20.01	23.3
Q 3 (5-7)	20.52	22.63	22.71	20.84	21.35	17.72	22.8	21.08
Q 4 (8-12)	22.73	**18.31**	20.02	**22.17**	18.21	19.07	14.55	18.09
Q 5 (≥13)	23.62	**14.72**	17.68	**22.47**	13.22	11.44	14.85	13.14

Table 2-1. (Continued)

Characteristics	Medicare Elderly (65 years or older)				Near-Elderly Controls			
	White	Black	Hispanic	Overall	White	Black	Hispanic	Overall
Experience with Providers								
Always Listens	65.13	**74.42**	**70.81**	**66.3**	62.11	**69.97**	67.29	63.14
Always Explains Care	60.91	**71.38**	**66.12**	62.16	62.45	**72.23**	61.69	63.34
Always Respects	67.59	**75.92**	**72.53**	68.63	65.8	**75.99**	65.08	66.73
Satisfaction with Healthcare								
Dissatisfied-Neutral	7.59	**10.86**	10.03	8.03	8.03	**11.55**	14.33	8.71
Satisfied	29.47	29.14	**23.24**	**29.07**	34.21	**28.5**	31.8	33.54
Very Satisfied	62.95	60	**66.73**	**62.91**	57.76	59.95	53.86	57.75

Boldface estimates are statistically significant at the 5% level and represent pairwise comparisons relative to reference groups: overall proportions among Medicare elderly were compared to the near-elderly controls, and minorities were compared to their white counterparts (within treated/control groups).

* Physical limitations included functional or sensory limitations, or limitation in the Instrumental Activities of Daily Living or in the Activities of Daily Living. Cognitive limitations included confusion, dementia, problems making decisions, or needing supervision for own safety.

† Excluded respondent-specific cardiovascular conditions. Charlson Score based on D'Hoore's version suing 3-digit ICD-9 codes.[96]

‡ Poor/Near-Poor: <125% FPL; Low-Income: ≥125 to <200 %FPL; Middle-Income ≥200 to <400% FPL; High Income (reference): ≥400% FPL.

§ Same-pill combination products were counted as one drug

CV: Cardiovascular; ACEI/ARB: Angiotensin-Converting Enzyme Inhibitors/Angiotensin II Receptor Blockers; SD: Standard Deviation; IQR: Interquartile Range; CHD: Coronary Heart Disease; CHF: Congestive Heart Failure; AMI: Acute Myocardial Infarction; BMI: Body Mass Index; FPL: Federal Poverty Line; HMO: Health Maintenance Organization.

to concurrently take multiple cardiovascular medications than whites, although they were not seeing physicians as much (in Medicare). Interestingly, both blacks and Hispanics tended to rate their relationship with providers more positively than whites.

Adherence Measurement and Validation

In validating our approach to derive refill days of supply from dispensed quantities, we compared continuous PDC and dichotomous adherence calculated using the derived distribution of supply days to those calculated using the actual days of supply data in the 2010 sub-sample of our study sample. As shown in **Table 2-2**, we found the PDC measurements based on derived days of supply to be in substantial agreement with PDC measurements based on actual days of supply. Agreement was highest when a refined approach was followed to derive days of supply from dispensed quantities (Discretization 3 in **Table 2-2**; Lin's concordance coefficient 0.97, κ-statistic 0.94). This level of agreement was also consistent across drug classes, and at all stages of PDC measurement. Using the "Discretization 3" scheme, we calculated PDCs for our entire sample.

Multivariable DID Logistic Regressions

To substantiate our DID analysis, we graphically assessed the adjusted trends in adherence disparities across treated and control groups from 2002 to 2010. Since Medicare seniors and the near-elderly were different in important ways, particularly health and socioeconomic status, examining trends adjusted for covariates was a more appropriate approach to assess the common trend assumption central to the validity of DID analysis. **Figure 2-3** provides visual evidence to suggest that adherence disparities in both groups were on similar trajectories until around 2005 when, interestingly, adherence trends started to change among both seniors and their near-elderly counterparts, even before the formal implementation of Part D in 2006.

In the main sample and subgroups, we estimated multivariable logistic models of adherence as a function of the DID interactions, as well as the full set of covariates. The magnitude of the DID coefficients, specifically the triple interactions of race, Medicare coverage, and post-Part D, remained relatively stable to sequential adjustment for covariates. This observation is illustrated in **Appendix Figure A-1**. Coefficient estimates expressed in terms of odds ratios for all models, are listed **Appendix Table A-3** and **A-4**. All models had non-significant P values in Hosmer-Lemeshow modified Goodness-of-Fit tests, indicating adequate fit for the data.

Ranking-and-Replacing *H* Distributions in the Main Analysis

Using the rank-and-replace procedure, we adjusted the marginal adherence predictions (specifically, average probabilities of adherence) based on our estimated

Table 2-2. Derivation of refill days of supply and validation of adherence measurement in the 2010 sub-sample (n= 1,282)

Deriving refill days of supply from dispensed quantities of pills			*Agreement between the original PDC distribution based on actual days of supply vs. PDC distributions derived via discretization of dispensed quantities of refills*				
			Continuous PDC		**Binary Adherence Classification**		
Scheme	**Dispensed Quantity**	**Corresponding Days of Supply**	**Pearson Correlation**	**Lin's Concordance**	**Observed Agreement**	**κ Statistic**	***C*-Statistic**
Discretization 1	≤45	30	0.94	0.94	94.07%	0.88	0.94
	>45 but ≤75	60					
	>75	90					
Discretization 2	≤75	30	0.96	0.95	95.71%	0.91	0.96
	>75	90					
Discretization 3	0-7	Same	0.98	0.97	96.96%	0.94	0.97
	8	16					
	9-14	Same					
	15-16	30					
	20-44	Same					
	45	90					
	46-75	30					
	76-119	90					
	120	30					
	>120	90					

Discretizations 1 and 2 are rather crude and have no concrete empirical basis. Discretization 3 is a refinement based on the actual empirical distributions of days of supply vis-à-vis dispensed quantities, where "Corresponding Days of Supply" was the most frequent (usually >90% of the time) days of supply observed for each quantity dispensed

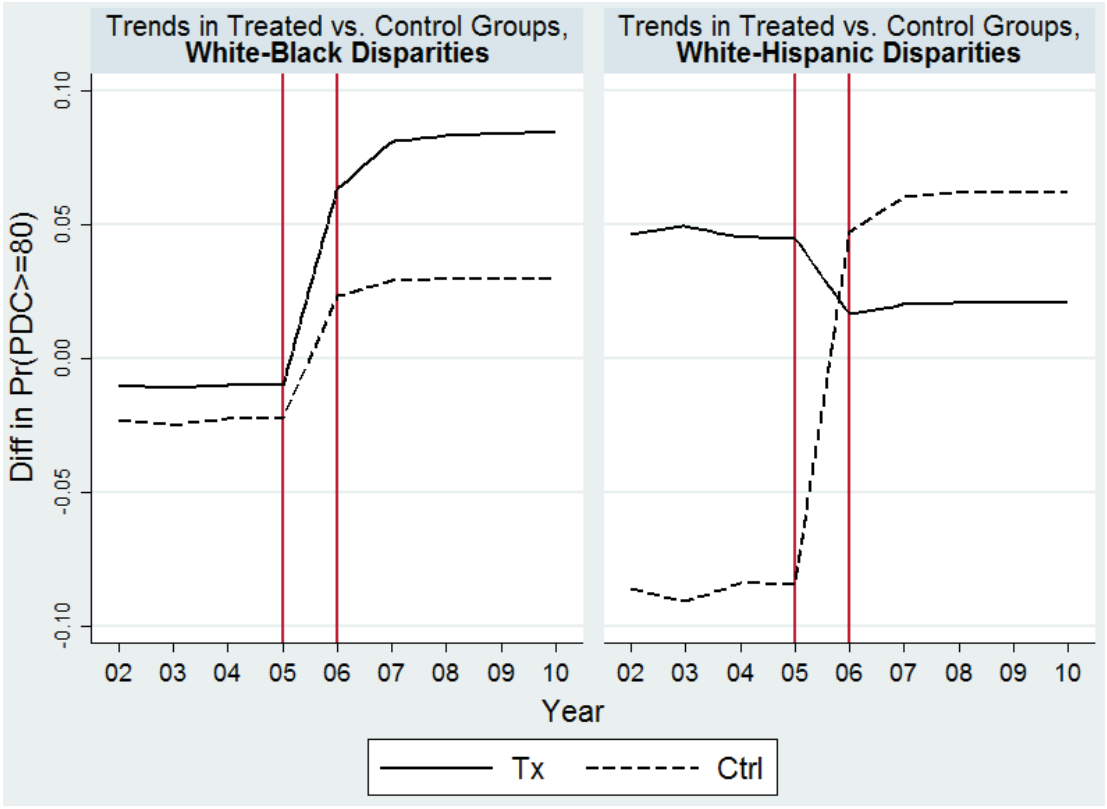

Figure 2-3. Graphical assessment of the common trend assumption of adherence disparities among Medicare seniors and near-elderly controls
Disparity is on the Y-axis and is empirically equal to the difference by race in the adjusted average probability of overall cardiovascular medication adherence (Pr(PDC≥80%)). PDC: Proportion of days covered; Tx: Treated; Ctrl: Control

models with full covariate specification, for the ***H*** variables, namely: demographics, health status, clinical need, and beliefs/preferences (including geography). By replacing the distributions of ***H*** variables of minorities with those of their white counterparts, we created counterfactual minority groups that possessed whites' ***H*** distributions while keeping their observed distributions of SES and other ***S*** variables. In essence, this is similar to a hypothetical experiment where two clinically similar groups are randomly assigned a treatment: here, the groups are the factual whites and the counterfactual minorities, and the "treatment" is minority race with all the relevant facets of disadvantage it typically involves. As **Figure 2-4** shows, after ranking-and-replacement, ***H*** distributions of minorities became virtually identical to those of whites.

Effect of Part D on Adherence Disparities in the Main Analysis

Table 2-3 shows the results of the main analysis. Following Part D introduction, rates of adherence to cardiovascular medications improved a significant 59% among Hispanic Medicare seniors (29% to 46%), 47% among whites (32% to 47%), and only 9% among blacks (35% to 38%). Among the near-elderly, adherence levels also improved in 2007-2010, but with smaller magnitudes and significantly favored whites over minorities. Prior to Part D, disparities in adherence were non-significant among seniors. Over the same period (2002-2005), adherence was significantly better among Hispanics than whites in the near-elderly population.

Following Part D implementation, there was a significant increase in white-black disparities among seniors (+11 percentage points, $P<0.01$), and no significant change among the near-elderly (+5% points, $P>0.05$). On the other hand, while there was no statistically significant change in white-Hispanic disparities among seniors (-2% points, $P>0.05$), there was a significant upsurge in these disparities among the near-elderly (+14% points, $P<0.05$). Taking the trends in the treated and control groups together, we estimated that Part D was associated with a significant 16%-point reduction in white-Hispanic disparities. There was however no statistically significant DID change due to Part D in black-white disparities in overall cardiovascular medication adherence. These findings are summarized in **Figure 2-5**.

Subgroup Analyses

In addition to estimating the overall average effect of Part D, we also assessed its impact on the racial disparities among men, women, the dually eligible for Medicaid, and the non-dually eligible. Additionally, we evaluated how results would change if we included 2006 data or restricted the treated group to seniors 65-70 years of age. As shown in **Figure 2-6**, the average DID estimate of Part D on adherence disparities in each of these groups. Including 2006 data in the post-Part D period pushed the increase in black-white disparities further towards the null (+0.03 vs. +0.06% points in the main analysis, $P>0.05$ for both), while yielding virtually the same reduction in white-Hispanic

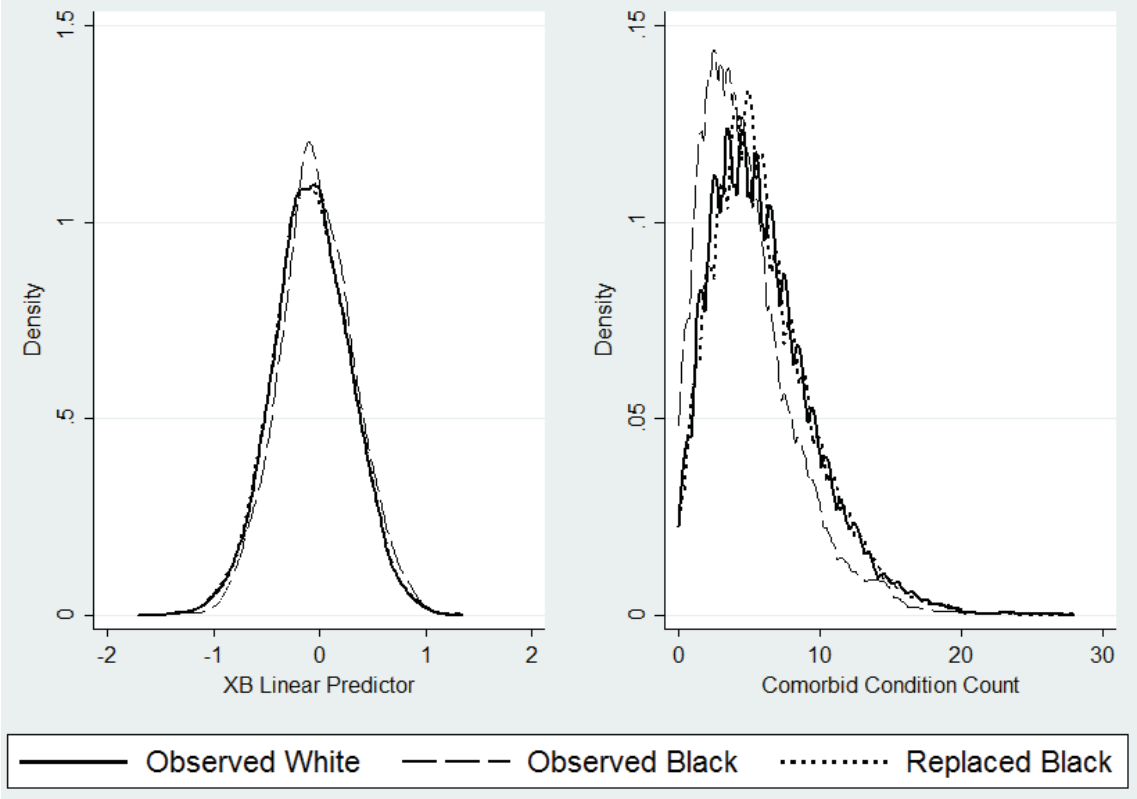

Figure 2-4. Observed and replaced distributions of the *H* linear predictor and conditions count for whites and blacks

P values for Kolmogorov-Smirnov tests for the equality of black and white distributions:
Xβ distributions: observed white & black: P<0.001, observed white vs. replaced black: P=1.000;
Condition Count: observed white & black: P<0.001, observed white vs. replaced black: P=0.903.

Table 2-3. Overall cardiovascular medication adherence levels and disparities in the treated/control groups before and after Medicare Part D

Outcome	Medicare Elderly		Near Elderly Controls	
	Pre-Part D (2002-05)	Post-Part D (2007-10)	Pre-Part D (2002-05)	Post-Part D (2007-10)
	Estimate [95% CI]			
Average Adherence				
White	**0.32 [0.30,0.34]**	**0.47 [0.45,0.48]**	**0.30 [0.26,0.34]**	**0.47 [0.43,0.51]**
Black	**0.35 [0.30,0.39]**	**0.38 [0.35,0.42]**	**0.34 [0.28,0.40]**	**0.46 [0.39,0.53]**
Hispanic	**0.29 [0.24,0.33]**	**0.46 [0.42,0.50]**	**0.39 [0.31,0.46]**	**0.42 [0.35,0.49]**
Adherence Disparities				
White-Black	-0.03 [-0.07,0.02]	**0.08 [0.04,0.12]**	-0.04 [-0.12,0.03]	0.01 [-0.09,0.07]
White-Hispanic	0.03 [-0.01,0.08]	0.01 [-0.04,0.05]	**-0.09 [-0.17,-0.01]**	0.05 [-0.03,0.13]
Change in Disparities over Time				
White-Black	**0.11 [0.05,0.17]**		0.05 [-0.05,0.15]	
White-Hispanic	-0.02 [-0.08,0.04]		**0.14 [0.03,0.25]**	
Difference-in-Differences				
White-Black	0.06 [-0.06,0.18]			
White-Hispanic	**-0.16 [-0.29,-0.03]**			

Boldface denotes P<0.05.
Estimates are probability-scale predictions, adjusted for health status/clinical need using the rank-and-replace procedure. Disparities are the differences in the average probability of adherence by race. Standard errors underlying confidence intervals were estimated via Taylor series linearization and combined across 5 multiply imputed datasets.

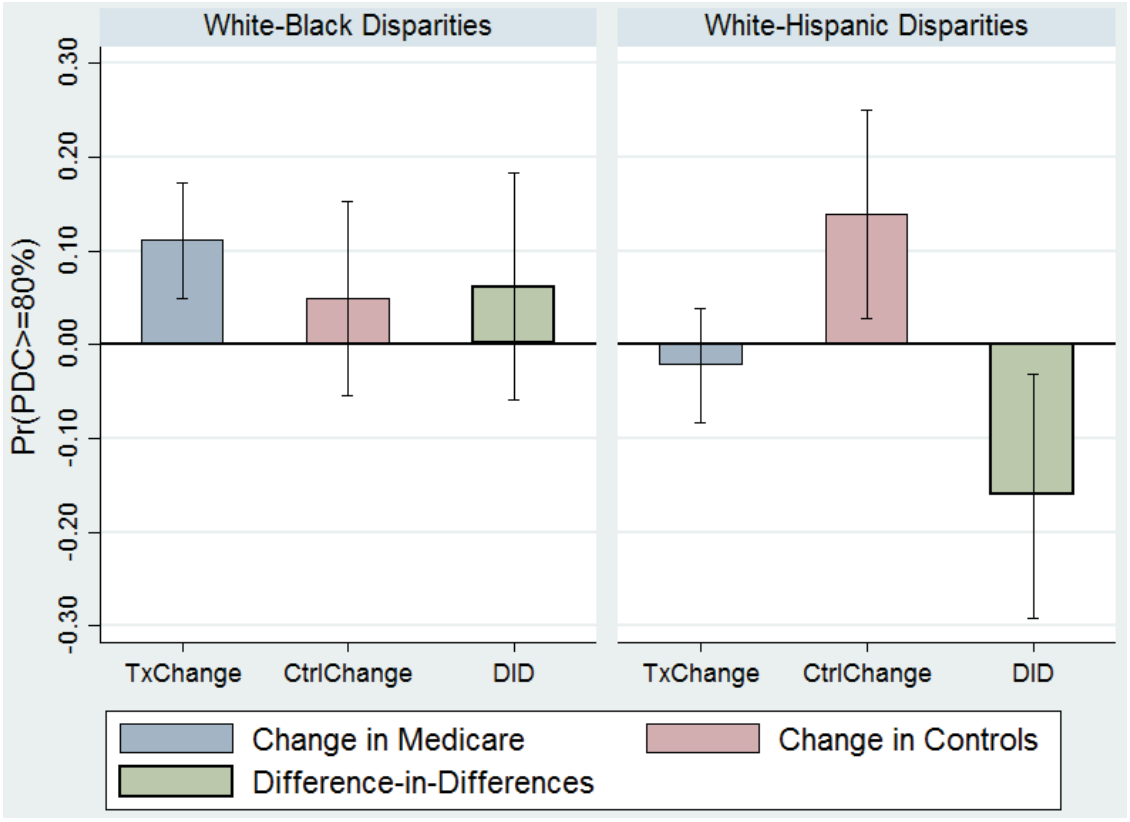

Figure 2-5. The impact of Part D impact on adherence disparities in overall cardiovascular medication adherence

Pr(PDC≥80%) is the average probability of adherence. Capped spikes represent 95% confidence intervals. Point estimates and 95% CIs are provided in the last four rows of **Table 2-3**. PDC: Proportion of days covered; Tx: Treated; Ctrl: Control; DID: Difference-in-differences

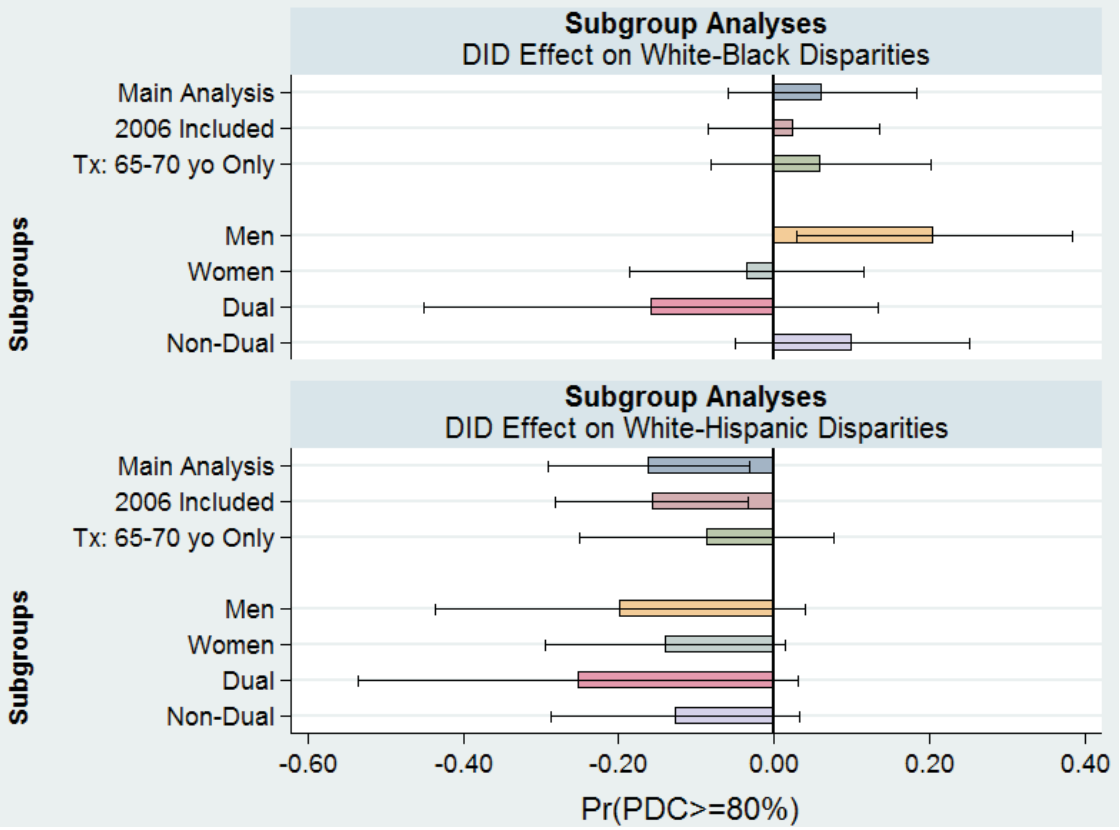

Figure 2-6. The impact of Part D on adherence disparities in subgroups
Pr(PDC≥80%): average probability of adherence. Capped spikes represent 95% confidence intervals. PDC: Proportion of days covered; DID: Difference-in-differences

disparities as the main analysis. Among seniors 65-70 years old, Part D had the same effect on white-black disparities, whereas the reduction in white-Hispanic disparities was lower in magnitude and statistically non-significant (-9% points).

Further, as in **Figure 2-6**, while Part D was associated with a non-significant change (-4%, P>0.05) in the disparity between white and black women, we found a significant increase in white-black disparities among men (+21% points, P<0.05). DID effects of Part D on white-Hispanic disparities by gender were statistically non-significant .Similarly, Part D effects on disparities by dual eligibility status were all non-significant.

We also investigated the DID effects of Part D on the disparities in adherence to each cardiovascular medication class. As in the main analysis, Part D was associated with no statistically significant changes in white-black disparities in adherence to each medication class. White-Hispanic disparities followed the same direction as in the main analysis, with beta-blocker adherence disparities showing a large, statistically significant decrease (-30% points, P<0.05). Other changes in white-Hispanic disparities by medication class were not significant. For reference, **Appendix Table A-5** (Column 1) lists all DID point estimates and confidence intervals for all subgroups.

Current Racial Disparities in Adherence in Medicare

While Part D was implemented to expand access to prescription drugs and improve the quality of medication use, our data suggest that the policy may have had some unintended consequences. In fact, as **Figure 2-7** shows, large and statistically significant disparities in adherence between white and black seniors remain in the post-Part D era. Over 2007-2010, the white-black disparity in overall adherence was 8% points in the entire sample, 11% points among men, 7% points among women, 8% points among the non-dually eligible, and a high 19% points among the dually eligible (P<0.01 for all). White-Hispanic disparities, on the other hand, were much smaller (and statistically non-significant), except among the dually eligible: 15% points (P<0.01).

We also examined levels of disparities in adherence to each drug class, over 2007-2010. While we did not detect statistically significant white-Hispanic disparities in adherence to each medication class (all below 5% points, P>0.05), we found larger white-black disparities in adherence to ACE inhibitors/ARBs (6% points, P<0.05), beta-blockers (8% points, P<0.01), and diuretic agents (8% points, P<0.01). All point estimates and 95% CIs for adherence disparities in Medicare over 2007-2010 are listed for reference in **Appendix Table A-5** (Column 2).

Sensitivity of Results to Disparity Definitions

Finally, we assessed the robustness of our estimates to various definitions of disparities, starting from racial differences in crude, unadjusted adherence proportions to

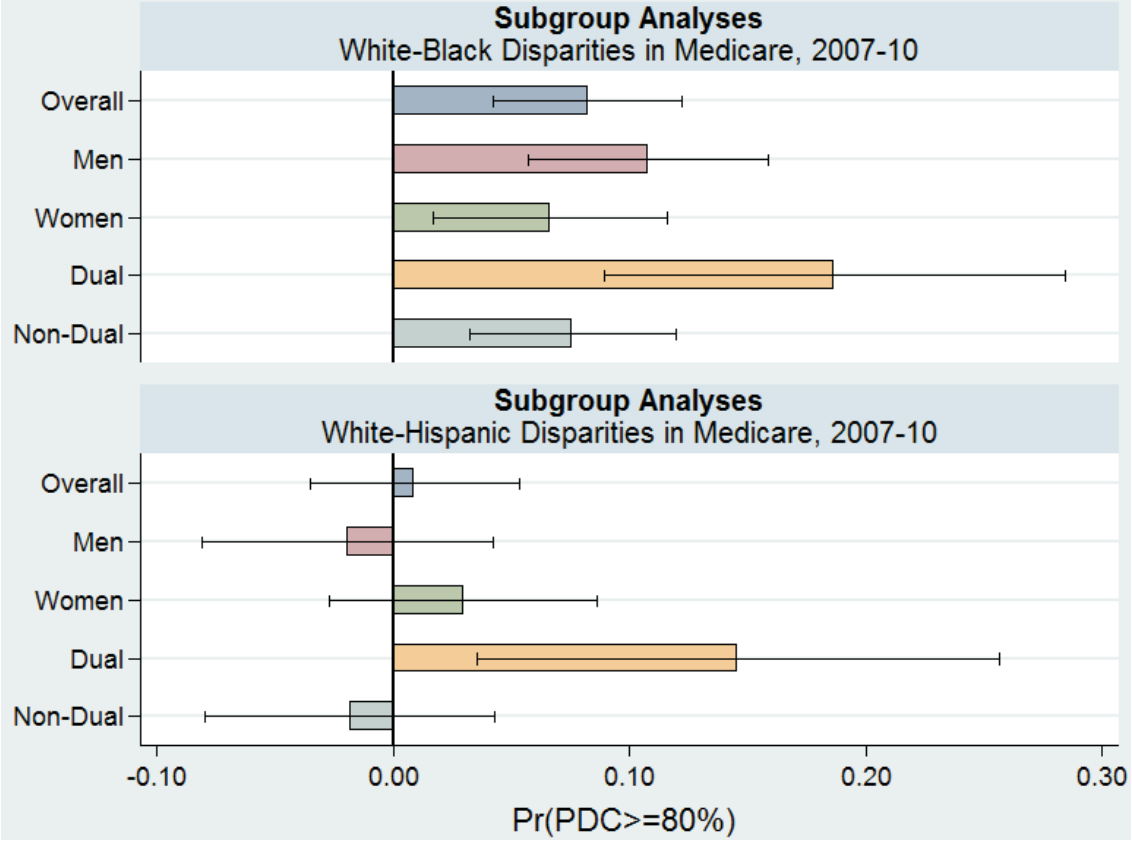

Figure 2-7. Racial disparities in overall cardiovascular medication adherence among Medicare seniors in 2007-2010 by subgroup

Pr(PDC≥80%) is the average probability of adherence, predicted for each group using the main logistic model and adjusted for ***H*** variables using the rank-and-replace procedure. Capped spikes represent 95% confidence intervals.

fully adjusted RDE disparities. **Appendix Table A-6** lists the results of these analyses, both DID estimates as well as estimates of disparities in the post-Part D period (2007-10).

When we estimated the DID effect of Part D on the racial differences in unadjusted adherence proportions, we found no statistically significant change in white-black differences (+5% points, P>0.05) while white-Hispanic differences decreased by 18% points (P<0.01). Further, regardless of the level of adjustment of disparities to various factors (e.g. demographics, health, beliefs, SES, etc), the DID effect of Part D remained virtually the same: no statistically significant effect on white-black disparities, and a 16%-point decrease in white-Hispanic disparities. As with our earlier analyses, the magnitude of adherence disparities among seniors in the 2007-2010 period was not sensitive to the how we empirically defined disparity (**Appendix Table A-6**, Column 2).

Discussion

Part D introduction was associated with a 59% improvement in cardiovascular medication adherence among Hispanics, 47% among whites, and only 9% among blacks. This finding largely agrees with a recent study, by Mahmoudi and Jensen, of the effects of Part D on disparities in drug use and expenditure (also used MEPS data in a difference-in-differences evaluation),[62] which found that Part D significantly reduced white-Hispanic disparities. These authors also reported Part D had no significant effect on white-black disparities in measures of drug use and expenditure, except on the disparity in total drug expenditure, which may have increased following Part D.[62]

The net reduction in white-Hispanic disparities is numerically the result of a modest decrease in this disparity in the Medicare population and a large increase among the near-elderly controls in the 2007-2010 period. There are a number of potential explanations for the reduction in white-Hispanic disparities. First, our data and recent literature[59] show that after 2006, Hispanics were primarily covered by Part D Medicare Advantage prescription drug (MA-PD) plans, significantly more so than whites and blacks (41%, vs 33 and 29% among blacks and whites, respectively, in our sample). Most MA-PD plan enrollees were enrolled in an MA plan prior to 2006;[103] these beneficiaries generally experienced a smoother transition to drug coverage with the advent of Part D thanks to the subtle integration of the new benefit into the already existing managed care structure.[59] Further, these plans have been offering more generous drug coverage than Part D stand-alone prescription drug plans (PDP),[103] and their design is associated with much less disparities in access to drugs and benefit information,[59] as well as better coordination of care.[104]

Hispanic seniors were more likely to be automatically eligible for the low-income subsidy than blacks and whites (46%, vs. 30 and 8% among blacks and whites, respectively, in our sample). They may also have been better primed for Part D given their presumably higher participation rates in the pre-Part D drug discount card program from 2004-2005 (this program was started by the Centers for Medicare and Medicaid Services (CMS) to subsidize drug costs for non-dually eligible low-income beneficiaries,

with income up to 135% of the federal poverty line, in anticipation of Part D implementation).[105] This could as well explain the decline in white-Hispanic adherence disparities in Medicare starting in 2005, even before Part D launch in 2006.

Among the near-elderly, where 80% receive employer-sponsored insurance, adherence disparities increased. As in **Table 2-3**, over 2007-2010, adherence rates rose most for near-elderly whites, rose modestly for blacks, and least for Hispanics; particularly worsening the disparity between whites and Hispanics. Our data show that rates of prescription drug coverage declined 11% among near-elderly Hispanics, 7% among blacks, and only 2% among whites, perhaps as a result of differential loss of employment and employer-sponsored coverage. The economic recession and rising unemployment rates that loomed in the 2007-2008 fiscal year might thus offer a potential explanation for the increase in adherence disparities among the near-elderly controls.

Except among men, where Part D was associated with a significant 21%-point increase in the white-black disparity, Part D was not associated with significant changes in white-black disparities. For those over 65, however, average adherence to all cardiovascular medications actually worsened 11% points more among blacks relative to their white counterparts. A number of factors might explain this widening of the white-black adherence disparity. First, black seniors,[60] especially non-duals and even those enrolled in MA-PD plans[59] found it much harder to get necessary information about their covered prescription drugs compared to whites and Hispanics. Second, blacks were more likely to enroll in Part D stand-alone PDPs, where they were more prone to significant disparities compared to whites in accessing medications and benefit information,[59] and to lower overall adherence levels,[106] relative to MA-PD plans. It is worth noting here that the greater enrollment in MA-PD plans among Hispanics compared to blacks may be a direct consequence of the disparate geographic concentration of these two groups: e.g. Hispanics in the West enjoy greater access to these plans since Western states have much higher market penetration by managed care plans.[107]

Third, our data show as above that black seniors were generally less likely than Hispanics to be automatically signed up for the LIS. Black females, however, were more likely than males to be eligible for the LIS, and, in fact, were more likely to enroll in Part D coverage from the outset.[60] This could explain why Part D was associated with a significant increase in white-black disparities among men but not women. Fourth, blacks are more likely than whites and Hispanics to have complex cardiovascular regimens, e.g. concurrently taking multiple drugs (**Table 2-1**), which could be predisposing them to persistently lower adherence rates compared to whites.

Our results, as in the literature,[28-31] expectedly show that racial disparities in adherence continue to exist in Medicare. White-black disparities were significant, while white-Hispanic disparities were significant only among the dually eligible. The disparate experiences we discussed above between minority seniors and their white counterparts undoubtedly account for a sizable portion of these disparities. Three more Part D-related issues set racial groups further apart. First, among non-Medicaid seniors who were still eligible for the LIS (below 150% of the poverty line), minorities are less likely to be

aware of this benefit,[103] and predictably less likely to receive it. Second, these beneficiaries (non-Medicaid, LIS-eligible minorities), especially high users, might be more likely to fall in the coverage gap (so-called "donut hole") further exacerbating their medication-taking behavior.[48] Third, recent evidence has shown that minorities are less likely to meet Part D utilization-based eligibility criteria for medication therapy management (MTM) services.[63,64] This deprives scores of minority patients from a benefit that is well-equipped to help them with their complex medication-related issues, including adherence behavior.[53]

While it is important to identify access/quality issues that may disparately compromise adherence behavior among minorities, it is at least equally as important to envision adherence as a reflection of the structural, physical, and psychosocial disadvantage racial minorities typically live in. Poverty, low educational attainment, disordered physical and social environments, and policies that institutionalize racism are systematically causal antecedents to almost every poor health outcome among minorities.[108] While achieving equity in these fundamental determinants of health must remain a long-term goal for society, collaborative, creative, and holistic interventions by healthcare professionals can provide some quick remedies in the short-run. In Medicare, MTM programs can offer a platform to empower minorities to adhere to their appropriate medication regimens and lifestyle recommendations, improve their health literacy, and enhance their self-efficacy, central to a variety of self-management behaviors.[109] Delivery of MTM in collaborative/referral networks that bring together providers, pharmacists, social workers, and community/home health workers can proactively identify and tackle issues compromising medication adherence (and potentially other aspects of healthcare). Further research[110] is needed on how to optimize MTM delivery for minority and low-SES patients.

For effective interventional research on how to reduce adherence disparities, greater appreciation of the complexity of adherence is warranted. Adherence should be understood as a series of behaviors that start with keeping doctor's appointments to actual administration of medications, involving steps such as regularly filling prescriptions, using reminders, exercising, and maintaining healthy diet.[111] These contiguous behaviors arise from complex interactions among multiple factors, pertinent to the patient and the environment. Given this complexity, we need to build a deeper mechanistic understanding of how this intricate system works and how/where it engenders disparities. Parsing out this intricacy, through complex systems science and simulation approaches, enables us to identify novel "leverage points" for effective intervention that were potentially otherwise unidentifiable.[112] Studying adherence this way can also help us answer interesting clinical questions, some of which does arise in this study, such as why the magnitude of adherence disparity differ by medication class (for example, why disparities are larger in adherence to beta-blockers more than other classes, and only among blacks).

Limitations

The results of this study should be understood in the light of its limitations. First, our derivation of refill days of supply from dispensed quantities was based on 2010 data of MEPS, without validation against an external standard, claims data for example. Given that previous research has demonstrated that MEPS prescription drug data are of comparable quality to Medicare claims data,[87] we believe benchmarking our analysis solely to MEPS 2010 is credible. An alternative to "manually" deriving refill days of supply from dispensed quantities would have been to formally impute days of supply in earlier years of MEPS using a multiple imputation regression model informed by refill- and respondent-level covariate data in the 2010 sample. We found however that dispensed quantities overwhelmingly accounted for the variation in days of supply, with all possible covariates explaining as little as 1% of the variation in days of supply (based on R^2 calculations). To do multiple imputation properly on missing data of this magnitude (nine tenths of the data are missing, essentially), we would have needed to impute over more than 90 datasets, which is computationally intensive and would require technically challenging handling in subsequent analyses. Notwithstanding these caveats, the substantial level of agreement we detected between adherence measures based on actual vs constructed days of supply, consistently at all stages of adherence measurements and across drug classes, reinforces the validity of our approach.

While data on dispensed quantities were 100% complete for all refills from 2002-2010, a large proportion of 2010 refills had missing days of supply data (about 33%). We found the pattern of missing data to be very consistent across drug class and respondent characteristics, indicating that a missing-completely-at-random (MCAR) assumption is likely plausible. As such, we examined the pattern of refill days of supply vis-à-vis dispensed quantities only among individuals with complete days of supply data for all their listed refills. We also assumed that the patterns of supply days vis-à-vis dispensed quantities in 2010 would hold in earlier years of MEPS. Although we believe this assumption is likely true on average, changes in treatment guidelines and generic availability might have affected the prescribed total daily doses of some cardiovascular medications, especially in earlier years of our study period (for example, in 2002 and 2003 before the 7th Joint National Committee (JNC-7) guidelines on hypertension management were issued/adopted).

Since we used the annual files of MEPS, sampled individuals were mostly prevalent, rather than incident, users of the study medications, as it was not possible to ascertain medication use in the year prior to the index refill. Although MEPS had dates for when a drug was first taken, these dates were missing for about 80% of refills and no inference could be made on whether respondents were new or prevalent users of medications on the basis of these dates. Another complication of using the annual files is that many covariates were not available at baseline (i.e. the first interview round), but, rather at other time points (e.g. physical activity available in last round of the year). This temporal ambiguity might have affected the identification of covariate associations with adherence. We were primarily interested, however, in the identification of DID effects, which we properly assessed over the pooled cross-sections before and after Part D. We

used covariates to make the DID assumptions more plausible and to fine-tune our definitions of disparities.

We encountered the rather surprising finding that predicted disparity estimates were not sensitive to various levels of adjustment using the rank-and-replace procedure. It is unclear whether this is a statistical consequence of covariate assessment, outcome variable construction, or it is indeed the case that our covariates could explain little about adherence disparities. In the 2010 sample, we compared coefficient estimates from models of adherence using: 1) actual vs constructed days of supply data and 2) using only covariates temporally antecedent to adherence (e.g. first-round covariates on the right-hand side with adherence in the remaining two rounds as the outcome) vs simultaneous outcome-covariate models. We found no statistically significant differences in coefficient estimates across these models.

An alternative to using the annual files would have been to use the longitudinal two-year panel version of MEPS. This, however, would have cut our sample in half (since annual files pool the two overlapping panels of the year), further inflating the standard errors and rendering point estimates unstable and untrustworthy. We encounter this problem to some extent in subgroup analyses (e.g. in the dually eligible sub-sample), where quite large estimates are statistically no different from zero!

Based on previous research,[47] we used the near-elderly as the control group that provides the counterfactual scenario that would have prevailed in Medicare had Part D not been implemented. Two issues challenge the validity of this control group. First, the Medicare Modernization Act of 2003, which created Part D, also established the pre-Part D drug discount card program for transitional assistance of low-income beneficiaries[105] and further subsidized MA plans to expand their benefits, in 2004-2005.[62] With minority seniors taking advantage of these two changes together, the trend of adherence disparities among seniors started to partially deviate from being parallel to its near-elderly counterpart before Part D implementation in 2006. Further, growing enrollment of minority beneficiaries in MA plans after Part D[62] could also mean that some of the observed changes in disparities might actually be attributed to changes in Medicare Advantage and not directly to Part D. Second, the near-elderly experienced the shock of the economic recession and job loss that loomed in 2007-2008. This has likely set the trend of disparities among the near-elderly on an ascending path that would not have been necessarily experienced by seniors in the absence of Part D (about 60% of the near-elderly were employed vs only 14% of seniors). Nonetheless, since the perfect control group is lacking in this policy space (that is, 65-year plus old seniors without Medicare), the near-elderly make a reasonable control group to study changes in healthcare delivery and financing in Medicare. Despite the aforementioned limitations, findings in this study are consistent with the published literature and can be readily accounted for by the observed changes in healthcare access and delivery among Medicare seniors and the near-elderly.

Conclusion

In a nationally representative sample from MEPS, we used a quasi-experimental difference-in-differences design to evaluate Medicare-wide effects of Part D introduction on the racial disparities in adherence to cardiovascular medications. We took a nuanced approach to conceptualizing and estimating adherence disparities according to the IOM framework, and performed multiple subgroup and sensitivity analyses to assess the robustness of our conclusions. Our results suggest that following Part D, the overall cardiovascular medication adherence disparity between white and Hispanic seniors has narrowed by 16% points, whereas there was no statistically significant change in the white-black disparity, except among men where it increased by 21% points.. Significant adherence disparities continue to remain among the elderly in Medicare, especially among dually eligible beneficiaries. Differential awareness of and access to benefits, such as the LIS among the non-dually eligible, as well as the institutionalized disparity in access to MTM services may be immediate targets for policy interventions to improve adherence behavior and the overall quality of medication therapy in Medicare. Research on the determinants of adherence disparities and on optimizing the delivery of interventions, such as MTM, to answer the needs of minority beneficiaries is much needed.

CHAPTER 3. RACIAL DISPARITIES IN ADHERENCE TO CARDIOVASCULAR MEDICATIONS AMONG THE ELDERLY IN MEDICARE: LOOKING BEYOND THE MEAN

Background

In cardiovascular diseases, adherence to evidence-based medication regimens is key to achieving the goals of pharmacotherapy and slowing disease progression.[15,74] Lower medication adherence rates exist among racial/ethnic minorities, relative to whites, even in settings with equitable access to prescription drugs.[11,33] In the Medicare program, where Part D introduction enhanced adherence by improving the affordability and quality of use of medications,[41,45,46,53] adherence disparities continue to persist. After Part D implementation, Holmes et al reported that among Medicare seniors with uncomplicated hypertension, blacks and Hispanics were about 45% less likely to be adherent to their antihypertensive medications, including alpha- and beta-blockers, angiotensin-converting enzyme (ACE) inhibitors, angiotensin II receptor blockers (ARBs), Calcium channel blockers (CCBs), diuretics and vasodilators.[28] Zhang et al examined adherence to ACE inhibitors/ARBs and diuretics among seniors with heart failure, and found blacks, Hispanics, and Native Americans to be about 40% less likely to achieve adherence than whites.[29] Zhang et al also reported that black and Hispanic seniors surviving acute myocardial infarction (AMI) were 20-30% less likely to adhere to beta-blocker, ACE inhibitor, or statin therapy for 6 months or a year post-infarction.[30] In an analysis across race and gender of AMI survivors, Lauffenburger et al reported that black and Hispanic women were least likely (having about 30-36% lower odds), compared with white men, to be adherent to these post-AMI preventive therapies.[31] In a meta-analysis of published studies, Lewey et al estimated that generally patients of non-white race were at about 50% higher odds of non-adherence to statins than whites.[32]

Substantial disparities exist between whites and racial minorities in the control of blood pressure and cholesterol levels,[10,113-115] and predictably in cardiovascular disease progression and mortality.[3,4,6,7] Among the multiple social and behavioral factors that might explain the disparities in these risk factors,[8,12-14] the disparities in cardiovascular medication adherence are repeatedly identified as a key culprit.[7,8,12,15] Although extant evidence documents adherence disparities, a full understanding of these disparities is still lacking. One missing piece in this puzzle is a greater appreciation of how these disparities vary across the distribution of adherence where different adherence levels may represent populations with distinct patterns of behavior. Current literature have predominantly documented disparities in the probability of 80% adherence, which has been the traditional cutoff for adherence classification. Apart from the arbitrary nature of this cutoff and its apparent lack of a clear clinical rationale,[16,116,117] it represents only one level of adherence behavior and indiscriminately lumps potentially distinct patterns of behavior below and above 80% medication possession.

Studying disparities in the probability of 80% adherence (or some other cutoff), albeit informative, thus risks ignoring disparities among populations at other levels of

adherence, which may be driven by potentially different factors and amenable to distinct interventions. Further, studying adherence (as a continuous outcome) in typical regression frameworks falls prey to a similar phenomenon, where the modeled outcome is mean adherence conditional on the included set of control variables. Because of the nature of the mean as a summary statistic of central tendency, disparities at other locations in the adherence distribution will only "show up" in the mean if they are relatively large. Thus, using a single cutoff or a continuous measure of adherence may obscure disparities that occur at other locations in the adherence distribution, even ones that may be significant and policy-relevant.

Quantile regression[70,118-120] is a powerful technique that allows assessment of how predictors (e.g. race in this study's context) influence the central and non-central locations, scale, and shape of the outcome distribution.[121] Widely applied in labor economic evaluations, such as in the study of wage inequality,[120] applications of quantile regression to study health disparities have increased in recent years,[122-127] including a few applications in the context of adherence disparities.[128,129] Besides enabling the investigation of the heterogeneity of adherence disparities across the distribution, quantile regression is well suited to accommodate the quasi-continuous left-skewed distributions of medication possession measures.[128] In one interesting example, Gebregziabher and colleagues[128] showed that black-white disparities in medication adherence among type 2 diabetes patients persisted across the distribution of the medication possession ratio (MPR) and particularly around 60% MPR, whereas white-other race disparities were significant *only* at the lowest quantile (corresponding to ~ 40% MPR) and were not detectable at the mean. Juarez et al[129] also examined disparities in adherence to anti-diabetic and lipid-lowering medications between Pacific Islander and white Americans in Hawaii. She found that disparities relative to whites were largest and most significant at the 25th percentile of the PDC (proportion of days covered; a variant of the MPR) distribution and decreased monotonically towards the higher percentiles of the distribution. These findings point to sub-populations where adherence disparities may be most amplified and potentially deserving priority intervention.

In this study, we sought to explore the heterogeneity of racial disparities across the distribution of adherence to cardiovascular medications, among Medicare seniors after 2006. We used a versatile unconditional quantile regression estimator, recently developed by Firpo, Fortin, and Lemieux.[70] As we further explain in the "Statistical Analysis" section, in multivariable regression settings where predictors may have interactive effects on the outcome, making the assumption of additive covariate effects unrealistic, unconditional quantile regression directly provides the appropriate estimates of marginal effects of covariates on outcome quantiles.[130]

Methods

Data Source

We used longitudinal data from the household component of the Medical Expenditure Panel Survey (MEPS), panels 11 to 14 spanning years 2006 to 2010. MEPS is an annual overlapping panel survey of the US civilian non-institutionalized population, administered by the US Agency for Healthcare Research and Quality (AHRQ).[131] The primary focus of MEPS is on healthcare access, use, and expenditure in the United States, enabling calculation of national impact estimates for a wide variety of health policy changes. Each year MEPS panel participants are sampled from the previous year's respondents to the National Health Interview Survey (NHIS), with oversampling of minorities and other policy-relevant groups (such as adults with functional limitations and low-income households).[131] Each panel is then prospectively followed for two calendar years and their data are collected over five rounds of computer-assisted personal interviewing. Rounds 1 and 2 fall in the first year, rounds 4 and 5 fall in the second year, while round 3 spans the end of the first and the beginning of the second year. AHRQ provides two types of main data files that can be linked to Medical Conditions and event files: longitudinal and annual/cross-sectional (known as Full Year Consolidated Data) files. For this study, we linked the longitudinal panel files to the Medical Conditions and Prescribed Medicines event files. Although all MEPS data are reported by respondents during round interviews, further detailed health service use data, including on prescription drugs, are collected from a sample of providers (e.g. medical and pharmacy) with respondents' permission. Then these data are used to supplement respondents' self-reports of health service use and expenditure. Of particular relevance to this study, the quality of MEPS prescription drug data, as well as Medicare Part D enrollment has been shown to be comparable to that of claims data.[87,88] MEPS also provides very rich data on respondents' sociodemographics, health and chronic conditions, as well as experience with providers and the healthcare system, allowing a thorough study of adherence as shaped by these determinants.

Cohort Identification

We included MEPS respondents who were:

1) Continuously included in all MEPS survey rounds for the two panel years, excluding those who went "out of scope" because of death, institutionalization, or other reasons.

2) Medicare beneficiaries 65 years or older as of Round 1, who reported receiving Medicare until the end of the second year (Round 5).

3) Non-Hispanic white (henceforth "white"), non-Hispanic black (henceforth "black"), or Hispanic. We excluded other racial/ethnic groups and did not further distinguish Hispanic subgroups as their small sample sizes limited such inferences. MEPS ascertains race/ethnicity as follows:[132] first, respondent's self-report of their race/ethnicity is the primary way to procure this data. Then, if not

available, race/ethnicity is obtained from the originally collected NHIS data in the year prior to joining the MEPS panel. Finally if not available either way, MEPS assigns race/ethnicity based on respondent's relationship to other members of his/her household starting with blood relatives in the immediate family. MEPS survey questions assessing race/ethnicity have been consistent since 2002.[132]

4) Had at least one of the following six prevalent conditions in both year 1 and year 2: hypertension, hyperlipidemia, angina, congestive heart failure, myocardial infarction, or stroke, listed in the linked Medical Conditions file. Clinical Classification Codes and 3-digit ICD-9 codes in MEPS were used to identify respondents with these conditions.[133] **Appendix Table A-1** (Chapter 2) lists all the conditions and their associated codes. Identified respondents had at least one event (inpatient, outpatient, or prescription drug) associated with one or more of these conditions.
5) Were prevalent users of at least one chronic cardiovascular medication of the following classes: ACE Inhibitors, Angiotensin II Receptor Blockers (ARBs), HMG-CoA Reductase Inhibitors (Statins), Beta-blockers, Calcium Channel Blockers, Diuretics, or combination products of these medications. Use was defined as having at least one refill for the same medication class in both years. Second-year refills were used to estimate adherence.

Since our study sample only included a small portion of MEPS respondents, we pooled MEPS panels 11-14 by year to create one analytical file with adequate sample size for our analyses. Pooling MEPS data is commonly practiced and survey design variables in MEPS files for our study period specify a common variance structure that takes into account pooling when calculating standard errors.[89] Our final analytical file contained pooled data for year 1 (2006-2009), the baseline year, and year 2 (2007-2010) where adherence was estimated.

Adherence Measurement

Using refill records for included respondents in the second year, we measured adherence to each medication class as the proportion of days covered (PDC) by refills for any medication from that class, expressed as a percentage and capped at 100%. Thus, in the case of overlapping refills for two beta-blockers, for example, only one refill was counted towards calculation of the beta-blocker-specific PDC. ACE inhibitors and ARBs were also considered a single class for this purpose. Component medications of combination products were also counted towards their respective classes. Since MEPS does not collect refill dates, an index date specific to each medication class was identified for each respondent as the first day of the round in which the first refill (for the specific class) occurred. These rounds were either the fourth, the fifth, or the portion of the third round that had fallen in the second year. Respondents were then followed until the last day of the fifth round, which corresponded to December 31st of the second year in the panel for all participants. Inpatient days were excluded from the follow-up period. For all classes, while a majority of respondents (55-60%) had January 1st of the second year (i.e. the part of round 3 that fell in year 2) as the class-specific index date, more than 95% of

index refills had occurred by March of the second year. To summarize adherence over all medication classes, we calculated a respondent-specific PDC that was the average of all his/her class-specific PDCs. The main outcome variable was the overall continuous PDC. We explored class-specific adherence in sub-group analyses.

Although MEPS provides extensive data on prescription refills, including dispensed quantity, strength, dosage form, and therapeutic class/subclass, data on days of supply were not routinely collected until 2010. We used 2010 data, which was the second year of Panel 14 in our sample, to characterize the patterns of observed days' supply as they relate to dispensed quantities of drug refills. In so doing, we identified the most frequent number of supply days furnished by each level of dispensed quantity. Next, we derived a scheme to smoothly approximate the distribution of days of supply for use in prior years of MEPS (where actual days of supply data are not available). Then, in 2010 data, we calculated PDCs as explained above using the actual and constructed days of supply distributions. To assess the validity of our derivation, we used Lin's concordance coefficient[90,91] to compare the constructed distribution of days of supply as well as the PDC based on it, to the actual distribution and its associated PDC. (We also derived binary adherence at PDC≥80% based on the two distributions, and compared them using *C*-statistics). Then, we used our validated scheme to construct refill days of supply from dispensed quantities in all panels. The validity of computing refill days of supply in earlier years using the pattern of days of supply vis-à-vis dispensed quantities in 2010 hinges on the potentially plausible assumption (based on discussions with two cardiologists with more than 20 years of practice experience) that the dosing frequency of a given strength of a specific cardiovascular drug has been stable over 2007-2010 in a specific patient population. (For example: for the same patient population, if a 30-pill refill of 40-mg simvastatin covers 30 days in 2010, on average, this would have also been true in 2007).

Covariates

We modeled the PDC distribution as a function of a series of baseline covariates assessed over the first year of the MEPS panel. In addition to race/ethnicity identifiers, which were the primary predictors of interest, we used data on respondents' demographic characteristics; geographic location; self-reported health and functional (physical/ cognitive) status; depressive symptoms;[134] cardiovascular conditions and other comorbid conditions; beliefs regarding health, risk, and insurance; income and poverty status, and educational attainment; health behaviors; type of primary insurance coverage for prescription drugs; financial and pill burden associated with medications; access to/use of primary care and other health services; and experience with providers and satisfaction with the healthcare system.

In addition to binary indicators of which cardiovascular condition(s) respondents had in the baseline year, we also enumerated other comorbid conditions, such as diabetes, asthma, and cancer, and calculated a modified version of the Charlson comorbidity score (excluding respondent-specific cardiovascular conditions and depression) adapted for use

with 3-digit ICD-9 codes in MEPS.[96] For socioeconomic status (SES), we used MEPS-provided categories of income as a percent of the Federal Poverty Line (FPL) and categorized years of education into three levels: less than high school, high school diploma (12 years), and above high school. High-income and having education beyond high school served as the reference categories.

For drug coverage status, we used a series of variables on insurance status as well as amounts paid by each payer for prescription drugs over the first year to ascertain drug coverage for each respondent. We identified three principal categories of coverage, as of December 31st of the first year: those who had no evidence of drug coverage by any payer, those who had Medicare Part D, and those who had a private source of drug coverage including employer-sponsored. Among Part D enrollees, we identified those who were concurrently enrolled in Medicare managed care and those who were not. Thus we were able to further split Part D recipients into those who had Medicare Advantage Part D plans (MA-PD) and those who were just enrolled in stand-alone Part D plans (PDPs) with no evidence of enrollment in MA. Further, we created an indicator for whether a Part D respondent was deemed eligible for auto-enrollment for the low-income subsidy (LIS), which included dually eligible beneficiaries and beneficiaries receiving Supplemental Security Income (SSI) (both variables were available in MEPS).[55,57] Other LIS-recipients who are not automatically enrolled but their income is below 150% FPL and have limited assets must apply to receive the LIS.[54] Although we validated the characteristics of these sub-categories of Part D recipients against the literature,[54,56,58,59,103] ascertaining drug plan type or actual receipt of the LIS is not possible in MEPS.

Disparity Definition

In the primary multivariable analysis, we defined disparities in adherence following the Institute of Medicine's (IOM) framework for assessing healthcare disparities.[66,92] The IOM contends that racial healthcare disparities are differences in healthcare that are not justified by the clinical appropriateness, health status needs, or by patients' informed preferences and attitudes towards medical care.[66] Healthcare disparities arise through two broad mechanisms:[66] first, the legal and regulatory environment in which healthcare systems operate, including policies and practice patterns, insurance coverage, SES, and other differential factors that constrain healthcare use disproportionately for minorities,[92] and second, discrimination at the patient-provider level, which may take multiple forms.[95] As such, the IOM framework attempts to identify the contributions of the current structural impediments to achieving equity in the healthcare system, which are extrinsic to patients and potentially amenable to appropriate policy and clinical practice interventions.

Accordingly, we defined racial disparities in adherence as the differences in adherence across clinically comparable racial groups that arise due to inequitable social and health-system factors, including SES, insurance coverage, access to primary care, and potential discrimination in the clinical encounter. Clinical comparability enables

isolating the disparities potentially engendered by social and health system factors, similarly to a hypothetical experiment where there are two groups with identical health profiles but only one receives racial disadvantage (socioeconomic and otherwise) as the treatment. Since the two groups possess identical health and disease burdens, their different rates of healthcare use (medication, in our case) must then be attributable to the "treatment," that is racial disadvantage.

We took a straightforward approach[67,122,125,126] to empirically study adherence disparities as defined above, where we adjusted the association between race/ethnicity and adherence only for the effects of demographics, geographic location, health status and medical conditions, and beliefs. Only controlling for these variables balances out health characteristics of minority and white groups and allows the effects of variables potentially mediating disparities, such as SES variables, to be reflected in the race/ethnicity coefficients. This is also consistent with the empirical principle that if one wishes to estimate the total effect of a variable, race/ethnicity in our case, one should not adjust for intermediate variables on the causal pathway between the variable of interest and the outcome.[135] Notwithstanding our *a priori* empirical definition of adherence disparities, we explored in secondary analyses the sensitivity of our primary findings to various definitions of disparities, through sequentially adjusting for groups of covariates up to full adjustment for all available covariates.

Statistical Analysis

We used *unconditional* quantile regression to explore how racial disparities change across the distribution of adherence. Quantile regression[118,120] is analogous to ordinary least squares (OLS) regression except that it models conditional outcome quantiles instead of conditional means. Originally started as median regression, quantile regression allows exploration of the dependence of the outcome on covariates at other locations of the distribution, i.e. other quantiles. Mathematically, as **Equation 3-1** shows, the q^{th} conditional quantile of an outcome variable Y on covariates X can be written as,

$$Q^q(Y|X) = \widehat{\alpha}^q + \sum_{k=1}^{K} X_k^q . \widehat{\beta}_k^q \quad \textbf{(Eq. 3-1)}$$

where $0 < q < 1$ is the modeled quantile, indicating that the proportion of the sample modeled is below the quantile q. This is not to say that quantile regression runs on a subset of the population. It means that the distance of data points from the quantile line, β_k, is measured as a weighted sum of the absolute vertical distances (deviations) from the line, and the weight is $(1-q)$ for the observations below the line and (q) for those above the line.[121] For example, the 70th quantile regression can be thought of as a plane that passes through the sample, weighing observations above it by 0.70 and observations below it by 0.30.[126] β_k is estimated by minimizing these *weighted* absolute deviations.

Typical quantile regression applications have used conditional quantile regression, as described above. The quantile regression coefficient of a variable is an estimate of the effect of that variable on the conditional outcome quantile. As in linear

regression, when there are no covariates or when covariate effects are assumed to be independent of the values of other covariates (that is, no interaction/effect modification), these coefficients are also consistent estimators of the effect on the unconditional mean of the outcome distribution.[130] This latter property of regression coefficients is what makes them interpretable as population-level effects, which are of primary interest in most empirical research.[130] When covariate effects are realistically not additive/parallel but rather interactive (for example, the association between race and adherence may differ by geographic region), conditional and unconditional effects start to diverge.[130] In such (fairly typical) cases, quantile regression coefficients do not provide consistent estimates of covariate effects on the unconditional distribution. In mean regressions, such as generalized linear models and logistic regression, unconditional (average) marginal effects can be recovered as recycled predictions following model estimation.[99,136] In the case of quantile regression, however, conditional effects captured by coefficients are very complicated to convert to unconditional effects.

Firpo, Fortin, and Lemieux[70] recently developed a computationally simple approach that directly estimates unconditional quantile regression coefficients. Their approach relies on modeling a quantity known as the re-centered influence function (RIF) of outcome quantiles directly instead of the outcome quantiles themselves. The influence function (IF) is a mathematical tool that assesses the "influence" of a particular observation on a distributional statistic without having to recalculate that statistic.[70] The RIF is obtained by adding the IF of the statistic to the statistic itself. An interesting property of the RIF is that its expected value is equal to the statistic. For example, if we regress RIF of mean PDC in a linear regression on X variables, the IF would basically be the residual (difference between observed y and estimated μ PDC) at a particular PDC value (the observation of interest). Estimated RIF gives the mean PDC itself. As shown in **Equation 3-2**, in simple notation,

$$IF(y;\mu)=(y-\mu)$$
$$RIF(y;\mu)=\mu+(y-\mu)=y \qquad \textbf{(Eq. 3-2)}$$

We would also get precisely the same coefficients as in the standard case of regressing the mean itself instead of its RIF. Using this approach, Firpo, Fortin, and Lemieux[70] demonstrated that modeling the RIF of each outcome quantile as a function of explanatory covariates in OLS regression yields coefficient estimates that are essentially the effects of covariates on the unconditional outcome distribution. Racial disparity would thus directly equal to the coefficient of the race variable, without the need to do any further computation.

Using the -`rifreg`- STATA routine,[137] and following the recommendations on estimating RIF and the probability density function at each quantile,[70,130] we estimated unconditional quantile regressions of PDC at the 10th, 20th, up to the 70th quantile (where adherence was almost perfect, PDC ~ 100%) as a function of race/ethnicity indicators as well as other covariates as explained above. All analyses accounted for MEPS survey design by including longitudinal weights and design variables as appropriate. We estimated standard errors using 5,000 block bootstrap replications, to account for

clustering of survey data in primary sampling units. Since rates of missing data in some covariates (e.g. belief and experience with providers) were as high as 13%, we used multiple imputation using chained equations (MICE) to impute missing data for each of these variables.[100] Regression analyses were estimated separately in each imputation dataset and then point estimates and standard errors were combined using Rubin's rules[138] to produce a single set of estimates that took into account uncertainty due to imputation. All analyses were carried out in STATA® 13 (StataCorp; College Station, TX).

Results

Sample Characteristics

The study sample included 3,749 MEPS respondents, nationally representing 20.7 million Medicare seniors with cardiovascular diseases. Average length of follow-up for adherence measurement was 342 days. **Table 3-1** lists characteristics of sampled respondents by race. Compared with their white counterparts, black seniors were more likely to be female, less likely to be married, and substantially more likely to reside in the South. Hispanic seniors were also less likely to be married and substantially more likely to reside in urban areas and in the West. Both black and Hispanic seniors had worse self-rated health and higher rates of cognitive limitation than whites. They were also more likely to have hypertension and diabetes but less likely to have hyperlipidemia. Interestingly, blacks were only half as likely to be diagnosed with depression but twice as likely to screen positive for depressive symptoms using the Patient Health Questionnaire ver. 2 (PHQ-2).[134] Hispanics were also about twice as likely as whites to report depressive symptoms on the PHQ-2 scale, but no more likely than whites to be diagnosed with depression. Both minority groups were also much less likely to believe they did not need medical care to manage illness. Both were less likely to exercise and more likely to be obese.

Black and Hispanic seniors were much more likely to be at the lowest levels of income and education. For more than 50% of Hispanics, English was not the primary language spoken at home or with others. For drug coverage, nearly 19% of the cohort had no evidence of drug coverage in MEPS, including from federal sources. Nonetheless, rates of plan enrollment were very similar to what the Kaiser Family Foundation (KFF) reported for January 2010.[54] Overall Part D enrollment was 61.8%. In our sample of elderly beneficiaries with cardiovascular diseases, the overall rate of auto-enrollment in the LIS was ~10% (15.5% among Part D enrollees in the sample). Whites were more likely than either minority group to have no drug coverage, and less likely to be eligible for automatic receipt of the LIS. While Hispanics were more likely to have MA-PD coverage, blacks were more likely to be enrolled in PDPs. Both minority groups were, however, less likely than whites to have employer-sponsored or other private coverage. These findings were also consistent with the literature on drug coverage by race.[59,103,139]

Table 3-1. Characteristics of sampled Medicare seniors by race

Characteristics	White	Black	Hispanic	Overall
		% (unless otherwise noted)		
Demographics				
Age (Mean±SD)	75.42±6.34	74.55±6.13	74.51±6.04	75.28±6.31
Female	56.69	**63.41**	58.74	57.44
Married	56.08	**31.31**	**45.14**	53.08
Urban/MSA	79.34	84.06	**91.77**	80.60
Census Region				
Northeast	21.24	18.22	**13.67**	20.46
Midwest	25.70	**15.41**	**6.95**	23.50
South	34.48	**59.88**	42.84	37.36
West	18.57	**6.49**	**36.53**	18.68
Self-Reported Health				
Excellent	13.40	**7.65**	**6.66**	12.42
Very Good	31.32	**23.72**	**17.08**	29.67
Good	33.61	35.31	35.00	33.86
Fair	16.58	**25.64**	**30.41**	18.34
Poor	5.09	**7.68**	**10.84**	5.71
Any Physical Limitation*	62.29	63.48	66.69	62.69
Any Cognitive Limitation*	9.78	**18.24**	**17.03**	11.04
Medical Conditions				
Quartiles of Charlson Comorbidity Score				
1st/2nd Quartiles	56.35	**46.43**	**43.37**	54.57
3rd Quartile	31.53	**39.52**	**40.54**	32.86
4th Quartile	12.12	14.05	16.09	12.56
Count of Comorbid Conditions,† Median(IQR)	5 (3, 8)	4 (2, 6)	4 (2, 7)	5 (3, 7)
Hypertension	82.57	**93.65**	**89.86**	84.07
Hyperlipidemia	66.24	**56.95**	**58.53**	64.88
Angina/CHD	21.79	**17.38**	21.26	21.35
CHF	4.02	3.54	2.80	3.90
AMI	8.89	7.21	7.63	8.65
Stroke	6.00	6.14	4.86	5.94
Depression Diagnosis	10.85	**5.35**	11.30	10.38
Depressive Symptoms	7.41	**14.69**	**16.42**	8.68
Diabetes	22.42	**36.50**	**41.71**	25.00

Table 3-1. (Continued)

Characteristics	White	Black	Hispanic	Overall
		% (unless otherwise noted)		
Asthma	8.40	**11.35**	9.98	8.78
Emphysema	6.90	5.12	**3.12**	6.48
Arthritis	60.21	**66.25**	57.22	60.56
Beliefs				
More Likely to Take Risks	16.45	14.13	12.84	16.00
Can overcome illness without medical care	11.31	**7.05**	**7.11**	10.64
Does not need health insurance	4.45	5.01	5.81	4.60
Behaviors				
Current Smoker	8.30	10.91	6.10	8.39
Had Moderate/Vigorous Exercise	47.43	**37.43**	**38.65**	45.92
Obese (BMI≥30)	28.53	**36.67**	**35.39**	29.73
Socioeconomic Status				
Income: ‡ Poor/Near-Poor	15.38	**32.56**	**31.51**	18.03
Low-Income	15.95	**20.71**	**21.05**	16.73
Middle-Income	31.44	31.15	30.54	31.35
High-Income	37.23	**15.58**	**16.89**	33.89
Education: Less than High School	19.73	**47.42**	**65.57**	25.31
High School Diploma	52.97	**39.00**	**22.77**	49.68
College and Beyond	27.30	**13.59**	**11.66**	25.01
Language: Interview Not in English	0.13	0.00	**52.00**	3.61
No English at Home	1.13	1.02	**59.91**	5.08
Primary Drug Coverage- End of Year 1				
No Known Rx Coverage	19.85	**12.99**	**11.77**	18.68
Part D: PDPs	35.96	**43.66**	39.55	36.91
Part D: MA-PD	23.00	**30.37**	**41.72**	24.93
Employer/Other Private	21.19	**12.97**	**6.96**	19.49
Auto Eligible for PD Low-Income Subsidy	5.72	**25.92**	**38.99**	9.81

Table 3-1. (Continued)

Characteristics	White	Black	Hispanic	Overall
		% (unless otherwise noted)		
Use of CV Drug Classes in Year 2				
ACE Inhibitors/ARBs	58.17	59.68	**69.16**	59.05
Statins	60.11	**49.56**	**48.71**	58.38
β-blockers	41.67	37.08	44.33	41.43
Ca Channel Blockers	19.72	**36.54**	**29.71**	21.93
Diuretics	43.85	**54.65**	**35.29**	44.26
Healthcare Use at Baseline				
No. of concurrent CV Medications §				
0-1	34.95	32.53	37.34	34.89
2-3	56.26	55.27	55.94	56.15
≥4	8.78	**12.21**	6.72	8.96
No. of concurrent medications overall				
0-1	9.96	**14.13**	12.82	10.54
2-4	44.51	44.51	48.76	44.80
≥5	45.53	41.37	38.42	44.67
No. of Pharmacies Used, Median(IQR)	1 (1, 2)	1 (1, 1)	1 (1, 1)	1 (1, 2)
Average Copay for CV Drugs ($2010), Median(IQR)	15.62 (6.70, 31.84)	9.17 (3.07, 21.31)	6.67 (2.38, 21.19)	14.44 (5.79, 30.69)
Had a Usual Source of Care	97.43	**95.58**	**95.13**	97.11
Any Inpatient Stay-Previous Year	17.23	17.88	14.81	17.13
Any Emergency Department Visit-Previous Year	17.33	**21.06**	20.12	17.86
Quintiles of ambulatory physician visits (range)				
Q 1 (0-2)	17.99	**28.83**	**24.92**	19.45
Q 2 (3-4)	18.12	21.21	22.09	18.67
Q 3 (5-7)	20.47	21.75	19.62	20.53
Q 4 (8-12)	22.18	**13.14**	17.85	21.07
Q 5 (≥13)	21.23	**15.08**	15.51	20.29
Experience with Providers				
Very Satisfied with Received Healthcare	58.67	53.87	52.69	57.83

Table 3-1. (Continued)

Characteristics	White	Black	Hispanic	Overall
		% (unless otherwise noted)		
Provider Always Explained	56.79	58.28	50.71	56.52
Provider Always Listened	61.24	62.36	54.69	60.90
Provider Always Respected	63.11	64.49	56.91	62.82
Sample Size	2,585	703	461	3,749
Weighted Population	17,447,543	1,891,319	1,396,116	20,734,978

Boldface estimates have P<0.05 for pairwise comparisons relative to whites.
* Physical limitations included functional or sensory limitations, or limitation in the Instrumental Activities of Daily Living or in the Activities of Daily Living. Cognitive limitations included confusion, dementia, problems making decisions, or needing supervision for own safety.
† Excluded respondent-specific cardiovascular conditions.
‡ Poor/Near-Poor: <125% FPL; Low-Income: ≥125 to <200 %FPL; Middle-Income ≥200 to <400% FPL; High Income (reference): ≥400% FPL.
§ Same-pill combination products were counted as one drug
CV: Cardiovascular; SD: Standard Deviation; IQR: Interquartile Range; CHD: Coronary Heart Disease; CHF: Congestive Heart Failure; AMI: Acute Myocardial Infarction; BMI: Body Mass Index; FPL: Federal Poverty Line; PDP: stand-alone prescription drug plan; MA-PD: Medicare Advantage Prescription Drug plan; PD: Part D; ACE: Angiotensin-Converting Enzyme; ARB: Angiotensin II Receptor Blocker

Exposure to ACE inhibitors was highest among Hispanics and was similar among whites and blacks. Statin use was much less among minorities compared to whites, perhaps reflecting the lower prevalence of (diagnosed) hyperlipidemia. The use of Calcium channel blockers was higher among minorities than among whites. Blacks were the most exposed to diuretics whereas Hispanics were exposed the least. Black seniors were more likely to concurrently take multiple cardiovascular medications, but nonetheless more likely to take less medications concurrently overall. Both blacks and Hispanics were less likely to report having a usual source of care and were more likely to have fewest ambulatory physician care. No statistically significant differences were present in rating the experience with providers or satisfaction with healthcare by race.

Adherence Validation

In the 2010 sub-cohort, we studied refill days of supply vis-à-vis dispensed quantities to build a scheme that would allow us to derive days of supply from dispensed quantities in earlier panels of MEPS, where days of supply data were not available. Based on identifying the most frequent number of supply days furnished by each level of dispensed quantity, we found the following scheme to work best for constructing days of supply from dispensed quantities, (quantity vs days of supply): [8: 16; 15-16: 30; 45: 90; 46-75: 30; 76-119: 90; 120: 30; >120: 90; all other quantities: identical days of supply]. This scheme also worked equally well across medication classes. Comparing the PDC distribution that is based on constructed days of supply versus the one based on actual days of supply in the 2010 sub-sample gave a Lin's concordance coefficient of 0.97, indicating substantial agreement. **Figure 3-1** shows how the two PDC distributions were almost identical. (We also observed agreement of similar proportions when we compared binary adherence classifications (at PDC≥80%) based on the two distributions: *C*-statistic 0.97).

Adherence Distribution by Race

Figure 3-2 and **Table 3-2** compare the observed distributions of the average overall PDC by race. Relative to whites, the PDC distribution for black seniors was shifted to the left at central and non-central quantiles, with higher density than whites at the lower quantiles (where adherence is poor). For Hispanics, the disparity relative to whites was not apparent at the center of the distribution, and fluctuated across the quantiles below the median. Adherence among white seniors was predominantly more likely to fall in upper PDC quantiles than either minority group.

Adjusted Adherence Disparity Estimates

In the primary quantile regression analyses, we adjusted the association between race/ethnicity and PDC for health/clinical need, including demographics, health status/medical conditions, and the number of concurrently used medications, as well as

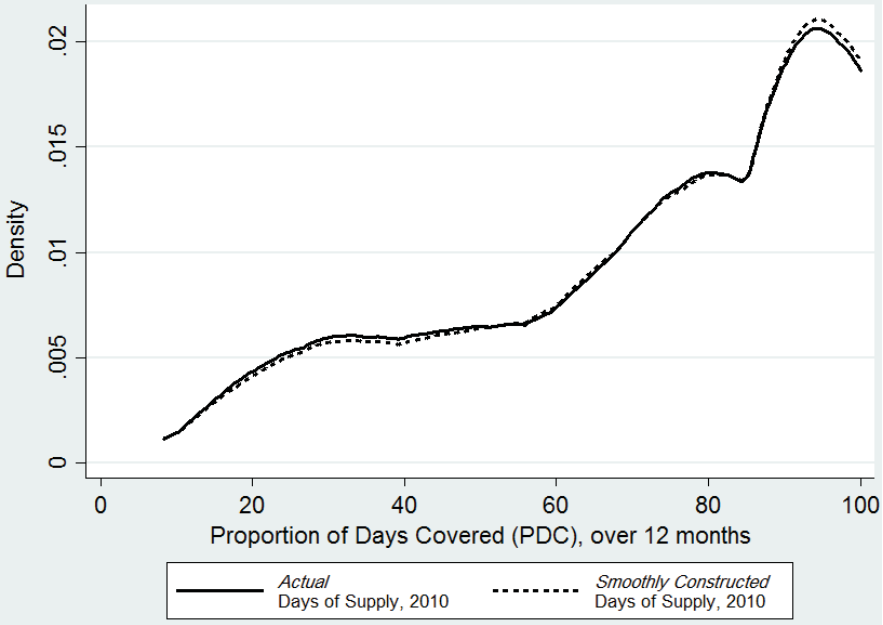

Figure 3-1. Comparing distributions of average overall adherence calculated using actual vs. constructed days of supply in the 2010 sample (n= 556)

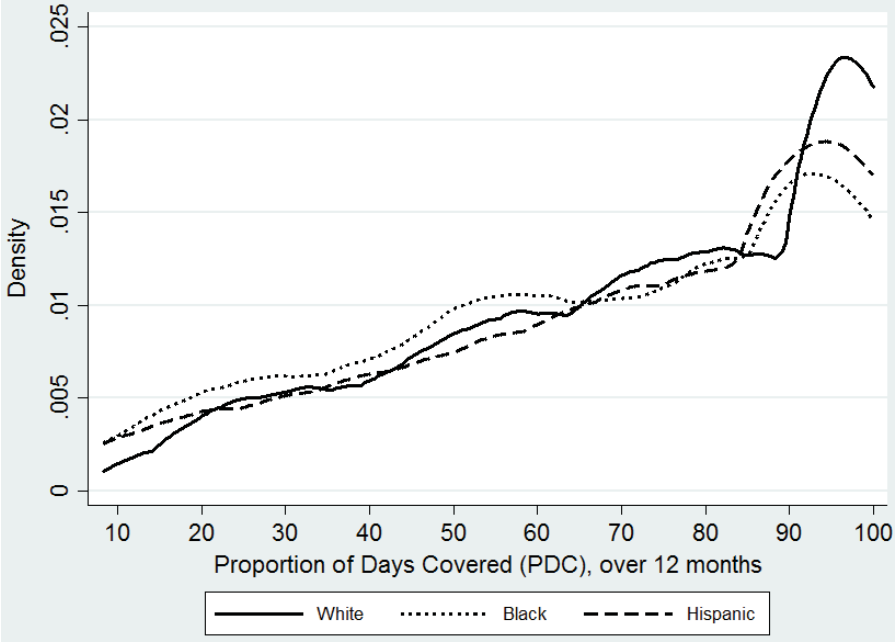

Figure 3-2. Observed distributions of average overall adherence by race

Table 3-2. Quantiles of the distributions of average overall adherence by race

PDC	White	Black	Hispanic	Overall
Mean ±SD	72.78±25.15	68.08±26.84	71.57±27.05	72.27±25.47
Q10	32.97	26.47	28.93	32.88
Q20	49.45	43.27	46.7	49.45
Q30	59.91	53.57	58.54	58.95
Q40	70.05	61.43	68.68	69.41
Q50	77.59	72.73	77.14	77.29
Q60	86.29	81.5	85.66	85.43
Q70	93.2	89.2	94.12	92.83
Q80	99.27	97.47	98.9	99.17

PDC: proportion of days covered; SD: standard deviation; Q: quantile.

beliefs and geographic location. **Appendix Table B-1** lists regression coefficients for all primary unconditional quantile regressions. **Figure 3-3** plots black and Hispanic coefficients from each unconditional quantile regression, graphically illustrating the heterogeneity of disparities across the adherence (PDC) distribution. Black-white disparities were large and statistically significant, starting with a spike of -9.05 PDC percentage points at the 30th percentile (PDC≈60%), and then monotonically decreased to -3.28% points as overall adherence approached its highest levels at the top quantile (PDC=100%). Hispanic-white disparities of -4.07% points and -1.40% points were statistically significant at the 20th and 40th percentiles (PDC≈48% and 74%), respectively.

Similarly to disparities in overall adherence, disparities in adherence to ACE inhibitors/ARBs were large below the 30th percentile, as listed in **Appendix Table B-2**. In contrast, black-white disparities in adherence to statins and diuretics were only notable at the 40th and 50th percentiles (PDC ≈ 73-89% and 58-70%, respectively). Blacks were less adherent to beta-blocker therapy than whites across all percentiles, with largest disparity (-10.39% points) at the 20th percentile. Hispanics were significantly much less adherent to diuretics than whites at every modeled quantile. Both black and Hispanic seniors were in fact much less adherent to diuretics than whites, with disparities as large as -19 and -15% points, respectively, at the 40th percentile (PDC ≈ 73%).

Regardless of how we empirically defined disparity, through various levels of adjustment for covariates, the recurring pattern was consistent with the primary findings above, despite a few changes in the statistical significance of estimates. Sensitivity of findings to various levels of covariate adjustment is illustrated in **Appendix Table B-3** and **Appendix Figure B-1**. Interestingly, full adjustment for all covariates resulted in larger disparity estimates than all other paradigms of adjustment, particularly in the case of black-white disparities.

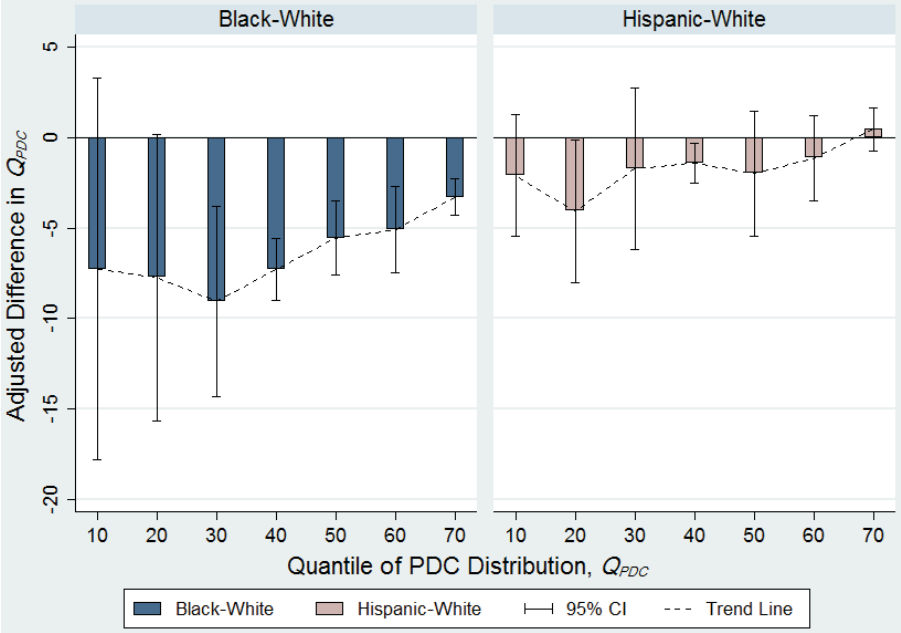

Figure 3-3. Heterogeneity in adjusted racial disparities across the distribution of average overall adherence (entire sample, n=3,749)
Quantiles 10, 20, 30, 40, 50, 60, and 70 correspond to PDC values of 30, 48, 63, 74, 82, 95, and 100%, respectively.

Racial Disparities by Gender and LIS Status

As **Figure 3-4** illustrates, elderly black men had lower adherence levels relative to their white counterparts at all PDC percentiles (i.e. their adherence distribution was significantly left-shifted), with largest disparities manifesting at the lowest percentiles (PDC below 60%). Among women, elderly blacks had significantly lower adherence rates starting at the 30th percentile (PDC≈61%). The disparity then declined as overall adherence approached 100% at the 70th percentile, notwithstanding a large disparity that re-emerged at the 60th percentile (PDC≈94%). Hispanic-white disparities, on the other hand, were not statistically significant across all modeled quantiles among both genders.

Figure 3-5 shows the pattern of disparities across the adherence distribution by LIS status. The lower panel shows the pattern among those who were auto-eligible for the LIS, including dually eligible beneficiaries as well as beneficiaries receiving SSI. The upper panel is for essentially the rest of the sample, who were not eligible for auto-enrollment in the LIS, including those below 150% FPL who might be receiving the LIS but not identifiable in MEPS. Not surprisingly, black-white disparities in the upper panel showed the same pattern observed in the overall sample, although Hispanic-white disparities were not significant across all percentiles. Among the auto-enrolled LIS population, disparities took interesting courses. Black-white disparities started with a peak of -15.7% points at the 10th percentile (PDC<30%) and then declined steadily until

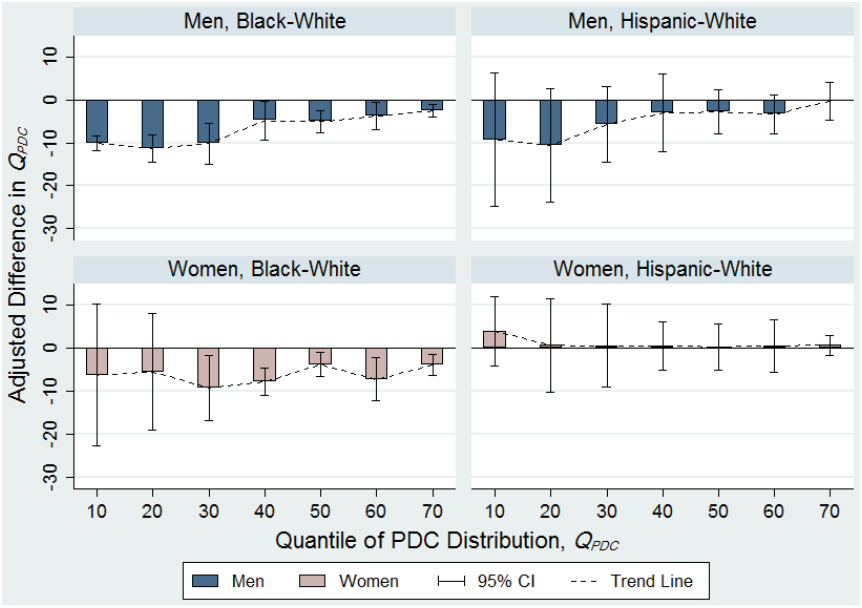

Figure 3-4. Pattern of adjusted racial disparities across the adherence distributions among men (n=1,569) and women (n=2,180)
Quantiles 10, 20, 30, 40, 50, 60, and 70 correspond to PDC values: 28, 49, 60, 72, 81, 95, and 99% among men, and 29, 51, 61, 74, 84, 94, and 100% among women, respectively.

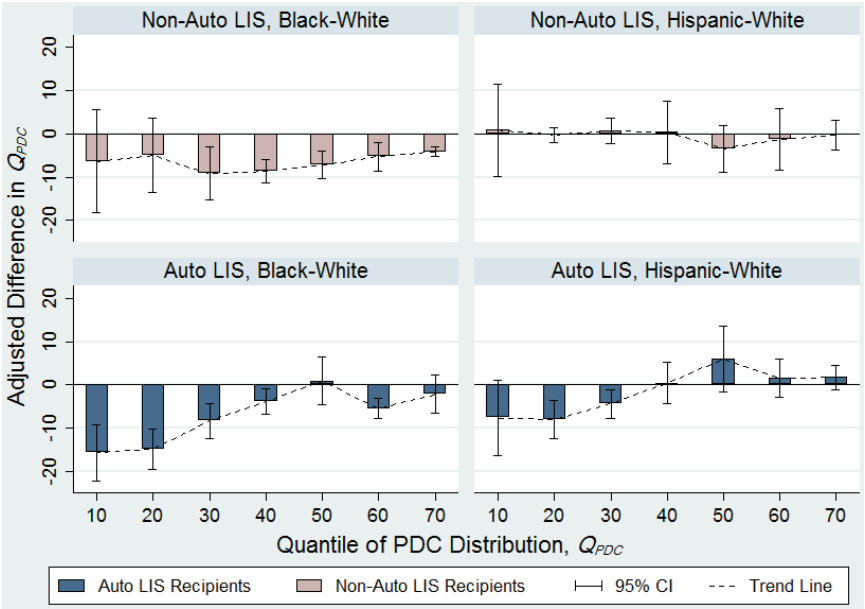

Figure 3-5. Adjusted racial disparities across the adherence distribution among auto-recipients of Part D LIS (n=617) and the rest of the sample (n=3,132)
Quantiles 10, 20, 30, 40, 50, 60, & 70 equal PDC values: 28, 47, 63, 73, 81, 94, & 100%.

the 50th percentile, where they disappeared and then re-emerged at the 60th percentile (PDC>90%). Hispanic-white disparities, though exhibited a similarly interesting trend, they were only significant at the 20th and 30th percentiles.

Discussion

In a nationally representative sample of Medicare seniors with cardiovascular conditions, we used unconditional quantile regression to unravel the heterogeneity of racial disparities across the distribution of average adherence to 5 cardiovascular medication classes. The most salient finding of our analysis was that disparities were generally largest at the lower quantiles of the adherence distribution, around the 20th to the 40th, corresponding to adherence levels of ~ 50 to 73% PDC. Notwithstanding a few exceptions where disparities existed even among those with adherence ~ 90%, generally speaking, as one moved towards the upper percentiles, race appeared to matter less as a determinant of adherence behavior, that is: disparities declined among the populations with increasingly better adherence. Statistically, these findings suggest that the adjusted distribution of adherence behavior among minorities is most left-shifted from whites' distribution at the lower quantiles. These findings align with the two other studies we could identify which studied adherence disparities using quantile regression.[128,129]

Although more research is needed to identify the specific drivers of disparities across the adherence distribution, available literature offer a number of possible explanations for our findings. One interesting observation we found was that although minorities were less likely to have healthcare events associated with depression, they were twice as likely as whites to suffer depressive symptoms (**Table 3-1**). Depression is known to compromise medication adherence and impair individuals' self-efficacy,[140] which is a key psychobehavioral determinant of adherence and a range of other self-management behaviors.[109] Self-efficacy refers to an individual's conviction that s/he can successfully carry out the behavior required to produce a desired outcome.[141] Screening minority patients for depression and promoting their self-confidence provides an invaluable opportunity for providers to proactively address these key culprits in poor adherence.[142,143] Also, the lack of sufficient social support is a relevant barrier. Family members, caregivers, friends, and providers can offer various forms of support, such as easing depression, anxiety, and stress, helping with reminders to take medications, and positively encouraging and reassuring patients of their ability to self-manage their health.[144] Unfortunately, no data on social support was available in MEPS.

A quality patient-provider relationship is crucial for helping patients with poor adherence.[142] Beyond behavioral support, provider communication can address patients' beliefs and concerns about how medications work and their side effects (such as frequent urination and impotence); issues identified to be barriers to adherence among hypertensive blacks.[144] Better communication with providers may particularly help with minorities' especially problematic adherence to diuretics and beta-blockers, as we report in this study. Another potential barrier to adherence peculiar to blacks is their higher likelihood to concurrently use multiple cardiovascular medications (**Table 3-1**). While

understandably this may be due to clinical need, black seniors are less likely to have a written list (record) of their medications and more likely to have medication-related problems, such as suboptimal monitoring.[145] They are also less likely to have adequate health literacy.[145,146] Further, elderly minorities who were not aware of Part D benefits were found to be less adherent to their antihypertensive medications.[147] Medicare Part D Medication Therapy Management (MTM) programs[148] provide an excellent mechanism to address these drivers of poor adherence among minority seniors. Through comprehensive medication reviews, collaboration with patient's providers, and establishing an empowering collaborative relationship with the patients themselves, pharmacists providing MTM can properly educate patients about their medications, address their medication-related problems and concerns, and promote their self-management behavior.[52,53,149] Towards this end, current evidence suggest that minorities' adherence to cardiovascular medications significantly improves when there is race and language concordance between them and their providers, which should be sought whenever possible.[150,151]

The large magnitude of disparities towards the lower end of the adherence distributions suggests that these barriers may be particularly pronounced among poorly adherent minority patients. Two issues need to be addressed, however, before we can effectively eliminate these barriers. First, although one could delineate the characteristics of these populations, identifying them in routine clinical practice is challenging. This is a result of the lack of alignment between the empirical refill-based measures of adherence typically employed in research, and the measures that can be used to assess patient adherence in routine clinical practice.[117,152] Second, although using quantile regression enabled us to get a more comprehensive picture of the adherence distribution, we still lump adherence into a single number without further parsing out the underlying behavioral details. Instead of using the PDC or MPR to summarize patient adherence over (say) a year, a more informative alternative would be to examine the developmental trajectories of adherence over time using group-based trajectory models.[153] This would enable us to capture more details about regimen execution, i.e. patterns of how the prescribed compares to the actual regimen taken, and persistence over time.[18,21] Identifiable patterns such as brief lapse in therapy due to occasional dose omissions, longer drug holiday but then continuation, periodic gaps in therapy, and early discontinuation provide a basis for more meaningful classification of adherence behavior with implications for intervention and for studying disparities. It is worth noting here that some recently developed questionnaire instruments, which can be administered in practice settings, can help identify these distinct patterns as well, and can thus offer a closer insight into real-world settings.[152,154]

Limitations

This study is not without limitations. First, our derivation of refill days of supply from dispensed quantities was based on the 2010 data in our MEPS sample, without validation against an external standard, e.g. Medicare claims data. Given that previous research documented the validity of MEPS prescription drug data against Medicare

claims,[87] we believe benchmarking our analysis solely to MEPS 2010 is sufficient. While data on dispensed quantities were complete for all refills in the study period, a large proportion of 2010 refills had missing days of supply data (about 30%). We found the pattern of missing data to be very consistent across drug class and respondent characteristics, indicating that a missing-completely-at-random (MCAR) assumption is likely plausible. As such, we examined the pattern of refill days of supply vis-à-vis dispensed quantities only among individuals with complete days of supply data for all of their listed refills.

We also assumed that the patterns of days of supply vis-à-vis dispensed quantities in 2010 would hold in earlier years of MEPS. Although we believe this assumption is likely true on average, changes in treatment guidelines, generic availability, and coverage tier classifications of drugs might have affected the prescribed total daily doses of some cardiovascular medications. Since MEPS did not have refill dates, a reasonable choice for the index date was the first day of the MEPS round in which the refill occurred. We might have thus underestimated adherence for respondents who started late in the round, although it is not possible to identify them. If a respondent had too few refills over a round (3-4 months), it might also be the case that they skipped refills and not necessarily they started taking the medication later in the round.

Our approach to estimating disparities might have suffered from omitted variable bias. As we adjusted the association between race and adherence for health-related covariates in concordance with the IOM definition, we assumed that omitted variables, such as income and education, would reflect predominantly in the race coefficients. It is well-known, however, that these and other omitted variables are correlated with health and demographics as well, and as such, race coefficients might not have necessarily captured the entirety of race-related disadvantage as we had hoped. Given the technical complexity of the analyses we undertook, it was more tractable to take this rather simple approach to estimate disparities. Our sensitivity analyses involving various levels of adjustment further confirmed the robustness of our primary findings. Last, although we ensured that sample sizes for all analyses were well above the minimum recommended by AHRQ, (n=100), we believe that small sample sizes may have contributed to the lack of statistical significance in some of our sub-group analyses, especially those involving Hispanics.

Conclusion

Using a nationally representative sample of Medicare seniors with cardiovascular conditions in MEPS, we have found racial disparities to be more pronounced at the lower end of the distribution of cardiovascular medication adherence. Among patient populations with overall better adherence, disparities declined (although retaining their statistical significance in the case of black-white disparities). The higher magnitude of disparities among poorly adherent populations suggests that currently known barriers to adherence, such as depression, low self-efficacy, lack of social support, and knowledge and beliefs about medications, may be worse among minorities in these populations than

among minorities in populations with better adherence. It may also suggest that other peculiar barriers might be at play among these minority patients. Either way, our results indicate that minority patients in poorly adherent populations may be deserving of priority intervention. There is a considerable need to understand the specific barriers that make these patients significantly lagging behind their white counterparts in adhering to their cardiovascular medications.

CHAPTER 4. EXPLAINING THE BLACK-WHITE GAP IN ADHERENCE TO CARDIOVASCULAR MEDICATIONS AMONG MEDICARE SENIORS: A DISTRIBUTION-WIDE APPLICATION OF OAXACA-BLINDER DECOMPOSITION

Background

Poor adherence to cardiovascular medications is a strong risk factor for falling short of drug therapy goals, such as blood pressure and cholesterol levels, with negative consequences for cardiovascular morbidity and mortality, and healthcare costs.[15,73,74,155] Several studies have found adherence levels among racial minorities, particularly black Americans, to be significantly lower than whites, even where equal access to prescription drugs is guaranteed.[11,33] Among elderly recipients of Medicare, the advent of Part D was an important step towards reducing the financial out-of-pocket burden of prescription drugs and improving the quality of medication use, thus eventually reducing the negative consequences of poor adherence.[36,37] Despite the relative success of Part D,[41,45,46,53] black seniors have continued to experience disproportionately lower levels of adherence. Among seniors with uncomplicated hypertension, Holmes and colleagues found blacks to be 47% less likely to be adherent to their antihypertensive medications, including alpha- and beta-blockers, angiotensin-converting enzyme (ACE) inhibitors, angiotensin II receptor blockers (ARBs), Calcium channel blockers (CCBs), diuretics and vasodilators.[28] Zhang et al estimated that blacks with heart failure were 39% less adherent to ACE inhibitors/ARBs and diuretics than whites.[29] In the year following acute myocardial infarction, black seniors were also about 25%-35% less likely to adhere to beta-blocker, ACE inhibitor, or statin therapy.[30,31] In **Chapter 2** of this dissertation, analyses of the Medical Expenditure Panel Survey data on elderly Medicare beneficiaries (2007-2010) have estimated an average black-white disparity of 8 percentage points (~17%) in the probability of adherence (≥80% medication possession) to ACE inhibitors/ARBs, statins, beta-blockers, CCBs, and diuretics. Further, in **Chapter 3**, as other studies have reported,[129] black-white disparities were most prominent towards the lower end of the adherence distribution (around the 30th percentile), namely, among those who were poorly adherent.

Not only does the black-white disparity appear to be the largest among racial disparities in cardiovascular medication adherence, it also appears to be especially consequential. Blacks bear the largest burden of cardiovascular morbidity, leading to 2-3 times higher likelihood of death due to cardiovascular disease at any given age.[3,4] This disparity in cardiovascular death accounts for the largest share (34%) of the black-white all-cause mortality differential in the United States, with the disparity in uncontrolled hypertension making up most of that share (44%).[5] In the CARDIA study, Bibbins-Domingo et al found adult blacks to be 20 times more likely than their white counterparts to develop heart failure before the age of 50, pursuant to a striking disparity in uncontrolled blood pressure that persisted over more than 10 years of follow-up.[6] Based on an analysis of the National Health and Nutrition Examination Survey, Fiscella et al estimated that bringing the blood pressure level among blacks to that among whites could

save more than 7,000 lives annually from death due to heart disease or stroke.[7] Among the social and behavioral factors that might explain the disparities in uncontrolled blood pressure and other risk factors,[8,12-14] the lower level of cardiovascular medication adherence among blacks stands out as a proximal culprit that is amenable for healthcare intervention.[7,8,12,15]

Adherence is shaped by the interplay of multiple patient-, environment-, disease-, regimen-, provider-, and health system-related factors.[77,156] Understanding how each of these factors influences adherence behavior disparately among whites and blacks brings us closer to comprehending adherence disparities. With a more concrete understanding of how these disparities develop, we would become better able to tailor interventions to reduce them. Despite a large literature on adherence behavior among blacks, the specific drivers of adherence disparities are still largely ambiguous. For example, in a review of the recent literature, Ogedegbe and colleagues have noted that self-efficacy, which is an individual's confidence that s/he can accomplish a desired outcome, particularly predicts medication adherence among blacks.[142] Depressive symptoms and younger age, on the other hand, appeared to reduce the likelihood of adherence.[142] Also, better provider communication, especially in race-concordant relationships, was reportedly associated with better adherence.[142,150,151] Other studies have also shown a link between poor adherence and inadequate health literacy.[145,146] The evidence on the degree to which social support and sociodemographic characteristics affected adherence among blacks remains inconclusive.[142] Among the elderly in Medicare, a national survey in 2003 found racial disparities only in cost-related non-adherence, whereas there were no differences in non-adherence due to experience with or beliefs about medications.[81] Another study among the elderly reported disparities in following provider recommendation but not in forgetting to take medications.[85] A systematic, deliberate comparison of how different predictors operate differently among black and white seniors to produce the observed patterns of adherence remains a critical gap in the literature.

In this study, we combined two powerful empirical techniques, Oaxaca-Blinder decomposition with unconditional quantile regression, to quantify the contributions of each predictor to the racial differences in cardiovascular medication adherence in a nationally representative sample of white and black Medicare seniors. As we explain below, these techniques enabled us to provide quantitative, "bottom-line," estimates of how much the differences in the distribution of individual characteristics as well as the differences in how these characteristics influenced adherence among blacks and whites, contributed to the observed racial differences in adherence. To our knowledge, this study is the first application of decomposition analysis in the adherence literature. This study contributes to the literature by identifying which predictors of adherence matter most, from a disparity-reduction point of view, and also among which population sub-groups.

Methods

Data Source

We used longitudinal data from the household component of the Medical Expenditure Panel Survey (MEPS), panels 11 to 14 spanning years 2006 to 2010. MEPS is an annual overlapping panel survey of the US civilian non-institutionalized population, administered by the US Agency for Healthcare Research and Quality (AHRQ).[131] The primary focus of MEPS is on healthcare access, use, and expenditure in the United States, enabling calculation of national impact estimates for a wide variety of health policy changes. Each year MEPS panel participants are sampled from the previous year's respondents to the National Health Interview Survey (NHIS), with oversampling of minorities and other policy-relevant groups (such as adults with functional limitations and low-income households).[131] Each panel is then prospectively followed for two calendar years and their data are collected over five rounds of computer-assisted personal interviewing. Rounds 1 and 2 fall in the first year, rounds 4 and 5 fall in the second year, while round 3 spans the end of the first and the beginning of the second year. AHRQ provides two types of main data files that can be linked to Medical Conditions and event files: longitudinal and annual/cross-sectional (known as Full Year Consolidated Data) files. For this study, we linked the longitudinal panel files to the Medical Conditions and Prescribed Medicines event files. Although all MEPS data are reported by respondents during round interviews, further detailed health service use data, including on prescription drugs, are collected from a sample of providers (e.g. medical and pharmacy) with respondents' permission. Then these data are used to supplement respondents' self-reports of health service use and expenditure. Of particular relevance to this study, the quality of MEPS prescription drug data, as well as Medicare Part D enrollment has been shown to be comparable to that of Medicare claims data.[87,88] MEPS also provides very rich data on respondents' sociodemographics, health and chronic conditions, as well as experience with providers and the healthcare system, allowing a thorough study of adherence as shaped by these determinants.

Cohort Identification

We included MEPS respondents who were:

1) Continuously included in all MEPS survey rounds for the two panel years, excluding those who went "out of scope" because of death, institutionalization, or other reasons.

2) Medicare beneficiaries 65 years or older as of Round 1, who reported receiving Medicare until the end of the second year (Round 5).

3) Non-Hispanic white (henceforth "white") and non-Hispanic black (henceforth "black"). MEPS ascertains race/ethnicity as follows:[132] first, respondent's self-report of their race/ethnicity is the primary way to procure this data. Then, if not available, race/ethnicity is obtained from the originally collected NHIS data in the year prior to joining the MEPS panel. Finally if not available either way, MEPS

assigns race/ethnicity based on respondent's relationship to other members of his/her household starting with blood relatives in the immediate family. MEPS survey questions assessing race/ethnicity have been consistent since 2002.[132]

4) Had at least one of the following six prevalent conditions in both year 1 and year 2: hypertension, hyperlipidemia, angina, congestive heart failure, myocardial infarction, or stroke, listed in the linked Medical Conditions file. Clinical Classification Codes and 3-digit ICD-9 codes in MEPS were used to identify respondents with these conditions.[133] **Appendix Table A-1** (Chapter 2) lists all the conditions and their associated codes. Identified respondents had at least one event (inpatient, outpatient, or prescription drug) associated with one or more of these conditions.
5) Were prevalent users of at least one chronic cardiovascular medication of the following classes: ACE Inhibitors, ARBs, HMG-CoA Reductase Inhibitors (Statins), Beta-blockers, CCBs, Diuretics, or combination products of these medications. Use was defined as having at least one refill for the same medication class in both years. Second-year refills were used to estimate adherence.

Since our study sample only included a small portion of MEPS respondents, we pooled MEPS panels 11-14 by year to create one analytical file with adequate sample size for our analyses. Pooling MEPS data is commonly practiced and survey design variables in MEPS files for our study period specify a common variance structure that takes into account pooling when calculating standard errors.[89] Our final analytical file contained pooled data for year 1 (2006-2009), the baseline year, and year 2 (2007-2010) where adherence was estimated.

Adherence Measurement

Using refill data for sampled respondents in the second year, we measured medication class-specific adherence as the proportion of days covered (PDC) by refills for any medication from that class, expressed as a percentage and capped at 100%. In the case of overlapping refills for two statins, for example, only one refill was counted towards calculation of the statin-specific PDC. ACE inhibitors and ARBs were counted as one class for this purpose. Component medications of combination products were also counted towards their respective classes. As refill dates were not available in MEPS, we determined the follow-up index date specific to each medication class for each respondent as the first day of the round in which the first refill (for the specific class) occurred. These rounds were either the fourth, the fifth, or the portion of the third round that had fallen in the second year. Respondents were then followed until the last day of the fifth round, which corresponded to December 31st of the second year in the panel for all participants. Inpatient days were excluded from the follow-up period. For all classes, while over 50% of respondents had January 1st of the second year (i.e. the part of round 3 that fell in year 2) as the class-specific index date, more than 96% of index refills had occurred by March of the second year. The main outcome variable was an overall continuous PDC summarizing adherence over all medication classes, calculated for each respondent as the average of all his/her class-specific PDCs. Dichotomous adherence

classification based on having a PDC of at least 80% was explored in a secondary analysis.

Although MEPS provided extensive data on prescription refills, including dispensed quantity, strength, dosage form, and therapeutic class/subclass, data on days of supply were not routinely collected until 2010. We used 2010 data, which was the second year of Panel 14 in our sample, to characterize the patterns of observed days' supply as they related to dispensed quantities of drug refills. In so doing, we identified the most frequent number of supply days furnished by each level of dispensed quantity. Next, we derived a scheme to smoothly approximate the distribution of days of supply for use in prior years of MEPS (where actual days of supply data are not available). Then, in 2010 data, we calculated PDCs as explained above using the actual and constructed days of supply distributions. To assess the validity of our derivation, we used Lin's concordance coefficient[90,91] to compare the constructed distribution of days of supply as well as the PDC based on it, to the actual distribution and its associated PDC. We also compared dichotomous adherence based on actual vs. constructed days of supply distributions using C-statistics. Then, we used our validated scheme to construct refill days of supply from dispensed quantities in all panels. The validity of computing refill days of supply in earlier years using the pattern of days of supply vis-à-vis dispensed quantities in 2010 hinges on the potentially plausible assumption (based on discussions with two cardiologists with more than 20 years of practice experience) that the dosing frequency of a given strength of a specific cardiovascular drug has been stable over 2007-2010 in a specific patient population. (For example: for the same patient population, if a 30-pill refill of 40-mg simvastatin covers 30 days in 2010, on average, this would have also been true in 2007).

Covariates

We modeled the PDC distribution for each racial group as a function of a series of baseline covariates assessed over the first year of the MEPS panel. We used data on respondents' demographic characteristics; geographic location; self-reported health and functional (physical/ cognitive) status; depressive symptoms;[134] cardiovascular conditions and other comorbid conditions; beliefs regarding health, risk, and insurance; income and poverty status, and educational attainment; health behaviors; type of primary insurance coverage for prescription drugs; financial and pill burden associated with medications; access to/use of primary care and other health services; and experience with providers and satisfaction with the healthcare system.

In addition to binary indicators of which cardiovascular condition(s) respondents had in the baseline year, we also incorporated other comorbid conditions, such as diabetes, asthma, and cancer, in a modified version of the Charlson comorbidity score (excluding respondent-specific cardiovascular conditions and depression) adapted for use with 3-digit ICD-9 codes in MEPS.[96] For socioeconomic status (SES), we used MEPS-provided categories of income as a percent of the Federal Poverty Line (FPL) and categorized years of education into three levels: less than high school, high school

diploma (12 years), and above high school. High-income and having education beyond high school served as the reference categories.

For identifying respondents' primary type of drug coverage, we used a series of variables on insurance status as well as amounts paid by each payer for prescription drugs over the first year to ascertain drug coverage for each respondent. We identified three principal categories of coverage, as of December 31st of the first year: those who had no evidence of drug coverage by any payer, those who had Medicare Part D, and those who had a private source of drug coverage including employer-sponsored. Among Part D enrollees, we identified those who were concurrently enrolled in Medicare managed care and those who were not. Thus we were able to further split Part D recipients into those who had Medicare Advantage Part D plans (MA-PD) and those who were just enrolled in stand-alone Part D plans (PDPs) with no evidence of enrollment in MA. Further, we created an indicator for whether a Part D respondent was deemed eligible for auto-enrollment for the low-income subsidy (LIS), which included dually eligible beneficiaries and beneficiaries receiving Supplemental Security Income (SSI) (both variables were available in MEPS).[55,57] Other LIS-recipients who are not automatically enrolled but their income is below 150% FPL and have limited assets must apply to receive the LIS.[54] Although we validated the characteristics of these sub-categories of Part D recipients against the literature,[54,56,58,59,103] ascertaining drug plan type or actual receipt of the LIS is not possible in MEPS.

Statistical Analysis

We used Oaxaca-Blinder decomposition (OBD)[157-159] to quantify the contributions of each covariate to the (unadjusted) racial difference in adherence. In contrast to earlier work in this dissertation, where we defined inequitable racial disparities and did *a priori* classification of covariates as to whether they represented sources of disparities or not, this decomposition analysis explores unadjusted racial differences in fitted levels of adherence allowing an empirical evaluation of how each covariate contributes to the adherence difference. OBD has been a popular analytical tool in labor economics, providing insights into the potential drivers of race and gender gaps in wages.[71] In prescription drug research, examples of OBD application include decomposition of the racial difference in prescription drug utilization and spending among Medicare beneficiaries,[160] the racial differences in anti-obesity medication use among US adults,[161] and the sources of regional variation in Medicare Part D drug spending.[162] Also, the study of racial differences in access to primary healthcare is another notable application of OBD in the US health services literature.[163]

Most commonly, OBD starts with estimating a separate regression model for each racial group, which is then used to estimate the outcome level for each individual in the dataset. Next, the difference in average estimated outcomes between the two racial groups is calculated. Finally, this unadjusted difference is broken down into 1) an "explained" component due to the difference in the distribution of individual characteristics, or "endowments" as termed in Blinder's original work,[158] and 2) an

"unexplained" component due to how these characteristics are associated with the outcome (as captured by their model coefficients) differently across racial groups.[71,159,164] This is termed two-fold decomposition. The explained component is interpreted as the expected change in the outcome difference had the two groups had the same overall composition or distribution of characteristics. For example, in decomposing the difference in adherence, the explained component is an estimate of the expected change in the adherence difference had blacks possessed the same demographic, social, health, etc characteristics as whites. The unexplained component is interpreted as the expected change in the outcome difference had the two groups had the same return on the outcome due to their characteristics. Again, the unexplained component of the adherence difference quantifies how much that difference would change had characteristics (e.g. education, insurance, depression) worked the same way to determine adherence among blacks and whites. Assuming no relevant covariates were left out of the model, the unexplained component is traditionally interpreted as indicating discrimination in the environment where covariates determine outcome levels (for instance, the healthcare or broader social environment where the same insurance plan works better for whites than blacks resulting in improved adherence for whites but not for blacks). A three-fold decomposition can also be formulated, in which a third component that captures the simultaneous effects of endowments and returns is calculated.[159]

Breaking down outcome differences into just the aggregate explained and unexplained components is known as aggregate decomposition. For estimation of these aggregate components, we have to invoke a conditional independence assumption, where no relevant covariates were omitted/unobserved, or at least an ignorability assumption, where unobservable characteristics correlated with controlled covariates in the same way across the two groups compared. By further assuming that the aggregate components are composed of additively separable linear functions, they can be further decomposed into the contributions of each individual covariate. This further breakdown is known as detailed decomposition.[71]

As the counterfactual language for interpreting decomposition components above entails, one must decide which group would serve as the viewpoint group for the analysis.[159,164] Three potential alternatives exist: the lower-outcome group, the higher-outcome group, or the pooled average of the two groups. For example, decomposing the racial difference from the viewpoint of whites confers the following interpretation on the explained component: how much would adherence level of whites change were they to have the characteristics of blacks? Alternatively, a black-viewpoint analysis would make the explained component interpretable as the expected change in black's adherence level were they to have the same characteristics as whites. Choosing the pooled average would mean that group-specific outcome estimates would come from a pooled regression model instead of a separate group-specific model as described earlier. Results of the decomposition analysis accordingly depend on which group is chosen, in what is termed as an "index number problem."[165]

OBD analyses have originally been based in the linear ordinary least squares (OLS) regression framework, for both continuous and binary outcomes (using a linear

probability model in this latter case). More generalized nonlinear extensions have been developed over the years, including for example decompositions based on logit, probit, and count regressions, such as Poisson and negative binomial.[166-168] Nonlinear decompositions work better when the racial difference is located in the tails of the distribution or when there are large differences between the covariates that the linear model's prediction would fall outside a meaningful range (e.g. predicting probabilities >1). In all these cases, decomposition of mean differences is carried out. Although studying differences in mean outcomes is informative, policy-relevant differences might exist elsewhere in the distribution but might be undetectable in the mean. In the case of the racial differences in adherence, our analyses as well as other studies in the literature[128,129] have demonstrated the existence of large, significant disparities in the lower percentiles of the adherence distribution. Conducting OBD across the adherence distribution, by estimating race-stratified quantile regressions, can reveal the potential heterogeneity in covariate contributions to the racial adherence gap.

Recently, OBD has been extended to quantile regression. Quantile regression is analogous to OLS, except that conditional outcome quantiles as opposed to the conditional mean are modeled, thus revealing how the outcome depends variably on the covariates at different locations of the distribution. Quantile regression does not run on a subset of the sample, but rather differentially weights the observations in the sample above and below the modeled quantile. For example, the 70th quantile regression can be thought of as a plane that passes through the sample, weighing observations above it by 0.70 and observations below it by 0.30.[126] Coefficient estimates are then estimated by minimizing weighted absolute deviations (as opposed to least squares in OLS). [118,120] Typical quantile regression modeling involves estimating covariate effects on conditional outcome quantiles. The conditional outcome distribution is expectedly different from the unconditional distribution, with the latter being integrated over all covariates.[130] As noted above, OBD breaks down the difference in estimated, unconditional outcome levels across groups. OBD is not possible in the context of conditional quantile regression,[71] except with computationally intensive calculations to generate the unconditional outcome quantiles.[169] Firpo, Fortin, and Lemieux[70] have developed a simple approach to estimating unconditional quantile regression, by first estimating a quantity known as the re-centered influence function (RIF) for the desired outcome quantile and then regressing it on the covariates in an OLS regression. This serves to readily generate the corresponding unconditional outcome quantile, which is then used to generate detailed OBD estimates as described above.[71] While we found no application of RIF-unconditional quantile regression-based OBD in the health services literature, recent applications involved studying rural-urban inequality in education in Senegal,[170] and racial inequality in wages and occupation in the United States and Brazil.[171,172]

In this study, we used RIF-unconditional quantile regression, as implemented in STATA® by Fortin[137], together with the OBD routine `-oaxaca-` developed by Jann,[159] to perform OBD on racial differences in adherence across the distribution of continuous PDC, namely 10th, 20th, to the 80th percentile, as a function of the full set of covariates described above. As **Equation 4-1** shows, RIF-based OBD starts with estimating the τ^{th} unconditional PDC quantile from race-stratified $Q\tau^{th}$ RIF-OLS models:

$\widehat{Q_B^\tau}=\overline{X_B^\tau}\,.\,\widehat{\beta_B^\tau}$, for blacks

and

$\widehat{Q_W^\tau}=\overline{X_W^\tau}\,.\,\widehat{\beta_W^\tau}$, for whites

and the racial difference in the τ^{th} PDC quantile, $\widehat{\Delta}_{Q_{PDC}^\tau}$, would be

$$\widehat{\Delta}_{Q_{PDC}^\tau}=\widehat{Q_B^\tau}-\widehat{Q_W^\tau}=\overline{X_B^\tau}\,.\,\widehat{\beta_B^\tau}-\overline{X_W^\tau}\,.\,\widehat{\beta_W^\tau}$$

which can be decomposed, in a two-fold black-viewpoint analysis, into:

$$\widehat{\Delta}_{Q_{PDC}^\tau}=\widehat{Q_B}\tau-\widehat{Q_W}\tau=\underbrace{\left(\overline{X_B^\tau}-\overline{X_W^\tau}\right).\widehat{\beta_B^\tau}}_{\substack{\textit{Difference in}\\ \textit{Composition}}}+\underbrace{\left(\widehat{\beta_B^\tau}-\widehat{\beta_W^\tau}\right).\overline{X_W^\tau}}_{\substack{\textit{Difference in}\\ \textit{Returns to Composition}}}\quad \textbf{(Eq. 4-1)}$$

For sensitivity analysis, we conducted a two-fold decomposition using $\widehat{\beta^\tau}$ from pooled RIF-unconditional quantile regressions. For comparability with the literature, we also estimated OBD of differences in mean PDC in OLS as well as differences in the average probability of 80% adherence in logit and linear probability models. All analyses accounted for MEPS complex design by using survey design variables. Standard errors were estimated by balanced repeated replications[173] using MEPS provided weights and half-sample indicators.[174] Since rates of missing data in some covariates (e.g. beliefs and experience with providers) were as high as 13%, we used multiple imputation using chained equations (MICE) to impute missing data for each of these variables.[100] Regression analyses were estimated separately in each imputation dataset and then point estimates and standard errors were combined using Rubin's rules[138] to produce a single set of estimates that took into account uncertainty due to imputation. Estimates with alpha less than 5% were considered statistically significant. All analyses were carried out in STATA® 13 (StataCorp; College Station, TX).

Results

The study sample included 3,288 MEPS respondents, nationally representative of about 19 million white and black Medicare seniors with cardiovascular disease. Each respondent was followed for an average period of 342 days. **Table 4-1** lists overall sample characteristics and **Appendix Tables C-1** and **C-2** list respondent characteristics across PDC quantile categories (10^{th} to 80^{th} percentiles). Overall, black seniors were more likely to be female, less likely to be married, and less likely to live in the Midwest or the West, while more likely to live in the South. Blacks were also less likely to rate their health status as "excellent" or "very good", while more likely to rate it as "fair" or "poor." The prevalence rates of cognitive limitations and depressive symptoms, as measured by the Patient Health Questionnaire (PHQ)-2,[134] were higher among blacks

Table 4-1. Overall characteristics of sampled Medicare seniors, by race

Characteristics	White	Black	Overall
	%, unless otherwise noted		
Demographics			
Female	56.69	**63.41**	57.34
Married	56.08	**31.31**	53.66
Urban/MSA	79.34	84.06	79.80
Census Region			
Northeast	21.24	18.22	20.95
Midwest	25.70	**15.41**	24.69
South	34.48	**59.88**	36.97
West	18.57	**6.49**	17.39
Self-Reported Health Status			
Excellent	13.40	**7.65**	12.84
Very Good	31.32	**23.72**	30.58
Good	33.61	35.31	33.78
Fair	16.58	**25.64**	17.46
Poor	5.09	**7.68**	5.34
Any Physical Limitation*	62.29	63.48	62.41
Any Cognitive Limitation*	9.78	**18.24**	10.61
Depressive Symptoms	7.41	**14.69**	8.13
Cardiovascular Conditions & Comorbidity			
Hypertension	82.57	**93.65**	83.65
Lipidemia	66.24	**56.95**	65.33
Angina/CHD	21.79	**17.38**	21.35
CHF	4.02	3.54	3.98
AMI	8.89	7.21	8.72
Stroke	6.00	6.14	6.02
Count of Comorbid Conditions,† Mean ±SD	5.61 ±3.53	**4.57 ±3.13**	5.51±3.51
Charlson Comorbidity Score† Q1-2	56.35	**46.43**	55.38
Charlson Comorbidity Score† Q3	31.53	**39.52**	32.31
Charlson Comorbidity Score† Q4	12.12	14.05	12.31
Beliefs			
More Likely to Take Risk	16.45	14.13	16.22
Can Overcome Illness without Medical Care	11.31	**7.05**	10.89
No Need for Health Insurance	4.45	5.01	4.51

Table 4-1. (Continued)

Characteristics	White	Black	Overall
	%, unless otherwise noted		
Behaviors			
Current Smoker	8.30	10.91	8.56
Moderate / Vigorous Exercise	47.43	**37.43**	46.45
Obese (BMI≥30)	28.53	**36.67**	29.32
Socioeconomic Status			
Income:‡ Poor/Near Poor	15.38	**32.56**	17.06
Low-Income	15.95	**20.71**	16.42
Mid-Income	31.44	31.15	31.41
High-Income (Ref)	37.23	**15.58**	35.11
Education: Less than High School	19.73	**47.42**	22.43
High School Diploma	52.97	**39.00**	51.60
Above High School (Ref)	27.30	**13.59**	25.96
Primary Drug Coverage at Baseline			
No Known Rx Coverage (Ref)	19.85	**12.99**	19.18
Part D: PDPs	35.96	**43.66**	36.71
Part D: MA-PD	23.00	**30.37**	23.72
Employer/Other Private	21.19	**12.97**	20.39
Auto Eligible for PD Low-Income Subsidy	5.72	**25.92**	7.70
Use of CV Drugs in Year 2			
ACEI/ARBs	58.17	59.68	58.31
Statins	60.11	**49.56**	59.08
Beta-Blockers	41.67	37.08	41.22
CCBs	19.72	**36.54**	21.36
Diuretics	43.85	**54.65**	44.90
Healthcare Use at Baseline			
No. of Concurrent CV Medications §			
0-1	34.95	32.53	34.72
2-3	56.26	55.27	56.17
≥4	8.78	**12.21**	9.12
No. of concurrent medications overall			
0-1	9.96	**14.13**	10.37
2-4	44.51	44.51	44.51
≥5	45.53	41.37	45.12
No. of Pharmacies Used	1.33 ±0.54	**1.17 ±0.44**	1.31±0.53

Table 4-1. (Continued)

Characteristics	White	Black	Overall
	%, unless otherwise noted		
Average Copay for CV Drugs ($2010)	25.21 ±31.34	**17.30 ±24.8**	24.44±30.85
Had a Usual Source of Care	97.43	**95.58**	97.25
Had any Inpatient Stay?	17.23	17.88	17.29
Had any ER visit?	17.33	**21.06**	17.70
Quintiles of ambulatory physician visits (range)			
Q 1 (0-2)	17.99	**28.83**	19.05
Q 2 (3-4)	18.12	21.21	18.43
Q 3 (5-7)	20.47	21.75	20.59
Q 4 (8-12)	22.18	**13.14**	21.30
Q 5 (≥13)	21.23	**15.08**	20.63
Experience with the Healthcare System			
Very Satisfied with Health Care	58.67	53.87	58.20
Provider Always Explained	56.79	58.28	56.94
Provider Always Listened	61.24	62.36	61.35
Provider Always Respected	63.11	64.49	63.25
Sample Size	2,585	703	3,288
Weighted Population	17,447,543	1,891,319	19,338,862

Boldface estimates have P<0.05 for pairwise comparisons relative to whites.
Refer to Appendix **Tables C-1** and **C-2** for characteristics by race across PDC quantiles 10^{th}-80^{th}.
* Physical limitations included functional or sensory limitations, or limitation in the Instrumental Activities of Daily Living or in the Activities of Daily Living. Cognitive limitations included confusion, dementia, problems making decisions, or needing supervision for own safety.
† Excluded respondent-specific cardiovascular conditions.
‡ Poor/Near-Poor: <125% Federal Poverty Line (FPL); Low-Income: ≥125 to <200 %FPL; Middle-Income ≥200 to <400% FPL; High Income (reference): ≥400% FPL.
§ Same-pill combination products were counted as one drug
MSA: Metropolitan Statistical Area; CHD: Coronary Heart Disease; CHF: Congestive Heart Failure; AMI: Acute Myocardial Infarction; SD: Standard Deviation; Q: Quantile; BMI: Body Mass Index; PD: Part D; PDP: stand-alone prescription drug plan; MA-PD: Medicare Advantage Prescription Drug plan; ACE: Angiotensin-Converting Enzyme; ARB: Angiotensin II Receptor Blocker

than whites. While hypertension was more prevalent among black seniors, hyperlipidemia was more prevalent among whites. Although blacks had less comorbid conditions in addition to cardiovascular disease, they were more likely to have higher severity of illness, as measured by the Charlson comorbidity score.[96] Blacks were also less likely to believe they could overcome illness without medical care. They were also less likely to exercise and more likely to be obese.

Black seniors were highly represented in lower SES categories, such as being poor/low-income or having no high-school diploma. While blacks were less likely to go without drug coverage, including greater enrollment in Part D MA-PD and PDP plans as well as being auto-enrolled in the LIS, they were less likely than whites to have employer-sponsored or private coverage. Blacks were less likely to use statins, while more likely to use CCBs or diuretics. Blacks were also more likely to concurrently use 4 or more cardiovascular medications, albeit using a smaller number of medications overall. Blacks had smaller copays for their cardiovascular medications. While whites were more likely to have a usual source of care, blacks were more likely to use the emergency department and much less likely to frequent ambulatory care. No significant differences were observed in rating of providers or satisfaction with care. With a few exceptions, such as blacks at the 30th PDC percentile being more likely to have a usual source of care or being substantially more likely to smoke at the 40th percentile, the patterns of association of characteristics with race seemed to hold across PDC quantile categories.

Adherence Validation

In the 2010 sub-sample where refill days of supply data were available, we studied days of supply vis-à-vis dispensed quantities so as to build a scheme to derive days of supply from dispensed quantities in earlier panels of MEPS (where days of supply data were not available). Based on identifying the most frequent number of supply days furnished by each level of dispensed quantity, we found the following scheme to perform best in constructing days of supply from dispensed quantities, (quantity vs days of supply): [8: 16; 15-16: 30; 45: 90; 46-75: 30; 76-119: 90; 120: 30; ≥120: 90; all other quantities: identical days of supply]. This scheme also worked equally well across medication classes. Comparing the PDC distribution that is based on constructed days of supply versus the one based on actual days of supply in the 2010 sub-sample gave a Lin's concordance coefficient of 0.98, indicating substantial agreement. **Figure 4-1** shows how the two PDC distributions were virtually identical. We also observed similarly substantial agreement between dichotomous adherence classifications (at PDC≥80%) based on the two distributions: *C*-statistic 0.98).

Racial Differences in Adherence

Estimated RIFs of PDC quantiles were used in OBD to calculate the racial difference across the PDC distribution. **Appendix Tables C-3** and **C-4** list coefficients

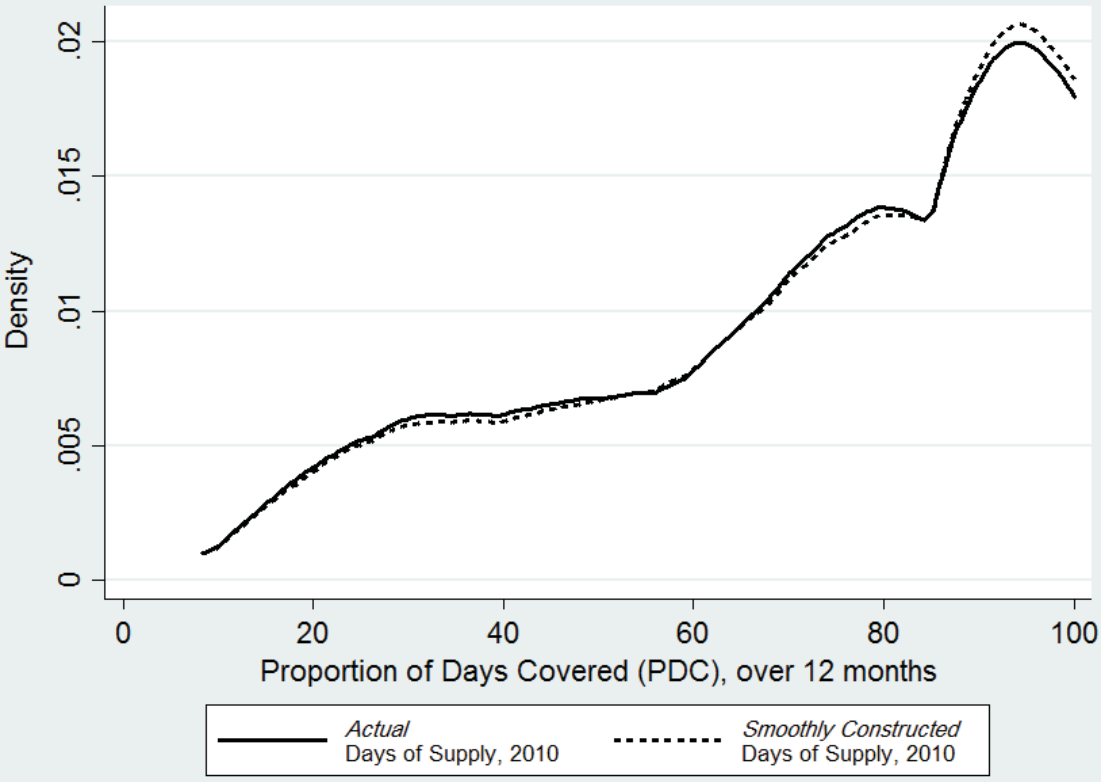

Figure 4-1. Comparing distributions of average overall adherence calculated using actual vs. constructed days of supply in the 2010 sample (n= 485)

estimated in each of the RIF unconditional quantile regressions used in OBD. **Figure 4-2** shows both the observed and fitted (unadjusted) differences in PDC across the distribution. Racial differences were largest below the median, spiking at the 40th percentile to about 9 percentage points, and then declining as one moves up the PDC distribution.

Decomposition of the Racial Differences in Adherence

Tables 4-2 and **4-3** list the results of OBD of the racial difference across the unconditional 10th-40th and 50th-80th of the PDC distribution, respectively. Black-white differences were significant at all percentiles, except at the 50th and 80th percentile, and as shown in Figure 3-2, they spiked at the 40th percentile to 9 percentage points. Except at the 40th percentile, the aggregate contributions of the racial differences in composition and the returns of compositional characteristics on adherence were not significant. Among seniors at the 40th percentile of the PC distribution (PDC ~ 69%), if the way covariates predicted adherence among blacks were identical to how they worked among whites, the black-white PDC difference would have been reduced by about 12 percentage points (~130%).

Demographics. The differences in neither the distribution of age, gender, urban residence, or geographic location were associated with the racial difference in adherence. Similarly for marital status, except at the 30th percentile. Had marriage been associated with adherence the same way among blacks and whites, the racial difference in adherence at the 30th percentile would have increased by 7.5 percentage points (~ 96%). In **Appendix Table C-2**, being married was significantly associated with a large improvement in adherence among blacks but not among whites.

Health. Two health-related factors appeared to matter for the racial difference in adherence: hyperlipidemia and activity limitation. As in **Table 4-2**, holding everything else constant, had the prevalence of hyperlipidemia been equal among whites and blacks at the 10th percentile of the PDC distribution, the racial difference in adherence would have increased by 0.93 percentage points (~15%). On the other hand, had the effect of having hyperlipidemia among blacks been similar to that among whites, the racial difference in adherence would have dropped by 9.7 percentage points (~150%). In **Appendix Table C-2**, we have underlined the coefficients of hyperlipidemia in the black and white RIF-Q10 models. Evidently, being black and hyperlipidemic reduced (i.e. left-shifted) the 10th PDC quantile significantly by about 13 percentage points, an effect that was much larger and opposite in direction to its counterpart among whites.

Another notable health-related factor was having activity limitation (**Table 4-3**). Among seniors at the 50th percentile of the PDC distribution (PDC ~77%), had physical limitation among blacks been associated with the adherence the same way as among whites, the racial difference in adherence would have increased by 7.32 percentage points

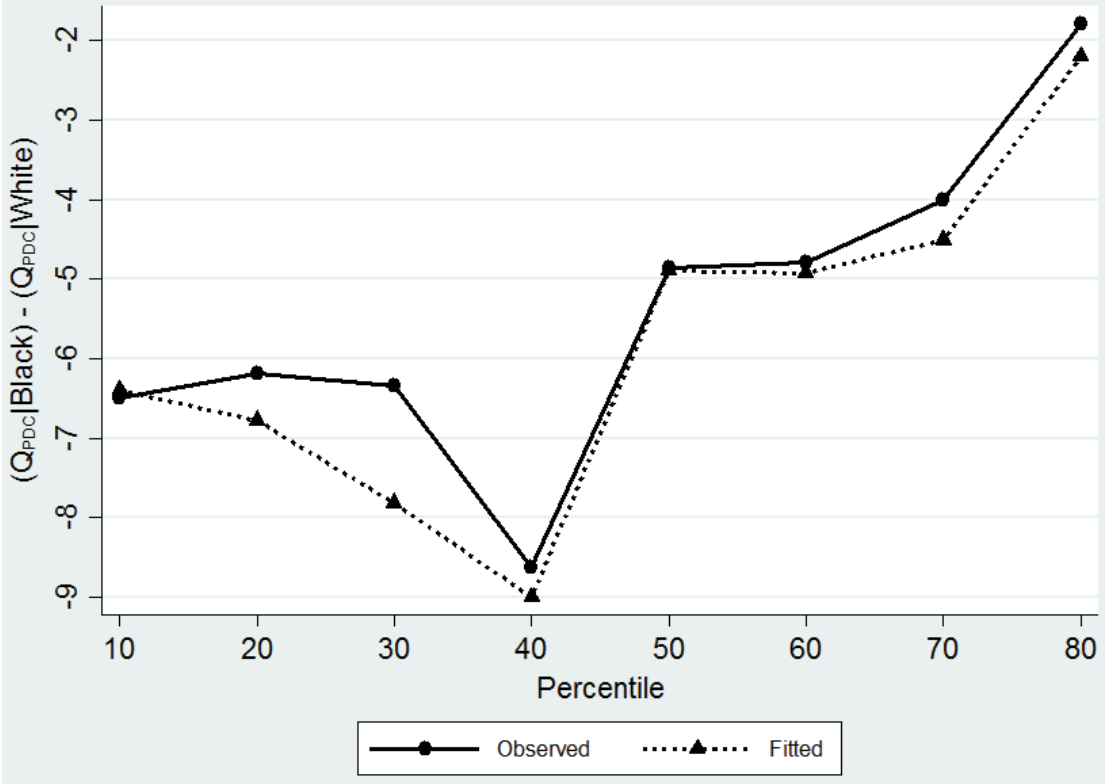

Figure 4-2. Comparing observed and fitted black-white differences across quantiles of the proportion of days covered (PDC)
Fitted values were estimated using race-stratified RIF-unconditional quantile regressions. See Panel-A of **Table 4-2 and 4-3** for point estimates and standard errors of the fitted values.

Table 4-2. Oaxaca-Blinder decomposition of black-white differences in adherence across PDC quantiles, 10th-40th, from the viewpoint of black seniors

Outcome	Q_{PDC} 10th		Q_{PDC} 20th		Q_{PDC} 30th		Q_{PDC} 40th	
	Estimate (Standard Error)							
***Panel A*: Fitted Adherence Levels and Differences**								
Q_{PDC}, Blacks	**27.10 (2.72)**		**42.99 (2.71)**		**52.69 (2.29)**		**61.59 (2.51)**	
Q_{PDC}, Whites	**33.50 (1.26)**		**49.77 (1.16)**		**60.51 (1.30)**		**70.60 (1.10)**	
Difference	**-6.40 (3.14)**		**-6.78 (3.05)**		**-7.82 (2.76)**		**-9.00 (2.84)**	
***Panel B*: Portion of Adherence Difference Due to:**								
Characteristics	Difference in Characteristics	Difference in *Returns* to Characteristics	Difference in Characteristics	Difference in *Returns* to Characteristics	Difference in Characteristics	Difference in *Returns* to Characteristics	Difference in Characteristics	Difference in *Returns* to Characteristics
Aggregate Contribution	-1.40 (5.34)	-5.00 (6.04)	-1.74 (4.71)	-5.04 (5.33)	1.59 (3.83)	-9.41 (4.83)	2.94 (4.43)	**-11.95 (5.42)**
Age 70-75	-0.71 (0.46)	-1.91 (1.82)	-0.06 (0.42)	1.07 (1.72)	0.11 (0.42)	1.38 (1.64)	0.02 (0.39)	0.61 (1.60)
Age 75-80	0.21 (0.31)	-1.50 (1.93)	0.05 (0.17)	0.52 (1.52)	-0.01 (0.17)	0.66 (1.43)	-0.01 (0.17)	0.56 (1.45)
Age ≥ 80	0.51 (0.56)	-0.42 (2.71)	0.17 (0.51)	0.93 (2.64)	-0.21 (0.44)	2.68 (2.25)	-0.20 (0.49)	2.43 (2.47)
Female	-0.07 (0.54)	0.38 (4.22)	0.53 (0.52)	4.90 (4.02)	0.19 (0.41)	2.93 (3.29)	-0.26 (0.45)	-0.50 (3.44)
Married	0.61 (2.07)	-0.36 (4.68)	-0.79 (1.83)	4.25 (4.20)	-1.87 (1.58)	**7.50 (3.80)**	-0.96 (1.71)	3.95 (3.90)
Urban Residence	0.23 (0.42)	3.90 (6.30)	-0.14 (0.40)	-2.73 (6.42)	-0.17 (0.40)	-2.40 (5.70)	-0.05 (0.45)	0.67 (6.71)
Census Region: Midwest	-0.62 (0.85)	1.10 (2.23)	-1.50 (0.87)	2.96 (2.20)	-0.20 (0.83)	-1.08 (2.31)	-0.83 (0.93)	1.75 (2.47)
South	0.99 (1.86)	3.55 (3.08)	1.87 (1.88)	3.34 (2.76)	0.19 (1.52)	0.67 (2.56)	0.86 (1.91)	2.47 (3.03)
West	1.90 (2.31)	-1.96 (3.79)	0.86 (1.81)	-1.49 (2.89)	0.67 (1.36)	-1.44 (2.29)	0.68 (1.52)	-1.18 (2.50)
Health Status: Very Good	0.02 (1.05)	-2.32 (4.32)	-0.15 (0.97)	-1.23 (3.98)	-0.38 (0.78)	0.24 (3.48)	0.07 (0.93)	-2.12 (4.01)
Good	0.01 (0.36)	-1.61 (4.52)	0.02 (0.32)	-1.85 (4.08)	-0.01 (0.26)	-1.91 (3.38)	-0.03 (0.33)	-2.94 (4.17)
Fair	-0.09 (1.50)	-2.37 (2.66)	0.73 (1.31)	-0.71 (2.27)	0.92 (1.03)	0.50 (2.01)	0.35 (1.20)	-0.63 (2.30)

Table 4-2. (Continued)

Characteristics	Q_{PDC} 10th		Q_{PDC} 20th		Q_{PDC} 30th		Q_{PDC} 40th	
	Estimate (Standard Error)							
	Difference in Characteristics	Difference in *Returns* to Characteristics	Difference in Characteristics	Difference in *Returns* to Characteristics	Difference in Characteristics	Difference in *Returns* to Characteristics	Difference in Characteristics	Difference in *Returns* to Characteristics
Poor	0.02 (0.51)	-0.24 (0.85)	0.34 (0.47)	0.38 (0.81)	0.29 (0.39)	0.54 (0.73)	0.23 (0.49)	0.56 (0.85)
Any Physical Limitation	0.07 (0.23)	2.00 (4.37)	0.03 (0.19)	3.20 (4.20)	-0.08 (0.20)	-0.34 (3.94)	0.08 (0.21)	3.94 (3.97)
Any Cognitive Limitation	-0.88 (0.68)	-0.45 (0.83)	0.05 (0.64)	0.49 (0.86)	0.55 (0.59)	1.05 (0.84)	0.59 (0.62)	0.88 (0.76)
Depressive Symptoms	-0.81 (0.78)	-0.27 (0.83)	-1.25 (0.73)	-0.89 (0.70)	-0.62 (0.62)	-0.38 (0.66)	-0.44 (0.60)	-0.13 (0.64)
Hypertension	-0.76 (1.29)	-9.90 (10.24)	-0.59 (1.35)	-7.54 (10.27)	0.87 (1.09)	1.78 (9.13)	0.69 (1.07)	1.30 (8.76)
Hyperlipidemia	**0.93 (0.47)**	**-9.70 (3.82)**	0.30 (0.42)	-3.59 (4.15)	-0.06 (0.34)	-0.54 (3.79)	-0.41 (0.40)	3.00 (4.02)
Angina/CHD	-0.24 (0.31)	1.64 (1.58)	-0.32 (0.36)	1.93 (1.75)	-0.20 (0.27)	0.51 (1.52)	-0.19 (0.26)	0.67 (1.46)
CHF	0.00 (0.10)	-0.16 (0.50)	0.03 (0.13)	-0.51 (0.54)	-0.00 (0.08)	0.06 (0.45)	-0.02 (0.10)	0.28 (0.49)
AMI	-0.03 (0.31)	-0.26 (1.09)	0.22 (0.33)	-1.22 (1.13)	0.20 (0.27)	-1.00 (0.90)	0.12 (0.28)	-0.80 (0.97)
Stroke	0.03 (0.18)	0.55 (0.69)	0.02 (0.16)	0.60 (0.71)	0.01 (0.12)	0.42 (0.56)	-0.00 (0.15)	0.16 (0.75)
Count of Comorbid Conditions	-1.61 (1.11)	8.72 (6.71)	-1.05 (1.00)	5.26 (6.29)	-0.30 (0.87)	3.43 (5.37)	-0.14 (0.96)	1.79 (5.75)
Charlson Comorbidity Score Q3	0.14 (0.55)	1.19 (2.34)	0.41 (0.55)	2.33 (2.06)	0.59 (0.45)	2.36 (1.89)	0.57 (0.50)	2.24 (1.79)
Charlson Comorbidity Score Q4	-0.00 (0.24)	0.37 (1.38)	0.10 (0.27)	0.95 (1.34)	0.19 (0.26)	1.13 (1.22)	0.24 (0.28)	1.59 (1.28)

Table 4-2. (Continued)

Characteristics	Q_{PDC} 10th		Q_{PDC} 20th		Q_{PDC} 30th		Q_{PDC} 40th	
	Estimate (Standard Error)							
	Difference in Characteristics	Difference in *Returns* to Characteristics	Difference in Characteristics	Difference in *Returns* to Characteristics	Difference in Characteristics	Difference in *Returns* to Characteristics	Difference in Characteristics	Difference in *Returns* to Characteristics
More Likely to Take Risks	-0.09 (0.19)	0.44 (1.27)	-0.17 (0.24)	1.59 (1.15)	0.03 (0.17)	-0.17 (1.23)	0.14 (0.21)	-0.77 (1.46)
Can overcome illness without medical care	0.09 (0.68)	-0.27 (1.45)	0.17 (0.65)	-0.67 (1.41)	0.63 (0.62)	-1.42 (1.28)	0.58 (0.68)	-1.25 (1.37)
Does not need health insurance	-0.07 (0.19)	0.04 (0.61)	-0.08 (0.17)	0.01 (0.67)	0.01 (0.14)	0.44 (0.62)	0.06 (0.17)	0.90 (0.67)
Current Smoker	0.17 (0.23)	0.67 (0.59)	0.02 (0.29)	0.37 (0.69)	-0.03 (0.21)	0.22 (0.60)	0.06 (0.24)	0.13 (0.64)
Had Moderate / Vigorous Exercise	-0.05 (0.60)	0.73 (3.31)	0.42 (0.64)	-0.34 (3.10)	0.14 (0.55)	1.48 (2.77)	0.12 (0.58)	0.90 (3.08)
Obese (BMI≥30)	**1.36 (0.66)**	**4.56 (1.98)**	1.09 (0.56)	3.03 (1.77)	**1.17 (0.53)**	**3.52 (1.66)**	0.85 (0.58)	2.19 (1.81)
Income: Poor/Near-Poor	-0.95 (1.48)	-0.58 (1.49)	-2.33 (1.60)	-2.04 (1.44)	-0.39 (1.29)	-0.46 (1.26)	-1.17 (1.52)	-1.32 (1.44)
Low-Income	-0.28 (0.41)	-0.81 (1.33)	-0.63 (0.47)	-2.56 (1.46)	-0.26 (0.40)	-0.71 (1.26)	-0.57 (0.54)	-1.95 (1.53)
Middle-Income	0.01 (0.22)	-2.62 (3.03)	0.01 (0.28)	-3.87 (3.19)	0.01 (0.20)	-1.74 (2.63)	0.01 (0.31)	-2.85 (3.26)
Education: Less than High School	-2.06 (1.70)	-1.03 (1.31)	1.01 (2.10)	1.14 (1.63)	0.17 (2.00)	0.17 (1.61)	0.51 (2.06)	0.01 (1.55)
High School Diploma	**1.93 (0.92)**	-7.28 (4.01)	0.12 (1.04)	1.74 (4.55)	0.37 (1.09)	-0.53 (4.86)	0.28 (1.17)	-1.48 (5.04)

Table 4-2. (Continued)

Characteristics	Q_{PDC} 10th		Q_{PDC} 20th		Q_{PDC} 30th		Q_{PDC} 40th	
	Estimate (Standard Error)							
	Difference in Characteristics	Difference in *Returns* to Characteristics	Difference in Characteristics	Difference in *Returns* to Characteristics	Difference in Characteristics	Difference in *Returns* to Characteristics	Difference in Characteristics	Difference in *Returns* to Characteristics
Drug Coverage Plan: Part D: PDPs	2.38 (1.38)	8.78 (4.55)	1.38 (1.16)	4.51 (4.17)	0.75 (0.88)	2.22 (3.28)	1.00 (0.93)	4.11 (3.23)
Part D: MA-PD	1.42 (0.85)	4.86 (2.98)	0.87 (0.73)	2.41 (2.68)	0.83 (0.58)	2.25 (2.22)	0.89 (0.67)	2.66 (2.25)
Employer/Other Private	-1.65 (1.11)	4.42 (2.95)	-1.59 (1.09)	3.71 (2.81)	**-1.82 (0.89)**	**4.37 (2.14)**	**-2.39 (0.99)**	**6.30 (2.10)**
Auto Eligible for PD Low-Income Subsidy	-2.78 (1.86)	**-1.05 (0.50)**	-2.76 (1.62)	-0.76 (0.43)	-2.63 (1.43)	**-0.83 (0.42)**	-0.93 (1.51)	-0.22 (0.42)
Average Copay for CV Drugs ($2010)	**-1.35 (0.68)**	**6.07 (2.47)**	0.44 (0.80)	0.34 (2.77)	0.97 (0.74)	-2.15 (2.58)	1.42 (0.87)	-3.40 (2.77)
Concurrently taking: 2-3 CV Drugs	-0.05 (0.33)	0.04 (4.15)	-0.02 (0.21)	-0.91 (3.53)	0.00 (0.15)	-0.98 (3.40)	0.04 (0.28)	-4.52 (3.51)
≥4 CV Drugs	0.49 (0.41)	-0.03 (1.02)	0.21 (0.39)	-0.10 (1.03)	0.06 (0.30)	-0.14 (0.89)	-0.44 (0.35)	-0.81 (0.82)
Quantiles of Ambulatory Visits: Q 3 (5-7)	-0.05 (0.30)	-0.34 (1.86)	-0.11 (0.30)	-2.04 (1.62)	-0.12 (0.28)	**-2.78 (1.36)**	-0.17 (0.34)	**-3.20 (1.37)**
Q 4 (8-12)	0.83 (0.90)	-1.64 (2.33)	0.22 (0.83)	-0.25 (2.13)	0.79 (0.71)	-2.35 (1.79)	1.01 (0.77)	-2.75 (2.05)
Q 5 (≥13)	-0.26 (0.53)	2.39 (1.79)	0.02 (0.59)	0.20 (1.97)	-0.14 (0.50)	0.78 (1.70)	0.05 (0.62)	0.43 (2.01)

Table 4-2. (Continued)

Characteristics	Q_{PDC} 10th		Q_{PDC} 20th		Q_{PDC} 30th		Q_{PDC} 40th	
	Estimate (Standard Error)							
	Difference in Characteristics	Difference in *Returns* to Characteristics	Difference in Characteristics	Difference in *Returns* to Characteristics	Difference in Characteristics	Difference in *Returns* to Characteristics	Difference in Characteristics	Difference in *Returns* to Characteristics
Had a Usual Source of Care	0.24 (0.21)	-2.03 (10.38)	0.12 (0.25)	-10.35 (14.40)	-0.12 (0.24)	4.50 (13.60)	-0.03 (0.28)	7.42 (14.52)
Any Emergency Department Visit-Baseline Year	-0.04 (0.24)	-0.83 (1.12)	0.21 (0.29)	0.51 (1.23)	0.40 (0.31)	1.09 (0.99)	0.35 (0.28)	1.39 (1.02)
No. of Pharmacies Used	-0.19 (1.03)	5.44 (9.33)	0.75 (1.04)	-0.14 (8.78)	0.69 (0.94)	2.45 (8.32)	0.73 (1.08)	1.80 (9.18)
Very Satisfied with Received Healthcare	-0.14 (0.40)	0.63 (4.31)	-0.70 (0.59)	6.87 (4.38)	-0.42 (0.42)	2.88 (4.01)	-0.38 (0.39)	2.10 (4.08)
Provider Always Explained	-0.03 (0.32)	-3.09 (5.42)	-0.06 (0.30)	-3.74 (5.10)	-0.07 (0.27)	-1.95 (4.51)	0.01 (0.24)	-0.33 (4.29)
Provider Always Listened	-0.06 (0.22)	-1.27 (4.98)	-0.10 (0.23)	-3.52 (4.79)	-0.04 (0.16)	-0.53 (4.43)	0.05 (0.23)	3.99 (5.00)
Provider Always Respected	-0.04 (0.20)	-1.14 (4.42)	-0.11 (0.30)	-4.21 (4.54)	-0.06 (0.22)	-3.63 (4.48)	-0.09 (0.31)	-5.31 (5.47)
Constant (Base Q_{PDC})		-10.03 (26.58)		-7.29 (27.29)		-34.15 (23.76)		-36.71 (28.67)
Sample Size	3,288							

Boldface estimates have P values <0.05. Standard errors were estimated by balanced repeated replications using MEPS-provided survey weights and half-sample identifiers.

Table 4-3. Oaxaca-Blinder decomposition of black-white differences in adherence across PDC quantiles, 50th-80th, from the viewpoint of black seniors

Outcome	Q_{PDC} 50th		Q_{PDC} 60th		Q_{PDC} 70th		Q_{PDC} 80th	
	Estimate (Standard Error)							
***Panel A*: Fitted Adherence Levels and Differences**								
Q_{PDC}, Blacks	**72.89 (2.42)**		**81.62 (1.76)**		**88.90 (1.22)**		**97.16 (1.06)**	
Q_{PDC}, Whites	**77.78 (1.02)**		**86.54 (0.94)**		**93.41 (0.65)**		**99.36 (0.43)**	
Difference	-4.89 (2.62)		**-4.93 (2.03)**		**-4.51 (1.44)**		-2.20 (1.17)	
***Panel B*: Portion of Adherence Difference Due to:**								
Characteristics	Difference in Characteristics	Difference in *Returns* to Characteristics	Difference in Characteristics	Difference in *Returns* to Characteristics	Difference in Characteristics	Difference in *Returns* to Characteristics	Difference in Characteristics	Difference in *Returns* to Characteristics
Aggregate Contribution	4.41 (4.50)	-9.31 (5.12)	2.19 (3.53)	-7.12 (4.25)	0.20 (2.95)	-4.70 (3.46)	1.33 (1.93)	-3.53 (2.24)
Age 70-75	0.09 (0.42)	0.81 (1.63)	-0.05 (0.34)	0.70 (1.38)	-0.20 (0.33)	-0.36 (1.19)	-0.01 (0.23)	0.17 (0.82)
Age 75-80	-0.01 (0.19)	0.65 (1.65)	-0.02 (0.16)	1.46 (1.39)	-0.05 (0.13)	1.68 (1.14)	-0.07 (0.11)	**1.56 (0.78)**
Age ≥ 80	-0.01 (0.48)	1.84 (2.61)	-0.01 (0.41)	2.18 (2.28)	0.03 (0.34)	1.04 (1.86)	-0.13 (0.23)	1.10 (1.32)
Female	-0.45 (0.48)	-3.82 (3.64)	-0.03 (0.33)	-0.72 (2.73)	-0.27 (0.26)	-2.22 (2.22)	-0.22 (0.19)	-1.61 (1.40)
Married	-0.26 (1.54)	1.35 (3.67)	0.84 (1.28)	-1.34 (3.17)	0.85 (0.96)	-1.16 (2.39)	0.66 (0.64)	-1.06 (1.56)
Urban Residence	0.04 (0.42)	1.87 (6.62)	-0.05 (0.31)	-0.40 (4.98)	-0.07 (0.25)	-2.38 (3.70)	-0.00 (0.19)	-1.10 (2.84)
Census Region: Midwest	-1.53 (0.90)	2.90 (2.20)	-0.91 (0.72)	1.91 (1.86)	-0.74 (0.52)	1.68 (1.32)	-0.30 (0.44)	0.75 (1.12)
South	1.87 (1.75)	3.39 (2.61)	0.02 (1.24)	0.32 (1.95)	0.06 (0.97)	0.07 (1.56)	0.13 (0.80)	0.17 (1.30)
West	0.18 (1.48)	-0.56 (2.37)	0.62 (1.34)	-1.33 (2.18)	-0.08 (1.18)	-0.07 (1.89)	0.29 (0.75)	-0.67 (1.21)
Health Status: Very Good	-0.31 (0.72)	-0.75 (3.03)	-0.39 (0.56)	0.37 (2.38)	-0.22 (0.51)	-0.04 (2.03)	-0.36 (0.39)	1.17 (1.47)
Good	0.05 (0.30)	0.25 (3.09)	0.07 (0.29)	1.52 (2.57)	0.06 (0.27)	1.62 (2.27)	0.04 (0.18)	0.95 (1.71)

Table 4-3. (Continued)

Characteristics	Q_{PDC} 50th		Q_{PDC} 60th		Q_{PDC} 70th		Q_{PDC} 80th	
	Estimate (Standard Error)							
	Difference in Characteristics	Difference in *Returns* to Characteristics	Difference in Characteristics	Difference in *Returns* to Characteristics	Difference in Characteristics	Difference in *Returns* to Characteristics	Difference in Characteristics	Difference in *Returns* to Characteristics
Fair	0.87 (0.92)	0.34 (1.75)	0.86 (0.81)	0.80 (1.46)	0.67 (0.66)	0.74 (1.21)	0.70 (0.52)	0.93 (0.95)
Poor	0.48 (0.43)	0.92 (0.70)	0.48 (0.38)	0.91 (0.59)	0.39 (0.29)	0.66 (0.47)	0.34 (0.23)	0.51 (0.36)
Any Physical Limitation	0.19 (0.34)	**7.32 (3.44)**	0.12 (0.23)	5.07 (2.90)	0.02 (0.13)	1.18 (2.37)	-0.02 (0.10)	0.09 (1.88)
Any Cognitive Limitation	0.44 (0.65)	0.87 (0.83)	0.03 (0.48)	0.33 (0.63)	-0.32 (0.37)	-0.14 (0.43)	-0.39 (0.27)	-0.15 (0.29)
Depressive Symptoms	-0.50 (0.58)	-0.60 (0.62)	-0.12 (0.46)	0.03 (0.52)	0.23 (0.36)	0.40 (0.38)	0.37 (0.29)	0.39 (0.28)
Hypertension	0.99 (1.10)	5.35 (8.62)	1.54 (0.96)	8.87 (7.26)	0.82 (0.86)	5.39 (6.76)	0.84 (0.61)	6.41 (4.45)
Hyperlipidemia	-0.08 (0.41)	-0.57 (3.91)	-0.18 (0.36)	0.64 (3.66)	-0.14 (0.25)	0.52 (2.56)	-0.10 (0.21)	0.85 (1.94)
Angina/CHD	-0.20 (0.26)	0.72 (1.40)	-0.13 (0.21)	0.38 (1.08)	-0.02 (0.19)	-0.34 (0.88)	0.00 (0.14)	-0.36 (0.63)
CHF	0.00 (0.11)	-0.20 (0.54)	0.00 (0.09)	-0.26 (0.46)	-0.01 (0.08)	0.18 (0.32)	0.01 (0.06)	-0.17 (0.26)
AMI	0.14 (0.21)	-0.87 (0.87)	0.04 (0.22)	-0.26 (0.82)	0.04 (0.21)	-0.30 (0.73)	0.06 (0.13)	-0.23 (0.45)
Stroke	0.01 (0.17)	0.44 (0.70)	0.01 (0.13)	0.08 (0.58)	-0.01 (0.11)	-0.20 (0.47)	0.00 (0.06)	0.03 (0.31)
Count of Comorbid Conditions	0.25 (0.89)	1.83 (5.19)	0.99 (0.89)	-2.60 (5.11)	0.67 (0.67)	-3.36 (3.67)	0.34 (0.55)	-2.49 (2.99)
Charlson Comorbidity Score Q3	0.72 (0.54)	2.95 (1.91)	0.24 (0.42)	1.53 (1.60)	-0.05 (0.30)	-0.25 (1.16)	-0.35 (0.27)	-1.43 (0.87)
Charlson Comorbidity Score Q4	0.21 (0.28)	1.31 (1.30)	0.08 (0.20)	0.77 (1.11)	0.11 (0.18)	1.08 (0.86)	-0.02 (0.12)	0.09 (0.56)

Table 4-3. (Continued)

Characteristics	Q_{PDC} 50th		Q_{PDC} 60th		Q_{PDC} 70th		Q_{PDC} 80th	
	Estimate (Standard Error)							
	Difference in Characteristics	Difference in *Returns* to Characteristics	Difference in Characteristics	Difference in *Returns* to Characteristics	Difference in Characteristics	Difference in *Returns* to Characteristics	Difference in Characteristics	Difference in *Returns* to Characteristics
More Likely to Take Risks	0.06 (0.18)	-0.03 (1.31)	0.06 (0.15)	-0.15 (1.11)	-0.00 (0.12)	0.41 (0.85)	0.03 (0.09)	-0.02 (0.59)
Can overcome illness without medical care	0.15 (0.67)	-0.45 (1.36)	-0.13 (0.60)	0.20 (1.25)	-0.17 (0.50)	0.18 (1.04)	-0.26 (0.40)	0.49 (0.81)
Does not need health insurance	-0.03 (0.15)	0.01 (0.62)	-0.01 (0.12)	0.14 (0.51)	-0.02 (0.09)	-0.06 (0.38)	0.03 (0.08)	0.20 (0.28)
Current Smoker	-0.19 (0.26)	-0.49 (0.64)	-0.12 (0.21)	0.14 (0.53)	-0.02 (0.15)	0.15 (0.39)	0.06 (0.12)	0.19 (0.32)
Had Moderate / Vigorous Exercise	0.10 (0.59)	1.01 (3.09)	-0.29 (0.51)	2.63 (2.65)	-0.16 (0.40)	1.38 (2.05)	-0.16 (0.29)	0.83 (1.41)
Obese (BMI≥30)	0.38 (0.52)	0.76 (1.69)	0.06 (0.44)	-0.39 (1.44)	0.13 (0.37)	0.36 (1.13)	0.29 (0.27)	0.64 (0.91)
Income: Poor/Near-Poor	-1.33 (1.41)	-1.16 (1.36)	-1.09 (1.20)	-1.02 (1.20)	-0.58 (1.05)	-0.33 (0.99)	-0.93 (0.82)	-0.77 (0.74)
Low-Income	-0.49 (0.54)	-1.58 (1.54)	-0.10 (0.42)	-0.48 (1.38)	-0.10 (0.40)	-0.45 (1.14)	-0.09 (0.27)	-0.13 (0.78)
Middle-Income	0.01 (0.25)	-1.42 (3.11)	0.01 (0.20)	-1.13 (2.54)	-0.00 (0.18)	0.18 (2.13)	0.00 (0.12)	-0.33 (1.38)
Education: Less than High School	-0.65 (2.07)	-1.01 (1.58)	-1.31 (1.70)	-1.29 (1.28)	-1.23 (1.58)	-0.94 (1.13)	0.01 (1.10)	-0.16 (0.82)
High School Diploma	0.51 (1.07)	-2.41 (4.76)	0.37 (0.87)	-1.47 (3.82)	0.42 (0.76)	-0.97 (3.27)	-0.07 (0.52)	0.67 (2.19)

Table 4-3. (Continued)

Characteristics	Q_{PDC} 50th		Q_{PDC} 60th		Q_{PDC} 70th		Q_{PDC} 80th	
	Estimate (Standard Error)							
	Difference in Characteristics	Difference in *Returns* to Characteristics	Difference in Characteristics	Difference in *Returns* to Characteristics	Difference in Characteristics	Difference in *Returns* to Characteristics	Difference in Characteristics	Difference in *Returns* to Characteristics
Drug Coverage Plan: Part D: PDPs	0.19 (0.86)	0.74 (3.05)	0.11 (0.76)	0.16 (2.59)	0.15 (0.65)	-0.26 (2.20)	-0.25 (0.49)	-1.38 (1.69)
Part D: MA-PD	0.11 (0.61)	-0.46 (2.04)	-0.21 (0.56)	-2.11 (1.89)	-0.13 (0.43)	-1.44 (1.53)	-0.17 (0.34)	-1.32 (1.09)
Employer/Other Private	-1.11 (0.76)	3.16 (1.84)	-0.77 (0.66)	1.86 (1.64)	-0.84 (0.56)	1.83 (1.37)	-0.71 (0.48)	1.79 (1.12)
Auto Eligible for PD Low-Income Subsidy	0.28 (1.44)	0.19 (0.41)	-0.04 (1.15)	0.00 (0.35)	-0.03 (0.91)	0.03 (0.26)	0.66 (0.62)	0.26 (0.18)
Average Copay for CV Drugs ($2010)	**1.78 (0.81)**	-4.53 (2.39)	1.24 (0.67)	-2.79 (1.98)	0.49 (0.52)	-0.51 (1.57)	0.29 (0.41)	-0.70 (1.25)
Concurrently taking: 2-3 CV Drugs	0.06 (0.35)	**-6.65 (3.24)**	0.05 (0.32)	-3.45 (3.05)	0.05 (0.30)	-3.09 (2.57)	0.04 (0.26)	**-3.71 (1.64)**
≥4 CV Drugs	-0.51 (0.36)	-1.01 (0.87)	-0.45 (0.31)	-0.47 (0.75)	-0.34 (0.26)	-0.10 (0.59)	-0.18 (0.18)	0.16 (0.38)
Quantiles of Ambulatory Visits: Q 3 (5-7)	-0.09 (0.24)	-1.94 (1.27)	0.02 (0.15)	-0.10 (1.18)	-0.02 (0.11)	-0.32 (0.92)	-0.00 (0.08)	-0.15 (0.68)
Q 4 (8-12)	1.36 (0.77)	**-3.86 (1.85)**	0.06 (0.62)	-0.44 (1.55)	-0.05 (0.49)	0.09 (1.21)	-0.07 (0.41)	0.33 (0.99)
Q 5 (≥13)	-0.16 (0.58)	0.77 (1.84)	-0.44 (0.50)	1.64 (1.56)	-0.27 (0.40)	1.46 (1.27)	0.04 (0.29)	0.04 (0.97)

Table 4-3. (Continued)

Characteristics	Q_{PDC} 50th		Q_{PDC} 60th		Q_{PDC} 70th		Q_{PDC} 80th	
	Estimate (Standard Error)							
	Difference in Characteristics	Difference in *Returns* to Characteristics	Difference in Characteristics	Difference in *Returns* to Characteristics	Difference in Characteristics	Difference in *Returns* to Characteristics	Difference in Characteristics	Difference in *Returns* to Characteristics
Had a Usual Source of Care	0.04 (0.28)	3.25 (14.38)	0.08 (0.24)	-4.22 (13.36)	0.12 (0.21)	-9.85 (11.05)	0.14 (0.16)	-7.59 (8.08)
Any Emergency Department Visit- Baseline Year	0.09 (0.20)	0.19 (0.98)	0.08 (0.19)	-0.08 (0.87)	0.08 (0.16)	0.12 (0.69)	0.14 (0.14)	0.47 (0.55)
No. of Pharmacies Used	1.10 (0.86)	-2.12 (7.53)	1.05 (0.75)	-6.34 (6.56)	1.11 (0.58)	-7.86 (5.11)	**0.86 (0.43)**	-6.52 (3.75)
Very Satisfied with Received Healthcare	-0.38 (0.39)	1.75 (3.57)	-0.13 (0.27)	0.79 (2.91)	-0.20 (0.24)	2.42 (2.46)	-0.19 (0.18)	1.79 (1.76)
Provider Always Explained	0.04 (0.28)	0.23 (4.54)	-0.00 (0.20)	-1.28 (3.88)	-0.04 (0.15)	-2.57 (2.89)	-0.09 (0.17)	-3.46 (2.26)
Provider Always Listened	0.00 (0.20)	1.96 (4.30)	0.05 (0.17)	2.85 (3.91)	0.03 (0.11)	1.78 (2.77)	0.03 (0.11)	2.22 (2.18)
Provider Always Respected	-0.08 (0.29)	-4.23 (5.23)	0.01 (0.22)	0.29 (4.76)	0.06 (0.18)	2.72 (3.30)	0.04 (0.12)	1.38 (2.43)
Constant (Base Q_{PDC})		-17.71 (27.77)		-11.54 (22.20)		5.49 (18.78)		5.32 (14.23)
Sample Size	3,288							

Boldface estimates have P values <0.05. Standard errors were estimated by balanced repeated replications using MEPS-provided survey weights and half-sample identifiers.

(~150%). As in **Appendix Table C-4**, having activity limitations was associated with better adherence among blacks but not among whites at the 50th PDC percentile. Differences in other health-related factors, including having depressive symptoms, were not associated with the racial difference in adherence.

Beliefs and Behaviors. Except for obesity among seniors at the 10th and 30th percentiles of the PDC distribution, none of the differences related to beliefs about healthcare, insurance, risk-taking, exercise, or smoking contributed to the racial difference in adherence. Among seniors at the 10th and the 30th percentiles of the PDC distribution, had whites and blacks had the same prevalence rates of obesity, or had obesity been associated with adherence to the same extent among both groups, the racial differences in adherence would have surprisingly *increased*. This follows from a strong positive association between adherence and obesity among black but not among white seniors at the 10th and 30th percentiles (see **Appendix Table C-2**).

Socioeconomic Status and Insurance. Income-related differences were not associated with the racial differences in adherence in this sample of Medicare seniors. Similarly education, except for the difference in completing high-school diploma among those at the 10th percentile. As in **Appendix Table C-2**, having high-school diploma, relative to having education beyond high-school, had a strong negative association with adherence among blacks but not among whites. Subsequently, if the rates of having a high-school diploma were equal among whites and blacks, the racial difference in adherence among seniors at the 10th percentile would have increased by about 30% (see **Table 4-2**).

The differences related to enrollment in Part D PDPs or MA-PDs did not appear to be associated with the racial difference in adherence. The lower likelihood among black seniors to have employer-sponsored drug coverage was a significant contributor to the racial difference in adherence. Among seniors at the 30th and 40th percentiles of the PDC distribution, had the rates of enrollment in employer-sponsored (mostly retiree) drug coverage been equal among blacks and whites, the racial difference in adherence would have dropped by 1.82 and 2.39 percentage points (about 23% and 27%), respectively. Having this type of coverage was associated with large improvements in adherence only among black seniors at the 30th and 40th percentiles (see **Appendix Table C-2**). Accordingly, making this coverage works the same way among blacks and whites, e.g. changes to benefit design or employee contribution, might increase the racial difference in adherence.

The difference in how being automatically eligible for the LIS is associated with adherence appears to play a role in the racial difference in adherence at the 10th and the 30th percentiles. **Appendix Table C-2** shows that auto-eligibility for LIS among black, but not white, seniors had a strong negative association with adherence. Had auto-eligibility for LIS (which also means receiving Medicaid) been associated with adherence in the same way across blacks and whites, the racial difference in adherence would have

been reduced by 1.05 and 0.83 percentage points (23% and 10%), respectively. Further, among seniors at the 10th percentile of the PDC distribution, matching average copay amounts for cardiovascular drugs among blacks to those among whites would reduce the racial difference in adherence, whereas doing so among seniors at the 50th percentile would increase the racial difference in adherence.

Use of the Healthcare System. Greater use of physician ambulatory care appeared to work disparately among blacks and whites. In **Appendix Table C-2**, greater use of ambulatory care was associated with a reduction in adherence among blacks but improvement in adherence among whites at the 30th and 40th percentiles of the PDC distribution. Making ambulatory care work equally well for black and white seniors would reduce the racial difference in adherence by 2.78 and 3.2 percentage points (about 35%), respectively (**Table 4-2**).

Among seniors at the 50th and 80th percentiles, the concurrent use of multiple (2-3) cardiovascular medications was associated with worsening adherence more among blacks than among whites (see **Appendix Table C-4**). Eliminating this differential in the return to using multiple cardiovascular medications would reduce the racial difference in adherence by 6.65 and 3.71 percentage points (more than 100%), respectively as listed in **Table 4-3**. Differences related to satisfaction with healthcare or provider relationship were not associated with the racial differences in adherence.

Results from Additional Analyses. In addition to the main analysis from the perspective of black seniors, we also calculated detailed OBD estimates using coefficients from race-pooled unconditional quantile regressions. These results, listed in **Appendix Tables C-5** and **C-6**, suggest the involvement of the same set of factors discussed above as potential sources of the racial difference in adherence. In these analyses, unexplained components of calculated differences were quite large, negative quantities and statistically significant across all modeled quantiles. Some explained components were significant only below the median and all had a plus sign. Mean OBD analyses based on logit, linear probability, and OLS models only identified differences related to employer-sponsored coverage rates and copay levels as potential sources of the racial difference in mean adherence.

Discussion

Differences in the distribution of and/or in the behavioral returns to marital status, having physical limitation, hyperlipidemia, obesity, enrollment in employer-sponsored coverage, being auto-eligible for the LIS, drug copay, use of ambulatory care, and use of multiple cardiovascular medications explained some of the racial differences in adherence among seniors, especially below the median, where disparities were largest and most significant. Such findings would not have been reachable if only differences in mean adherence were studied as traditionally carried out. In fact, our OBD analyses of the differences in mean adherence were of limited value.

The large magnitude and significance of the unexplained component that corresponds to the aggregate differential in returns to individual characteristics, especially as demonstrated by OBD pooled-coefficient analyses, suggest a discrimination-based explanation of adherence disparities. With discrimination, we specifically mean how the (causal) process (es) linking individual characteristics to adherence have been operating differently for blacks and whites. Although we found this differential operation of characteristics on adherence to be a recurrent theme, the validity of a discrimination argument further depends on whether relevant covariates were left out from the analysis. Although we controlled for a rich set of covariates, data on individuals' self-efficacy, health literacy, degree of social support, neighborhood/household environment, and the degree of mistrust of the healthcare system,[175,176] all relevant covariates, were not available in MEPS.

We have found marriage to have a protective effect against poor adherence among blacks, suggesting an element of social support, which seems to particularly help those attempting to improve their adherence level (at the 30th percentile, ~ 59% PDC). This finding is corroborated by what qualitative studies of adherence among blacks reported of the positive association between family/friends' support with adherence.[144,176] Another finding that also alludes to social support is the role of having physical limitation. Having physical limitation was independently associated with better adherence among black but not among white seniors. A potential explanation might be that with physical limitation, seniors might be getting more time with their caregivers who maybe further assisting them with their medication-taking behavior, which may be tapping as well into the social support construct.

Although the lower prevalence of hyperlipidemia among blacks relative to whites appeared protective, having hyperlipidemia, which is a largely asymptomatic condition, differentially worsened adherence among blacks but not nearly as much among whites at the lower end of the distribution (those who were most poorly adherent). This finding is suggestive of a higher likelihood of early discontinuation of lipid-lowering therapy among hyperlipidemic blacks than whites, leading to much less exposure to statins, a finding also reported by several studies.[177,178] **Table 4-1** and **Appendix Table C-1** show that blacks were substantially less likely to use statins than whites.

We have found ambulatory care to work differently in determining adherence for blacks and whites, where greater use of ambulatory care among blacks was associated with lower adherence whereas the opposite was true for whites. The specific reasons for why this was the case warrant investigation. A number of factors, however, can be hypothesized as potential remedies for this disparate effect. The quality of communication and compassion in the patient-provider relationship, especially when race-concordance is possible,[150,151] has been repeatedly cited as a versatile avenue for intervention on medication adherence among blacks.[142] Quality provider communication can address patients' beliefs and concerns about how medications work and their side effects, and can address issues such as early discontinuation of statins, and the

complexity of multi-drug regimens which we found to be associated with disproportionately lower adherence among blacks.

Insurance benefit design and cost-sharing schemes may be another set of factors amenable for intervention for disparity reduction. We found that employer-sponsored coverage was associated with improved adherence among blacks, being auto-eligible for the LIS worked worse among blacks, and matching white and black copay levels was associated with opposing effects on disparities in two different locations in the distribution. Optimizing the design and administration of prescription drug benefits and setting copay amounts in Part D plans in a way so as to increase medication use among those who would benefit the most out of using those drugs (e.g. by eliminating copays on ACE inhibitors, statins, and beta-blockers after acute MI),[179,180] in a value-based benefit design framework,[181] can improve adherence where it matters most and reduce disparities, not only in adherence but also in associated clinical and economic outcomes.[180,182] Combining these reforms in benefit design with medication therapy management services[52,53] under Part D, can together address multiple dimensions of patients' pharmacotherapy experience, from affordability and access, to appropriateness of prescribed medications, education about medications, resolution of medication-related problems, and addressing issues that might be particular to individual patients.

In addition to the factors we have found to be significantly associated with the racial difference in adherence, other factors that have been reported in the literature, such as depression, did not turn out to be significant. Our analysis was limited to the Medicare elderly population. Our results are certainly not generalizable to the general adult population where depression and other factors that were not significant in our analysis (such as SES) might be playing a greater role than in our sample. We've also encountered the counterintuitive finding that higher rates of obesity among blacks were protective against worse adherence especially among seniors at the 10th and 30th percentiles of the PDC distribution. This findings is in contrast with research documenting that obesity is associated with poor adherence[183] and that blacks were more likely to experience weight-based discrimination which compromised their self-efficacy and consequently their adherence behavior.[184] Whether this effect is a statistical artifact or can be potentially explained by other factors that were not accounted for in the analysis is a matter for further investigation.

Limitations

Decomposition analyses are powerful in that they provide a breakdown of how the differences in covariates contribute to the overall difference in the outcome. As we have reported, these analyses only offer bottom-line estimates of the quantitative contributions of covariates to the outcome difference, without providing any information on the underlying mechanisms. These mechanisms are left for the analyst to hypothesize and test in future research using appropriate methods. The analyses we reported here were not meant to be comprehensive. It is very possible that the variables we did not have data on may be playing a role in the racial differences in adherence. We also suspect that the small sample size we had might have affected the statistical significance for some of

our estimates. Although all multivariable analyses had sample sizes above the limit recommended by the AHRQ (n>100), our descriptive statistics across PDC quantile categories had sample sizes less than 100, which may have rendered those estimates unstable.

Our adherence estimation might have suffered a number of limitations. First, our derivation of refill days of supply from dispensed quantities was based on the 2010 data in our MEPS sample, without validation against an external standard, e.g. Medicare claims data. Given that previous research documented the validity of MEPS prescription drug data against Medicare claims,[87] we believe benchmarking our analysis solely to MEPS 2010 is sufficient. While data on dispensed quantities were complete for all refills in the study period, a large proportion of 2010 refills had missing days of supply data (about 30%). We found the pattern of missing data to be very consistent across drug class and respondent characteristics, indicating that a missing-completely-at-random (MCAR) assumption is likely plausible. As such, we examined the pattern of refill days of supply vis-à-vis dispensed quantities only among individuals with complete days of supply data for all of their listed refills.

We also assumed that the patterns of days of supply vis-à-vis dispensed quantities in 2010 would hold in earlier years of MEPS. Although we believe this assumption is likely true on average, changes in treatment guidelines, generic availability, and coverage tier classifications of drugs might have affected the prescribed total daily doses of some cardiovascular medications. Since MEPS did not have refill dates, a reasonable choice for the index date was the first day of the MEPS round in which the refill occurred. We might have thus underestimated adherence for respondents who started late in the round, although it is not possible to identify them. If a respondent had too few refills over a round (3-4 months), it might also be the case that they skipped refills and not necessarily they started taking the medication later in the round.

Conclusion

In this study, we combined the two powerful empirical techniques of Oaxaca-Blinder decomposition and unconditional quantile regression, to explore the potential sources of black-white differences in adherence to cardiovascular medications in a nationally representative sample of Medicare seniors. Our findings suggest that adherence differences were largely driven by differences in how the determinants of adherence operated differently for blacks than whites, including marital status, having hyperlipidemia, physical limitations, drug coverage, enrollment in Part D LIS, copay amounts, cardiovascular drug regimen, and use of ambulatory care. As such, these findings suggest a discrimination-based explanation of the racial differences in adherence. Interventions focusing on promoting social support in patients' environment, more collaborative and compassionate patient-provider relationship, and value-based drug benefit design along with medication therapy management may be immediate avenues for intervention.

CHAPTER 5. CONCLUSION

Summary of Findings

Our difference-in-differences analyses showed that Medicare Part D was associated with a 16-percentage-point decrease in the white-Hispanic disparity in overall average adherence to cardiovascular medications among the elderly. This decrease was most visible in adherence to beta-blockers, where the white-Hispanic disparity decreased by 30 percentage points. While there was no significant change in overall and medication class-specific black-white disparities, overall adherence among black men disproportionately fell by 21 percentage points, relative to white men. Other subgroup analyses across gender and Medicaid eligibility lines suggested no statistically significant changes in disparities among these subgroups following Part D introduction. Estimates of racial disparities in the post-Part D era, 2007-2010, indicate the existence of large and significant black-white disparities, overall and in each sub-group. Overall adherence levels among both black and Hispanic Medicaid-eligible seniors were 19- and 15-percentage points lower than whites, which were the largest among all subgroups. Using the near-elderly as a control group, with a few caveats, these findings took into account the potential level of disparities had Part D not been implemented. These findings also remained robust to the levels of empirical adjustment for covariates.

Among seniors, black-white disparities in adherence were largest (and statistically significant) towards the lower end of the distribution, below the 40th percentile and peaking around the 30th percentile, namely, among populations with poor adherence levels (70 and 60% adherence, respectively). Disparities progressively waned towards the upper end of the distribution. This pattern generally recurred among subgroups, with some variation in magnitude and statistical significance. Additionally, among men and the auto-enrolled LIS population (including Medicaid-eligibles), disparities were most concentrated among populations at and below the 30th percentile (adherence levels < 60%). Although white-Hispanic disparities exhibited a similar pattern, they were smaller in magnitude and sporadically significant.

Distribution-wide Oaxaca-Blinder decompositions analyzed how the racial inequality in the determinants of adherence contributed to the adherence differential between black and white seniors. These analyses suggested that differences in most demographics, income, education, depression and most conditions, type of Part D drug coverage plan, or covariates measuring experience with healthcare providers were not associated with the adherence differential. Marriage and activity limitations appeared protective against poor adherence more among black than among white seniors with adherence levels below 60%, tapping into social support as the possibly underlying mechanism. Having diagnosed hyperlipidemia, which is mostly an asymptomatic condition, was mroe strongly associated with poorer adherence among blacks than among whites with very poor adherence (30%), suggestive of higher likelihood of early discontinuation of drug therapy (potentially statins) among blacks than among whites in this population.

The racial differential in enrollment rates in employer-sponsored insurance was strongly associated with the adherence differential among seniors with adherence below 70%. This type of coverage was also independently associated with much higher adherence among blacks than among whites. Eliminating the racial differential in employer coverage rates was associated with an expected ~ 25% reduction in the adherence differential. Being an auto-recipient of the LIS was independently associated with worse adherence among blacks than among whites in this population. Matching the average copay levels among poorly adherent blacks and whites was associated with an increase in the adherence differential, whereas doing do among those with adherence close to 80% would reduce the differential. Greater use of ambulatory physician visits was associated with better adherence among whites but worse adherence among blacks with adherence below 70%. This differential in how visits determined adherence was responsible for about 35% of the adherence differential. Among seniors with adherence above 77%, taking multiple cardiovascular medications was associated with much worse adherence among blacks than among whites.

Implications for Research

One key limitation of current research on adherence, including this dissertation, is studying adherence as an isolated behavioral phenomenon. Greater appreciation of the complexity of adherence is much needed. Adherence should be understood as a series of behaviors that start with keeping doctor's appointments to actual administration of medications, involving steps such as regularly filling prescriptions, using reminders, exercising, and maintaining healthy diet.[111] These contiguous behaviors arise from complex interactions among multiple factors, pertinent to the patient and the environment. Given this complexity, we need to build a deeper mechanistic understanding of how this intricate system works and how/where it engenders disparities. Parsing out this intricacy, through complex systems science and simulation approaches, enables us to identify novel "leverage points" for effective intervention that were potentially otherwise unidentifiable.[112] Studying adherence this way can also help us answer interesting behavioral and clinical questions, including ones identified in this dissertation (for example: how the use of ambulatory care disparately affects adherence between blacks and whites; why black LIS recipients fare worse than their white counterparts in terms of their adherence behavior; and why disparities in adherence to beta-blockers and diuretics are the largest among all cardiovascular drug classes).

Although one could delineate the characteristics of populations where adherence disparities were found to be worst, identifying them in routine clinical practice is challenging. This is a result of the lack of alignment between the empirical refill-based measures of adherence typically employed in research (such as the proportion of days covered, PDC, used here), and the measures that can be used to assess patient adherence in routine clinical practice.[117,152] Further, although using quantile regression enabled us to get a more comprehensive picture of the adherence distribution, we still lumped adherence into a single number without further parsing out the underlying behavioral

details. Instead of summarizing patient adherence over (say) a year into a single number, a more informative alternative would be to examine the developmental trajectories of adherence over time using group-based trajectory models.[153] This would enable us to capture more details about regimen execution, i.e. patterns of how the prescribed compares to the actual regimen taken, and persistence over time.[18,21] Identifiable patterns such as brief lapse in therapy due to occasional dose omissions, longer drug holiday but then continuation, periodic gaps in therapy, and early discontinuation provide a basis for more meaningful classification of adherence behavior with implications for intervention and for studying disparities. It is worth noting here that some recently developed questionnaire instruments, which can be administered in practice settings, can help identify these distinct patterns as well, and can thus offer a closer insight into real-world settings.[152,154]

Implications for Policy

While it is important to identify access/quality issues that may disparately compromise adherence behavior among minorities, it is at least equally as important to envision adherence as a reflection of the structural, physical, and psychosocial disadvantage racial minorities typically live in. Poverty, low educational attainment, poor social support, disordered physical and social environments, and policies that institutionalize racism are systematic, causal antecedents to almost every poor health outcome among minorities.[108] One example of how social determinants affected adherence in this dissertation manifested in the rates of employer-sponsored coverage. The black-white differential in employer-sponsored insurance coverage (mostly retiree coverage) was responsible for a sizable portion of the adherence differential. Our results suggest that if blacks were equally likely to have been employed in a way that provides them with generous insurance coverage upon retirement, the adherence differential would have been reduced. The nature of employment and type of occupation are direct correlates of educational attainment, which is much lower among blacks than whites (in our sample, ~50% of black seniors had less than high school education, compared with only 20% among whites). Achieving equity in these fundamental determinants of health ought to remain a long-term goal for society.

Under Medicare Part D, MTM programs offer a versatile mechanism to address the drivers of poor adherence among minorities and to reduce adherence disparities. First, however, the utilization-based eligibility criteria for MTM services continue to be an impediment to improving the quality of medication use in this population as it deprives minorities who would greatly benefit from this service.[63,185] Investigating more equitable alternatives for these criteria remains an important step. Further, although having an opt-out, rather than an opt-in, policy for enrollment in MTM is a good step towards greater enrollment of seniors for this service, there is still a low turnout rate in keeping up with MTM appointments and medication reviews.[148] Increasing awareness of the value of MTM, particularly among minorities, may prove to be a good step towards improving adherence among seniors and particularly minorities. Through comprehensive medication reviews, collaboration with patient's providers (including social workers, and

community/home health workers), and establishing an empowering collaborative relationship with the patients themselves, pharmacists providing MTM can proactively identify and tackle issues compromising medication adherence (and potentially other aspects of healthcare). [52,53,109,149] Examples of what MTM and, broadly, what other providers can do, include: educating patients about their medications, addressing their medication-related problems and concerns (e.g. issues related to discontinuation of statin therapy, poor adherence to diuretics and beta-blockers, having to take multiple medications), promoting their self-management behavior, improving their health literacy, screening for depression, and enhancing their self-efficacy. Current evidence suggest that minorities' adherence to cardiovascular medications significantly improves when there is race and language concordance between them and their providers, which should be sought whenever possible.[150,151] Further research[110] is needed on how to optimize MTM delivery for minority and low-SES patients.

Insurance benefit design and cost-sharing schemes may be another set of factors amenable for intervention for disparity reduction. We found that employer-sponsored coverage was associated with improved adherence among blacks, being auto-eligible for the LIS worked worse among blacks, and matching white and black copay levels was associated with opposing effects on disparities in two different locations in the distribution. Optimizing the design and administration of prescription drug benefits and setting copay amounts in Part D plans in a way so as to increase medication use among those who would benefit the most from using those drugs (e.g. by eliminating copays on ACE inhibitors, statins, and beta-blockers after acute MI),[179,180] in a value-based benefit design framework,[181] can improve adherence where it matters most and reduce disparities, not only in adherence but also in associated clinical and economic outcomes.[180,182] Combining these reforms in benefit design with medication therapy management services[52,53] under Part D, can together address multiple dimensions of patients' pharmacotherapy experience, from affordability and access, to appropriateness of prescribed medications, education about medications, resolution of medication-related problems, and addressing issues that might be particular to individual patients.

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APPENDIX A. SUPPLEMENTAL MATERIALS FOR CHAPTER 2

Table A-1. Identifying information for included cardiovascular conditions

Condition	CCC	ICD-9 Codes						
Essential Hypertension	**98**	4011	4019					
Hypertension with complications / Secondary Hypertension	**99**	4010	40200	40201	40210	40211	40290	40291
		4030	40300	40301	4031	40310	40311	4039
		40390	40391	4040	40400	40401	40402	40403
		4041	40410	40411	40412	40413	4049	40490
		40491	40492	40493	40501	40509	40511	40519
		40591	40599	4372				
Hyperlipidemia	**53**	2720	2721	2722	2723	2724		
Angina and Coronary Heart Disease (atherosclerosis)	**101**	4110	4111	4118	41181	41189	412	4130
		4131	4139	4140	41400	41401	41406	4148
		4149	V4581	V4582				
Congestive Heart Failure	**108**	39891	4280	4281	42820	42821	42822	42823
		42830	42831	42832	42833	42840	42841	42842
		42843	4289					
Acute Myocardial Infarction	**100**	4100	41000	41001	41002	4101	41010	41011
		41012	4102	41020	41021	41022	4103	41030
		41031	41032	4104	41040	41041	41042	4105
		41050	41051	41052	4106	41060	41061	41062
		4107	41070	41071	41072	4108	41080	41081
		41082	4109	41090	41091	41092		
Acute Cerebrovascular Disease	**109**	34660	34661	34662	34663	430	431	4320
		4321	4329	43301	43311	43321	43331	43381
		43391	4340	43400	43401	4341	43410	43411
		4349	43490	43491	436			

Table A-1. (Continued)

Condition	CCC	ICD-9 Codes					
Transient Cerebral Ischemia	**112**	4350	4351	4352	4353	4358	4359

CCC: Clinical Classification Codes; ICD-9-CM: International Classification of Diseases, Ninth Revision, Clinical Modification.

Source: AHRQ. *MEPS HC-137: 2010 Medical Conditions- Appendix 3: Clinical Classification Code to ICD-9-CM Code Crosswalk.* Rockville, MD 2012.

Table A-2. Included cardiovascular medications

Drug Class	Multum-Lexicon ® Class	Multum-Lexicon ® Subclass 1	Specific Agents
Angiotensin-Converting Enzyme (ACE) Inhibitors	42	None	Benazepril, Captopril, Enalapril, Fosinopril, Lisinopril, Moexipril, Perindopril, Quinapril, Ramipril, Trandolapril
Angiotensin II Receptor Blockers	56	None	Candesartan, Eprosartan, Irbesartan, Losartan, Olmesartan, Telmisartan, Valsartan
HMG-CoA Reductase Inhibitors (Statins)	173	None	Atorvastatin, Fluvastatin, Lovastatin, Pitavastatin, Pravastatin, Rosuvastatin, Simvastatin
Beta-Blockers	47	274, 275	Acebutolol, Atenolol, Betaxolol, Bisoprolol, Carvedilol, Labetalol, Metoprolol, Nadolol, Nebivolol, Penbutolol, Pindolol, Propranolol, Sotalol, Timolol
Calcium Channel Blockers	48	None	Amlodipine Besylate, Diltiazem, Felodipine, Isradipine, Nicardipine, Nifedipine, Nisoldipine, Verapamil
Diuretics	49	154-158	Acetazolamide, Spironolactone, Amiloride, Bumetanide, Chlorothiazide, Chlorthalidone, Furosemide, Hydrochlorothiazide, Indapamide, Methyclothiazide, Metolazone, Torsemide, Triamterene
Antihypertensive Combinations	55	None	Multiple combinations of these drugs with diuretics, especially

Source: AHRQ. *MEPC HC-135A: 2010 Prescribed Medicines.* Rockville, MD 2012.

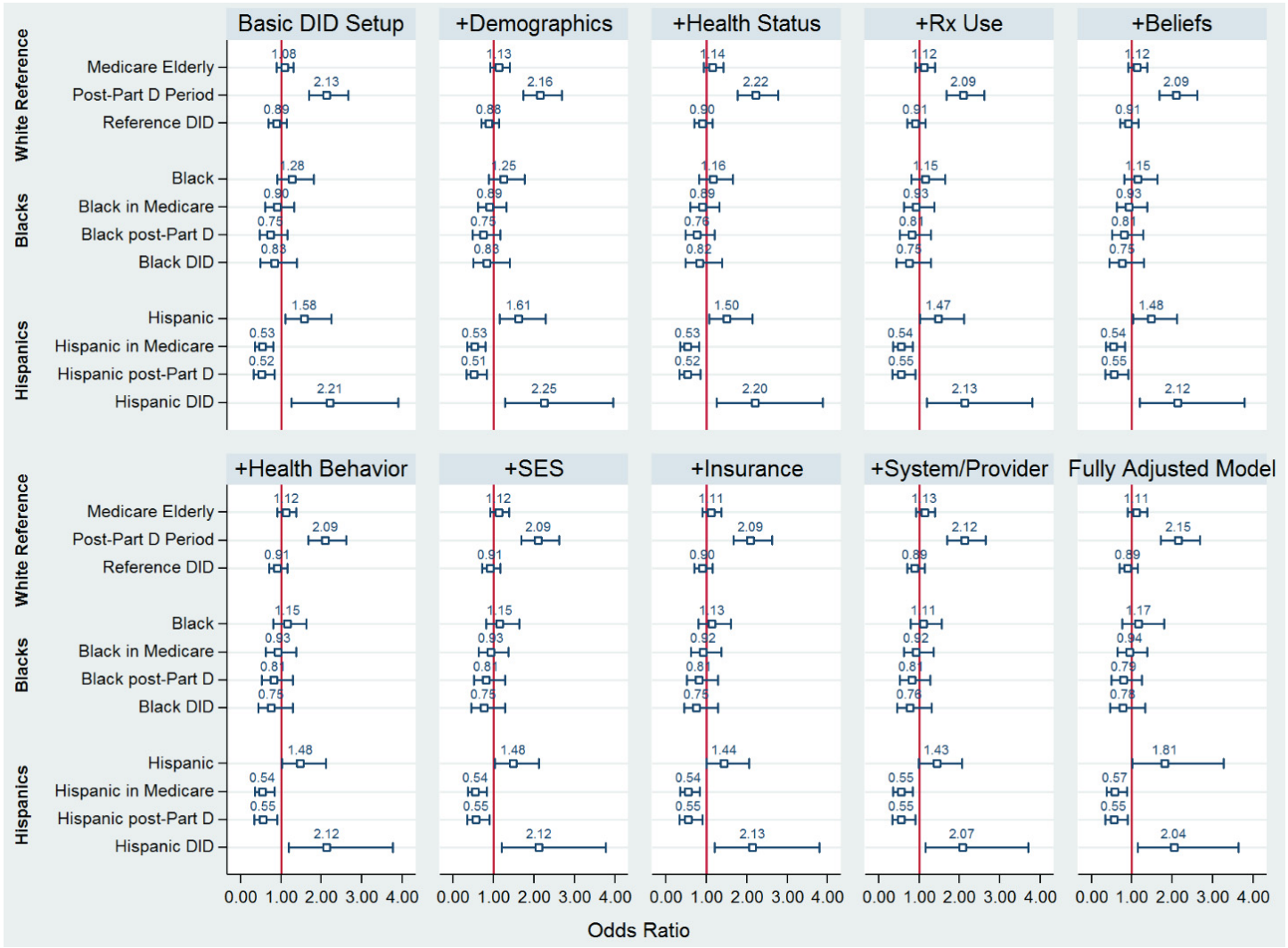

Figure A-1. Sequential adjustment for covariates and the magnitude of the difference-in-differences coefficients
DID: Difference-in-Differences. All analyses were conducted in the main sample (n=17,677), excluding 2006 data.

Table A-3. Multivariable logistic regression results in the main sample and by subgroup

Covariate	Main Analysis	2006 Analysis	Medicare 65-70 Tx Group	Men	Women	Non-Dual	Dual Eligibles
				Odds Ratio [95%CI]			
Difference-in-Difference Setup							
Treated Group (Medicare Seniors)	1.11 [0.90,1.38]	1.13 [0.92,1.39]	0.95 [0.70,1.28]	1.12 [0.83,1.51]	1.08 [0.84,1.41]	1.08 [0.87,1.36]	1.86 [0.87,3.96]
Post-Part D Period	2.15 [1.71,2.69]‡	1.80 [1.44,2.24]‡	2.09 [1.66,2.63]‡	2.70 [1.93,3.77]‡	1.76 [1.35,2.29]‡	2.12 [1.68,2.68]‡	2.53 [1.05,6.13]†
Medicare Post Part D	0.89 [0.70,1.14]	0.89 [0.70,1.14]	1.09 [0.82,1.46]	0.89 [0.62,1.27]	0.95 [0.71,1.28]	0.91 [0.70,1.18]	0.71 [0.27,1.86]
Black	0.97 [0.18,5.09]	1.34 [0.26,6.78]	1.28 [0.10,15.87]	0.60 [0.05,8.02]	1.11 [0.60,2.03]	3.27 [0.29,36.74]	0.62 [0.06,6.25]
Black in Medicare	0.94 [0.64,1.39]	0.93 [0.63,1.37]	0.87 [0.54,1.41]	1.12 [0.64,1.97]	0.85 [0.50,1.46]	1.08 [0.66,1.76]	0.37 [0.14,0.99]†
Black Post-Part D	0.79 [0.50,1.24]	0.74 [0.48,1.14]	0.80 [0.50,1.27]	1.04 [0.46,2.36]	0.64 [0.36,1.13]	0.89 [0.51,1.53]	0.35 [0.10,1.22]*
Black in Medicare Post-Part D	***0.78 [0.45,1.33]***	***0.91 [0.56,1.49]***	***0.78 [0.41,1.47]***	***0.42 [0.18,0.96]†***	***1.17 [0.60,2.29]***	***0.64 [0.33,1.25]***	***2.06 [0.53,8.03]***
Hispanic	1.35 [0.62,2.95]	1.69 [0.77,3.69]	1.13 [0.46,2.80]	0.97 [0.23,4.13]	1.20 [0.42,3.41]	1.38 [0.43,4.49]	2.26 [0.28,18.40]
Hispanic in Medicare	0.57 [0.37,0.88]†	0.56 [0.36,0.86]‡	0.76 [0.46,1.25]	0.47 [0.19,1.17]	0.64 [0.39,1.05]*	0.52 [0.32,0.87]†	0.45 [0.15,1.34]
Hispanic Post-Part D	0.55 [0.34,0.90]†	0.54 [0.33,0.87]†	0.54 [0.33,0.89]†	0.55 [0.20,1.50]	0.57 [0.32,1.01]*	0.68 [0.38,1.22]	0.31 [0.09,1.10]*
Hispanic in Medicare Post-Part D	***2.04 [1.14,3.63]†***	***2.04 [1.17,3.55]†***	***1.34 [0.66,2.76]***	***2.44 [0.81,7.32]***	***1.88 [0.94,3.75]****	***1.83 [0.93,3.63]****	***3.03 [0.75,12.25]***

Table A-3. (Continued)

Covariate	Main Analysis	2006 Analysis	Medicare 65-70 Tx Group	Men	Women	Non-Dual	Dual Eligibles
Demographics							
Age	0.99 [0.99,1.00]*	0.99 [0.98,1.00]‡	1.00 [0.96,1.05]	0.99 [0.98,1.01]	0.99 [0.98,1.00]	0.99 [0.98,1.00]*	1.00 [0.98,1.02]
Female gender	1.05 [0.96,1.14]	1.05 [0.97,1.14]	1.02 [0.89,1.16]	N/A	N/A	1.06 [0.97,1.16]	0.93 [0.70,1.23]
Married	0.94 [0.86,1.03]	0.92 [0.84,1.00]†	1.00 [0.87,1.15]	1.02 [0.88,1.18]	0.90 [0.81,1.01]*	0.94 [0.85,1.04]	1.01 [0.71,1.42]
Urban Residence	1.07 [0.95,1.20]	1.04 [0.93,1.16]	1.18 [0.99,1.41]*	1.01 [0.85,1.19]	1.11 [0.96,1.27]	1.08 [0.95,1.22]	0.89 [0.66,1.21]
Census Region							
Midwest	1.23 [1.07,1.41]‡	1.20 [1.05,1.37]‡	1.29 [1.05,1.57]†	1.31 [1.06,1.61]†	1.20 [1.02,1.41]†	1.25 [1.08,1.44]‡	1.02 [0.70,1.46]
South	1.04 [0.91,1.18]	1.03 [0.91,1.17]	1.07 [0.89,1.30]	1.13 [0.93,1.37]	0.98 [0.84,1.15]	1.04 [0.91,1.20]	0.91 [0.64,1.30]
West	1.02 [0.88,1.18]	1.01 [0.87,1.16]	1.09 [0.87,1.37]	1.09 [0.89,1.34]	0.97 [0.80,1.18]	1.04 [0.89,1.21]	0.86 [0.59,1.27]
Self-Reported Health							
Very Good	1.01 [0.89,1.15]	1.02 [0.90,1.15]	0.98 [0.80,1.21]	1.11 [0.89,1.37]	0.97 [0.82,1.14]	0.99 [0.86,1.13]	2.07 [1.07,3.97]†
Good	0.95 [0.83,1.09]	0.95 [0.83,1.08]	0.87 [0.70,1.07]	0.90 [0.74,1.11]	0.99 [0.84,1.17]	0.94 [0.81,1.08]	1.40 [0.75,2.61]
Fair	1.01 [0.86,1.19]	1.00 [0.86,1.16]	0.96 [0.74,1.25]	1.04 [0.82,1.33]	1.01 [0.83,1.22]	1.01 [0.85,1.20]	1.38 [0.74,2.57]
Poor	1.06 [0.87,1.29]	1.05 [0.88,1.26]	1.00 [0.73,1.36]	1.32 [0.97,1.80]*	0.94 [0.74,1.21]	1.10 [0.89,1.37]	1.19 [0.59,2.37]

Table A-3. (Continued)

Covariate	Main Analysis	2006 Analysis	Medicare 65-70 Tx Group	Men	Women	Non-Dual	Dual Eligibles
Any Physical Limitation	1.07 [0.98,1.17]	1.06 [0.98,1.15]	1.01 [0.88,1.16]	1.06 [0.92,1.22]	1.07 [0.95,1.20]	1.07 [0.98,1.18]	1.06 [0.74,1.52]
Any Cognitive Limitation	1.14 [0.99,1.31]*	1.11 [0.97,1.26]	1.14 [0.85,1.55]	1.10 [0.88,1.38]	1.17 [0.98,1.39]*	1.14 [0.96,1.34]	1.15 [0.84,1.57]
Conditions (over survey year)							
Charlson Score Q3	0.85 [0.77,0.93]‡	0.89 [0.82,0.97]‡	0.83 [0.72,0.96]†	0.82 [0.71,0.95]‡	0.87 [0.78,0.98]†	0.84 [0.76,0.93]‡	0.90 [0.68,1.19]
Charlson Score Q4	0.82 [0.70,0.97]†	0.89 [0.76,1.03]	0.83 [0.65,1.04]	0.77 [0.60,0.98]†	0.89 [0.73,1.08]	0.77 [0.64,0.91]‡	1.20 [0.80,1.79]
Comorbidity Count	0.96 [0.94,0.97]‡	0.96 [0.95,0.97]‡	0.96 [0.94,0.99]‡	0.94 [0.91,0.96]‡	0.97 [0.95,0.99]‡	0.95 [0.94,0.97]‡	0.97 [0.93,1.02]
Hypertension	1.47 [1.30,1.65]‡	1.48 [1.32,1.66]‡	1.55 [1.26,1.90]‡	1.41 [1.19,1.68]‡	1.51 [1.27,1.79]‡	1.45 [1.28,1.65]‡	1.84 [1.18,2.88]‡
Lipidemia	1.03 [0.94,1.13]	1.03 [0.95,1.12]	1.13 [0.97,1.31]	1.02 [0.88,1.18]	1.02 [0.91,1.14]	1.02 [0.93,1.13]	1.08 [0.80,1.45]
Angina/CHD	1.05 [0.94,1.17]	1.16 [1.05,1.30]‡	1.06 [0.88,1.29]	1.14 [0.97,1.35]	0.94 [0.80,1.11]	1.07 [0.95,1.20]	0.94 [0.66,1.33]
CHF	1.20 [0.98,1.48]*	1.15 [0.95,1.40]	1.57 [1.03,2.39]†	1.22 [0.89,1.66]	1.20 [0.91,1.58]	1.18 [0.95,1.47]	1.39 [0.85,2.26]
AMI	0.92 [0.77,1.10]	0.99 [0.83,1.17]	1.15 [0.84,1.57]	0.86 [0.68,1.09]	0.96 [0.72,1.28]	0.93 [0.76,1.12]	0.92 [0.55,1.53]
Stroke	0.87 [0.72,1.06]	0.90 [0.75,1.08]	0.72 [0.52,1.00]*	0.94 [0.70,1.27]	0.84 [0.66,1.07]	0.89 [0.72,1.10]	0.82 [0.51,1.31]
Depression	1.04 [0.91,1.19]	1.06 [0.93,1.20]	0.94 [0.76,1.15]	1.18 [0.90,1.53]	0.98 [0.84,1.14]	1.05 [0.91,1.22]	0.94 [0.67,1.31]

Table A-3. (Continued)

Covariate	Main Analysis	2006 Analysis	Medicare 65-70 Tx Group	Men	Women	Non-Dual	Dual Eligibles
Beliefs & Behaviors							
More Likely to Take Risks	0.94 [0.85,1.05]	0.94 [0.85,1.05]	0.92 [0.79,1.07]	0.94 [0.80,1.10]	0.94 [0.81,1.10]	0.94 [0.83,1.06]	1.01 [0.72,1.41]
Do Not Need Insurance	0.96 [0.78,1.18]	0.90 [0.74,1.09]	0.96 [0.66,1.39]	1.03 [0.74,1.42]	0.92 [0.69,1.23]	1.00 [0.80,1.25]	0.67 [0.39,1.15]
Can Overcome Illness without Medical Care	1.03 [0.91,1.17]	1.05 [0.93,1.18]	1.09 [0.91,1.30]	1.03 [0.84,1.27]	1.04 [0.88,1.23]	1.03 [0.90,1.18]	0.95 [0.65,1.40]
Currently Smoking	0.99 [0.87,1.13]	1.00 [0.89,1.13]	1.08 [0.92,1.28]	0.98 [0.80,1.19]	0.99 [0.84,1.17]	0.99 [0.86,1.14]	0.95 [0.68,1.33]
Moderate/Vigorous Exercise	1.03 [0.95,1.12]	1.01 [0.93,1.10]	0.99 [0.87,1.11]	1.18 [1.02,1.35]†	0.94 [0.84,1.04]	1.03 [0.94,1.12]	0.97 [0.73,1.29]
Socioeconomic Status & Insurance							
Income: Poor	1.06 [0.92,1.22]	1.06 [0.93,1.21]	1.21 [0.95,1.53]	1.14 [0.91,1.45]	1.04 [0.87,1.24]	0.98 [0.84,1.15]	1.60 [0.65,3.92]
Low-Income	1.06 [0.92,1.23]	1.04 [0.91,1.19]	1.04 [0.82,1.32]	1.05 [0.84,1.32]	1.04 [0.87,1.26]	1.07 [0.92,1.23]	1.06 [0.41,2.75]
Middle-Income	1.02 [0.93,1.13]	1.01 [0.92,1.11]	1.06 [0.90,1.25]	0.98 [0.84,1.15]	1.05 [0.92,1.20]	1.01 [0.92,1.12]	1.57 [0.60,4.10]
Education: Less than High School	1.14 [1.00,1.30]*	1.11 [0.98,1.26]*	1.10 [0.89,1.36]	1.25 [1.01,1.54]†	1.06 [0.88,1.27]	1.15 [1.00,1.33]*	0.84 [0.43,1.62]
High School Diploma	1.05 [0.95,1.16]	1.04 [0.95,1.15]	1.04 [0.89,1.21]	1.04 [0.89,1.23]	1.04 [0.90,1.20]	1.05 [0.94,1.16]	1.01 [0.48,2.12]
Language: Interview in English	0.78 [0.46,1.32]	0.94 [0.54,1.61]	0.63 [0.34,1.18]	0.35 [0.14,0.87]†	1.26 [0.60,2.64]	0.76 [0.30,1.94]	1.15 [0.65,2.02]

Table A-3. (Continued)

Covariate	Main Analysis	2006 Analysis	Medicare 65-70 Tx Group	Men	Women	Non-Dual	Dual Eligibles
Insurance: Medicaid	1.00 [0.86,1.16]	0.97 [0.84,1.11]	0.95 [0.76,1.20]	1.06 [0.82,1.37]	0.98 [0.83,1.15]	N/A	N/A
Private, Non-HMO	0.96 [0.87,1.05]	0.90 [0.83,0.99]†	1.00 [0.86,1.17]	0.94 [0.82,1.07]	0.97 [0.85,1.10]	0.97 [0.88,1.06]	0.81 [0.36,1.81]
Private, HMO	0.98 [0.85,1.13]	0.94 [0.82,1.08]	1.00 [0.82,1.22]	0.98 [0.81,1.20]	1.00 [0.83,1.19]	0.99 [0.85,1.14]	0.32 [0.13,0.78]†
Healthcare Use (over survey year)							
Concurrently Taken Drugs							
2-3 CV Drugs	0.58 [0.52,0.64]‡	0.58 [0.53,0.63]‡	0.58 [0.50,0.68]‡	0.58 [0.50,0.68]‡	0.57 [0.50,0.64]‡	0.58 [0.52,0.64]‡	0.51 [0.37,0.70]‡
≥4 CV Drugs	0.41 [0.34,0.50]‡	0.40 [0.34,0.48]‡	0.41 [0.29,0.58]‡	0.36 [0.27,0.47]‡	0.46 [0.36,0.60]‡	0.39 [0.32,0.48]‡	0.57 [0.32,1.03]*
2-4 Other Drugs	1.66 [1.46,1.89]‡	1.63 [1.44,1.84]‡	1.58 [1.31,1.91]‡	1.67 [1.38,2.01]‡	1.66 [1.39,1.99]‡	1.68 [1.47,1.92]‡	1.61 [1.00,2.59]†
≥5 Other Drugs	2.83 [2.41,3.33]‡	2.65 [2.28,3.09]‡	2.84 [2.19,3.68]‡	2.97 [2.33,3.79]‡	2.75 [2.22,3.40]‡	2.89 [2.42,3.45]‡	2.69 [1.62,4.47]‡
No. of Pharmacies Used	0.78 [0.72,0.84]‡	0.77 [0.71,0.83]‡	0.81 [0.72,0.90]‡	0.76 [0.67,0.85]‡	0.79 [0.72,0.88]‡	0.76 [0.70,0.83]‡	1.01 [0.77,1.33]
Had a Usual Source of Care	1.18 [0.93,1.51]	1.12 [0.89,1.41]	1.10 [0.77,1.56]	1.25 [0.91,1.73]	1.15 [0.82,1.60]	1.15 [0.89,1.50]	1.41 [0.79,2.53]
Quintiles of Ambulatory Physician Visits							
Q 2 (3-4 Visits)	1.03 [0.92,1.16]	1.00 [0.89,1.12]	1.03 [0.87,1.23]	1.02 [0.85,1.22]	1.05 [0.91,1.23]	1.06 [0.94,1.20]	0.78 [0.54,1.14]
Q 3 (5-7 Visits)	0.92 [0.80,1.05]	0.88 [0.77,1.00]†	0.92 [0.76,1.12]	0.95 [0.77,1.17]	0.91 [0.78,1.07]	0.94 [0.81,1.09]	0.79 [0.54,1.14]

Table A-3. (Continued)

Covariate	Main Analysis	2006 Analysis	Medicare 65-70 Tx Group	Men	Women	Non-Dual	Dual Eligibles
Q 4 (8-12 Visits)	0.91 [0.79,1.04]	0.86 [0.76,0.98]†	0.97 [0.80,1.18]	1.00 [0.81,1.24]	0.86 [0.72,1.02]*	0.93 [0.80,1.08]	0.75 [0.49,1.16]
Q 5 (≥13 Visits)	0.93 [0.80,1.07]	0.86 [0.75,0.99]†	1.06 [0.86,1.32]	0.94 [0.74,1.19]	0.93 [0.78,1.11]	0.97 [0.83,1.14]	0.72 [0.46,1.13]
Experience with Providers							
Always Listens	1.08 [0.86,1.34]	1.06 [0.87,1.29]	1.21 [0.85,1.72]	1.09 [0.77,1.54]	1.08 [0.81,1.43]	1.14 [0.89,1.45]	0.81 [0.45,1.46]
Always Explains	1.00 [0.83,1.19]	1.02 [0.86,1.21]	0.77 [0.57,1.05]	0.98 [0.73,1.33]	1.03 [0.80,1.34]	0.97 [0.79,1.18]	1.21 [0.73,2.00]
Always Respects	1.01 [0.81,1.25]	1.05 [0.86,1.27]	1.26 [0.92,1.73]	0.95 [0.67,1.35]	1.04 [0.78,1.39]	1.00 [0.79,1.28]	0.98 [0.56,1.73]
Satisfied with Healthcare	1.08 [0.92,1.26]	1.09 [0.94,1.26]	1.02 [0.81,1.28]	1.03 [0.79,1.34]	1.08 [0.90,1.30]	1.06 [0.90,1.26]	1.13 [0.76,1.69]
Very Satisfied with Healthcare	1.02 [0.87,1.19]	1.03 [0.88,1.20]	1.01 [0.79,1.29]	0.95 [0.72,1.25]	1.04 [0.87,1.25]	1.02 [0.86,1.22]	0.91 [0.62,1.34]
H-L GOF P Value	0.7	0.93	0.97	0.83	0.39	0.79	0.88
Sample Size	17,677	19,919	7,447	7,180	10,495	15,012	2,665
Weighted Population	24,915,354	24,801,597	10,757,736	10,688,687	14,225,567	22,746,778	2,168,576

*P <0.1 † P<0.05 ǂ P<0.01

Estimates were also adjusted for interactions terms of black and Hispanic indicators with income and education levels. CV: Cardiovascular; Q: Quartile; CHD: Coronary Heart Disease; CHF: Congestive Heart Failure; AMI: Acute Myocardial Infarction; HMO: Health Maintenance Organization; H-L GOF: Hosmer-Lemeshow Goodness-of-Fit test (modified for survey data).

Table A-4. Multivariable logistic regressions of adherence to each cardiovascular medication class

Covariate	ACEIs/ARBs	Statins	Beta Blockers	Ca Channel Blockers	Diuretics
			Odds Ratio[95%CI]		
Difference-in-Difference Setup					
Treated Group (Medicare Senior)	1.11 [0.87,1.43]	0.94 [0.69,1.29]	1.12 [0.77,1.62]	1.15 [0.75,1.78]	1.06 [0.78,1.46]
Post-Part D Period	1.99 [1.51,2.62]***	2.29 [1.68,3.13]***	1.37 [0.95,1.98]*	1.71 [1.06,2.76]**	1.56 [1.08,2.24]**
Medicare Post Part D	0.84 [0.62,1.15]	1.06 [0.75,1.50]	1.02 [0.68,1.53]	0.83 [0.49,1.40]	0.85 [0.57,1.26]
Black	1.64 [0.17,15.64]	0.68 [0.04,10.48]	0.56 [0.27,1.14]	1.33 [0.62,2.88]	1.53 [0.11,21.47]
Black in Medicare	0.83 [0.51,1.35]	1.79 [1.00,3.20]**	1.14 [0.57,2.28]	0.71 [0.34,1.51]	1.36 [0.78,2.40]
Black Post-Part D	0.77 [0.42,1.43]	1.21 [0.64,2.27]	1.49 [0.67,3.32]	1.06 [0.43,2.62]	1.22 [0.62,2.40]
Black in Medicare Post-Part D	***0.98 [0.51,1.86]***	***0.50 [0.23,1.08]****	***0.49 [0.19,1.23]***	***0.99 [0.35,2.80]***	***0.56 [0.27,1.18]***
Hispanic	1.80 [0.63,5.16]	2.00 [0.19,20.82]	1.18 [0.32,4.33]	2.85 [0.55,14.88]	0.95 [0.19,4.88]
Hispanic in Medicare	0.66 [0.37,1.18]	0.50 [0.21,1.19]	0.59 [0.27,1.33]	0.43 [0.18,0.99]**	0.45 [0.21,0.99]**
Hispanic Post-Part D	0.67 [0.34,1.35]	0.61 [0.26,1.44]	0.40 [0.16,1.00]*	0.90 [0.33,2.46]	0.68 [0.28,1.67]
Hispanic in Medicare Post-Part D	***1.59 [0.74,3.43]***	***2.30 [0.83,6.32]***	***3.35 [1.21,9.28]****	***1.06 [0.35,3.23]***	***1.76 [0.65,4.81]***

Table A-4. (Continued)

Covariate	ACEIs/ARBs	Statins	Beta Blockers	Ca Channel Blockers	Diuretics
Demographics					
Age	1.00 [0.99,1.01]	1.00 [0.99,1.01]	0.99 [0.98,1.00]*	0.99 [0.98,1.01]	0.99 [0.98,1.00]
Female gender	1.02 [0.91,1.13]	1.02 [0.90,1.15]	1.11 [0.98,1.26]	1.13 [0.95,1.35]	0.95 [0.83,1.09]
Married	0.93 [0.83,1.04]	0.97 [0.85,1.10]	0.98 [0.85,1.14]	0.87 [0.74,1.03]	0.92 [0.80,1.05]
MSA residence	0.98 [0.86,1.12]	1.07 [0.92,1.25]	0.94 [0.81,1.09]	0.97 [0.79,1.20]	1.11 [0.95,1.29]
Census Region					
Midwest	1.18 [1.01,1.39]**	1.16 [0.95,1.42]	1.13 [0.94,1.36]	1.26 [0.98,1.62]*	1.30 [1.08,1.57]***
South	0.93 [0.80,1.09]	0.96 [0.81,1.15]	1.10 [0.92,1.32]	1.17 [0.93,1.47]	1.04 [0.89,1.23]
West	1.01 [0.84,1.22]	0.94 [0.79,1.12]	1.02 [0.84,1.25]	1.03 [0.80,1.33]	1.03 [0.85,1.25]
Self-Reported Health					
Very Good	1.09 [0.90,1.32]	1.11 [0.92,1.35]	1.10 [0.89,1.35]	1.03 [0.76,1.39]	0.96 [0.78,1.17]
Good	1.10 [0.92,1.31]	0.97 [0.80,1.16]	1.02 [0.81,1.28]	0.98 [0.73,1.32]	1.01 [0.83,1.24]
Fair	1.18 [0.96,1.44]	1.08 [0.88,1.33]	1.03 [0.81,1.32]	0.96 [0.69,1.33]	0.98 [0.78,1.23]
Poor	1.19 [0.93,1.52]	1.03 [0.75,1.41]	1.00 [0.75,1.33]	1.14 [0.75,1.74]	0.93 [0.68,1.27]

Table A-4. (Continued)

Covariate	ACEIs/ARBs	Statins	Beta Blockers	Ca Channel Blockers	Diuretics
Any Physical Limitation	0.97 [0.87,1.09]	1.11 [0.98,1.26]*	1.12 [0.97,1.28]	1.21 [1.02,1.44]**	1.01 [0.88,1.16]
Any Cognitive Limitation	1.08 [0.90,1.29]	1.09 [0.88,1.34]	1.14 [0.92,1.42]	1.07 [0.83,1.39]	1.15 [0.93,1.42]
Conditions (over survey year)					
Condition Count	0.96 [0.94,0.98]***	0.97 [0.94,0.99]***	0.98 [0.96,1.01]	0.98 [0.95,1.01]	0.96 [0.94,0.99]***
Charlson Comorbidity Score Q3	0.90 [0.79,1.02]*	0.84 [0.73,0.96]***	0.83 [0.72,0.95]***	0.81 [0.69,0.96]**	0.79 [0.69,0.91]***
Charlson Comorbidity Score Q4	0.94 [0.77,1.14]	0.82 [0.66,1.01]*	0.82 [0.64,1.04]*	0.66 [0.49,0.89]***	0.99 [0.79,1.24]
Hypertension	1.49 [1.12,1.97]***	1.19 [0.99,1.44]*	1.54 [1.20,1.96]***	1.22 [0.79,1.90]	1.29 [0.94,1.77]
Lipidemia	1.02 [0.92,1.13]	1.79 [1.31,2.44]***	1.05 [0.91,1.20]	0.96 [0.81,1.14]	1.01 [0.88,1.15]
Angina/CHD	1.05 [0.90,1.22]	1.08 [0.94,1.25]	1.18 [1.00,1.40]*	1.35 [1.05,1.73]**	1.09 [0.91,1.31]
CHF	1.17 [0.92,1.48]	1.04 [0.75,1.44]	1.38 [1.04,1.83]**	0.86 [0.56,1.32]	1.12 [0.89,1.42]
AMI	0.78 [0.63,0.96]**	0.97 [0.77,1.21]	0.91 [0.74,1.10]	1.09 [0.76,1.55]	0.98 [0.75,1.27]
Stroke	0.87 [0.68,1.12]	0.98 [0.76,1.27]	1.00 [0.75,1.35]	0.96 [0.68,1.36]	0.82 [0.61,1.11]

Table A-4. (Continued)

Covariate	ACEIs/ARBs	Statins	Beta Blockers	Ca Channel Blockers	Diuretics
Depression	0.93 [0.78,1.10]	1.24 [1.04,1.48]**	0.94 [0.77,1.15]	0.97 [0.72,1.29]	1.01 [0.81,1.27]
Beliefs & Behaviors					
More Likely to Take Risks	0.91 [0.79,1.06]	1.03 [0.88,1.21]	1.04 [0.86,1.24]	0.92 [0.74,1.16]	0.91 [0.77,1.07]
Do Not Need Insurance	1.04 [0.80,1.36]	0.85 [0.62,1.17]	0.83 [0.60,1.15]	0.82 [0.52,1.30]	1.15 [0.84,1.57]
Can Overcome Illness without Medical Care	1.05 [0.89,1.24]	0.97 [0.80,1.17]	1.14 [0.93,1.40]	1.27 [0.94,1.70]	0.93 [0.76,1.13]
Currently Smoking	1.13 [0.95,1.34]	1.03 [0.86,1.23]	1.03 [0.84,1.26]	1.12 [0.85,1.47]	0.97 [0.79,1.18]
Moderate/Vigorous Physical Activity	0.96 [0.86,1.07]	1.10 [0.98,1.23]*	0.99 [0.85,1.15]	1.01 [0.86,1.19]	1.08 [0.96,1.21]
Socioeconomic Status & Insurance					
Income: Poor	1.09 [0.90,1.32]	1.09 [0.91,1.32]	1.05 [0.83,1.33]	1.01 [0.74,1.38]	0.98 [0.78,1.22]
Low-Income	0.95 [0.80,1.14]	1.03 [0.85,1.24]	1.08 [0.87,1.34]	1.04 [0.79,1.36]	1.15 [0.91,1.46]
Middle-Income	1.00 [0.87,1.16]	1.02 [0.88,1.19]	1.12 [0.94,1.33]	1.02 [0.82,1.27]	1.07 [0.91,1.26]
Education: Less than High School	1.12 [0.93,1.34]	1.23 [1.02,1.48]**	1.06 [0.84,1.33]	1.26 [0.95,1.67]	1.07 [0.87,1.31]

Table A-4. (Continued)

Covariate	ACEIs/ARBs	Statins	Beta Blockers	Ca Channel Blockers	Diuretics
High School Diploma	1.11 [0.97,1.28]	1.05 [0.91,1.21]	1.04 [0.86,1.25]	1.06 [0.85,1.32]	0.98 [0.82,1.16]
Language: Interview in English	0.84 [0.40,1.79]	0.86 [0.11,6.60]	0.72 [0.31,1.68]	0.85 [0.28,2.57]	1.30 [0.42,4.00]
Insurance: Received Medicaid	1.01 [0.84,1.21]	1.08 [0.87,1.36]	0.97 [0.78,1.22]	1.07 [0.81,1.42]	1.03 [0.83,1.28]
Had Private Non-HMO Coverage	1.03 [0.91,1.16]	1.04 [0.92,1.18]	0.92 [0.79,1.07]	1.02 [0.84,1.24]	0.95 [0.82,1.11]
Had Private HMO Coverage	1.00 [0.84,1.20]	1.12 [0.94,1.35]	1.06 [0.85,1.33]	1.12 [0.86,1.47]	0.90 [0.74,1.10]
Use of Healthcare (over survey year)					
Concurrently Taken Drugs					
2-3 CV Drugs	0.90 [0.78,1.04]	0.90 [0.74,1.09]	1.01 [0.86,1.20]	0.70 [0.57,0.86]***	0.77 [0.65,0.92]***
≥4 CV Drugs	0.79 [0.64,0.98]**	0.81 [0.63,1.04]	0.96 [0.74,1.23]	0.50 [0.37,0.68]***	0.69 [0.55,0.87]***
2-4 Other Drugs	1.65 [1.35,2.01]***	1.82 [1.46,2.27]***	1.02 [0.80,1.31]	1.92 [1.44,2.57]***	1.60 [1.29,1.99]***
≥5 Other Drugs	2.87 [2.25,3.66]***	2.96 [2.29,3.81]***	1.47 [1.10,1.98]**	2.94 [2.10,4.13]***	2.56 [2.01,3.27]***
Number of Pharmacies Used	0.75 [0.68,0.83]***	0.84 [0.76,0.93]***	0.73 [0.64,0.82]***	0.69 [0.59,0.81]***	0.76 [0.68,0.86]***
Had a Usual Source of Care	1.09 [0.79,1.50]	0.99 [0.72,1.36]	1.30 [0.90,1.87]	1.07 [0.64,1.81]	1.04 [0.73,1.48]

Table A-4. (Continued)

Covariate	ACEIs/ARBs	Statins	Beta Blockers	Ca Channel Blockers	Diuretics
Quintiles of Ambulatory Physician Visits					
Q 2 (3-4 Visits)	0.87 [0.74,1.02]*	1.09 [0.92,1.30]	0.91 [0.74,1.12]	1.03 [0.80,1.32]	1.04 [0.86,1.26]
Q 3 (5-7 Visits)	0.93 [0.78,1.11]	1.03 [0.87,1.23]	0.85 [0.69,1.05]	0.91 [0.71,1.18]	0.96 [0.80,1.16]
Q 4 (8-12 Visits)	0.92 [0.77,1.10]	1.07 [0.89,1.29]	0.94 [0.75,1.17]	1.03 [0.78,1.37]	0.86 [0.71,1.05]
Q 5 (≥13 Visits)	0.86 [0.71,1.04]	0.99 [0.80,1.24]	0.85 [0.67,1.08]	0.84 [0.63,1.11]	0.96 [0.77,1.20]
Experience with Providers					
Always Listens	0.98 [0.73,1.31]	1.06 [0.78,1.45]	1.15 [0.80,1.65]	1.13 [0.73,1.75]	0.80 [0.56,1.15]
Always Explains Care	1.29 [1.00,1.67]**	1.08 [0.82,1.42]	1.00 [0.75,1.34]	0.82 [0.57,1.17]	0.93 [0.67,1.28]
Always Respects:	0.90 [0.68,1.18]	1.12 [0.82,1.54]	0.97 [0.69,1.37]	1.24 [0.82,1.88]	1.07 [0.76,1.52]
Satisfied with Healthcare Received	1.00 [0.80,1.24]	0.98 [0.78,1.23]	0.96 [0.76,1.23]	1.14 [0.84,1.56]	1.27 [1.02,1.58]**
Very Satisfied with Healthcare	0.97 [0.79,1.21]	0.91 [0.72,1.15]	0.98 [0.77,1.25]	1.18 [0.88,1.60]	1.22 [0.96,1.55]
H-L GOF P Value	0.95	1.00	0.88	0.89	0.44
Sample Size	9,917	8,851	6,535	4,649	7,228
Weighted Population	13,802,972	13,139,144	9,253,278	6,123,863	10,084,654

*P <0.1 † P<0.05 ǂ P<0.01

Estimates were also adjusted for interactions terms of black and Hispanic indicators with income and education levels. CV: Cardiovascular; Q: Quartile; CHD: Coronary Heart Disease; CHF: Congestive Heart Failure; AMI: Acute Myocardial Infarction; HMO: Health Maintenance Organization.

Table A-5. Effect of Part D on adherence disparities, and estimates of disparities among seniors in 2007-2010 by subgroup

Analysis	Sample Size	(1) Difference-in-Differences Effect				(2) Current Racial Disparities in Medicare (2007-10)			
		White-Black Disparities		White-Hispanic Disparities		White-Black Disparities		White-Hispanic Disparities	
Main Analysis	17,677	0.06	[-0.06,0.18]	-0.16	[-0.29,-0.03]†	0.08	[0.04,0.12]‡	0.01	[-0.04,0.05]
Main Analysis, including 2006	19,919	0.03	[-0.08,0.14]	-0.16	[-0.28,-0.03]†	0.06	[0.03,0.10]‡	0.02	[-0.03,0.06]
Medicare 65-70 Tx Group	7,447	0.06	[-0.08,0.20]	-0.09	[-0.25,0.08]	0.10	[0.05,0.16]‡	0.05	[-0.03,0.14]
Men	7,180	0.21	[0.03,0.38]†	-0.20	[-0.44,0.04]	0.11	[0.06,0.16]‡	-0.02	[-0.08,0.04]
Women	10,495	-0.04	[-0.19,0.12]	-0.14	[-0.29,0.01]*	0.07	[0.02,0.12]‡	0.03	[-0.03,0.09]
Non-Dual	15,012	0.10	[-0.05,0.25]	-0.13	[-0.29,0.03]	0.08	[0.03,0.12]‡	-0.02	[-0.08,0.04]
Dual Eligibles	2,665	-0.16	[-0.45,0.13]	-0.25	[-0.54,0.03]*	0.19	[0.09,0.28]‡	0.15	[0.04,0.26]‡
ACEIs/ARBS	9,917	0.01	[-0.14,0.16]	-0.09	[-0.27,0.09]	0.06	[0.01,0.11]†	-0.01	[-0.06,0.04]
Statins	8,851	0.15	[-0.02,0.33]*	-0.21	[-0.45,0.02]*	0.04	[-0.02,0.10]	-0.01	[-0.07,0.05]
Beta-Blockers	6,535	0.17	[-0.04,0.39]	-0.30	[-0.55,-0.06]†	0.08	[0.03,0.14]‡	-0.03	[-0.11,0.04]
Ca Channel Blockers	4,649	0.01	[-0.22,0.24]	0.00	[-0.25,0.26]	0.01	[-0.07,0.08]	0.05	[-0.05,0.15]
Diuretics	7,228	0.12	[-0.06,0.30]	-0.15	[-0.38,0.09]	0.08	[0.02,0.13]‡	0.02	[-0.05,0.10]

* P <0.1; † P<0.05; ǂ P<0.01

CI: confidence interval. ACEIs/ARBs: Angiotensin-Converting Enzyme Inhibitors/Angiotensin II Receptor Blockers. Estimates in Column (1) are the double differences between race-specific adherence margins, across time and treatment/control groups. Column (2) estimates are the differences between race-specific adherence margins among Medicare seniors in the post-Part D period only. All estimates are probability-scale predictions, and all were adjusted for health status and clinical need using the rank-and–replace procedure. Standard errors underlying confidence intervals were estimated via Taylor series linearization and combined across 5 multiply imputed datasets.

Table A-6. Sensitivity of results to various definitions of adherence disparities

Disparity Definition		(1) Difference-in-Differences Effect				(2) Current Racial Disparities in Medicare (2007-10)			
		White-Black Disparities		White-Hispanic Disparities		White-Black Disparities		White-Hispanic Disparities	
		Estimate [95% CI]							
Unadjusted		0.05	[-0.07,0.17]	-0.18	[-0.31,-0.05]‡	0.08	[0.04,0.12]‡	0.01	[-0.04,0.05]
Adjusted	Demographics	0.06	[-0.06,0.18]	-0.16	[-0.29,-0.02]†	0.08	[0.04,0.12]‡	0.01	[-0.04,0.05]
	Demo+Health	0.06	[-0.06,0.18]	-0.16	[-0.29,-0.03]†	0.08	[0.04,0.12]‡	0.01	[-0.04,0.05]
	Demo+Health+Rx	0.06	[-0.06,0.18]	-0.16	[-0.29,-0.02]†	0.08	[0.04,0.12]‡	0.01	[-0.04,0.05]
	Demo+Geography+Health+Rx	0.06	[-0.06,0.18]	-0.15	[-0.28,-0.02]†	0.08	[0.04,0.12]‡	0.01	[-0.04,0.05]
	Main Analysis: Demo+Geo+Health+Rx+Beliefs	0.06	[-0.06,0.18]	-0.16	[-0.29,-0.03]†	0.08	[0.04,0.12]‡	0.01	[-0.04,0.05]
	Full Adjustment, RDE	0.06	[-0.06,0.18]	-0.15	[-0.28,-0.02]†	0.10	[0.06,0.15]‡	0.02	[-0.05,0.08]

* P <0.1; † P<0.05; ǂ P<0.01.
CI: confidence interval; RDE: residual direct effect (of race).
All analyses were conducted on the main sample (n=17,677, representing 24,915,354 treated and control individuals).
As in Table 2, demographics included age, gender, marital status, and urban residence. Health included self-reported health as well as diagnosed conditions. "Rx" included the number of other prescription drugs concurrently taken. Geography was represented by the Census Region. Unadjusted disparities (and difference-in-differences) were calculated as differences across race-specific adherence proportions. RDE disparities, were estimated directly from the main analysis using predictive margins. All other stages of adjustment were conducted using the rank-and-replace procedure prior to estimating race-specific, probability-scale predictions. Disparities were then the differences between these predictions (margins) Standard errors underlying confidence intervals were estimated via Taylor series linearization and combined across 5 multiply imputed datasets.

APPENDIX B. SUPPLEMENTAL MATERIALS FOR CHAPTER 3

Table B-1. Main unconditional quantile regression analyses of overall adherence

Characteristics (at baseline)	10th Q_{PDC}	20th Q_{PDC}	30th Q_{PDC}	40th Q_{PDC}	50th Q_{PDC}	60th Q_{PDC}	70th Q_{PDC}
	Coefficient [95% Confidence Interval]						
Black	-7.26 [-17.80,3.28]	-7.73 [-15.67,0.21]	**-9.05 [-14.32,-3.77]**	**-7.28 [-8.97,-5.59]**	**-5.55 [-7.60,-3.50]**	**-5.08 [-7.49,-2.67]**	**-3.28 [-4.29,-2.27]**
Hispanic	-2.09 [-5.44,1.26]	**-4.07 [-8.04,-0.10]**	-1.71 [-6.18,2.76]	**-1.40 [-2.48,-0.32]**	-1.98 [-5.42,1.47]	-1.12 [-3.48,1.24]	0.48 [-0.70,1.67]
Age 70-75	-2.62 [-6.52,1.29]	**-3.80 [-6.39,-1.22]**	**-4.91 [-7.99,-1.83]**	-3.56 [-7.65,0.53]	**-3.23 [-6.18,-0.29]**	**-4.24 [-5.74,-2.74]**	-1.37 [-4.41,1.67]
Age 75-80	**-10.47 [-17.37,-3.57]**	**-8.44 [-11.55,-5.34]**	**-4.77 [-7.00,-2.53]**	-3.43 [-7.22,0.35]	-2.82 [-7.15,1.51]	**-5.75 [-9.78,-1.72]**	**-3.42 [-5.24,-1.59]**
Age ≥ 80	-5.61 [-19.70,8.49]	-4.99 [-14.44,4.46]	-4.75 [-12.21,2.71]	-5.40 [-14.12,3.32]	-6.44 [-14.92,2.05]	**-6.62 [-12.67,-0.57]**	-3.63 [-7.92,0.67]
Female	1.82 [-2.88,6.51]	1.05 [-7.90,9.99]	-0.07 [-4.50,4.36]	-0.39 [-2.14,1.35]	1.72 [-1.42,4.85]	1.27 [-0.17,2.70]	0.41 [-0.67,1.49]
Married	-0.55 [-8.18,7.08]	-5.30 [-13.63,3.02]	-6.66 [-13.32,0.00]	-4.47 [-11.86,2.91]	-3.77 [-9.35,1.80]	**-2.46 [-4.33,-0.59]**	**-1.99 [-2.59,-1.38]**
Urban Residence	-2.54 [-16.51,11.44]	-0.50 [-8.20,7.20]	-0.80 [-10.41,8.81]	-1.55 [-16.55,13.44]	-0.79 [-18.09,16.50]	-0.74 [-21.57,20.09]	0.73 [-15.17,16.63]
Census Region: Midwest	2.25 [-6.62,11.12]	2.21 [-5.54,9.96]	3.82 [-1.47,9.11]	**2.26 [0.26,4.27]**	**4.02 [1.53,6.52]**	1.62 [-0.36,3.60]	0.94 [-2.22,4.09]
South	-4.69 [-12.32,2.94]	-2.22 [-8.00,3.57]	-2.80 [-7.75,2.15]	**-2.41 [-4.30,-0.52]**	**-2.15 [-3.30,-1.00]**	-2.00 [-5.23,1.23]	-0.18 [-2.43,2.06]
West	**-4.09 [-7.76,-0.42]**	-1.23 [-4.11,1.64]	0.79 [-1.65,3.22]	0.75 [-2.33,3.84]	1.47 [-0.11,3.05]	1.57 [-2.73,5.87]	1.06 [-3.26,5.37]
Health Status: Very Good	**6.18 [1.60,10.75]**	**6.16 [2.88,9.44]**	**4.87 [1.79,7.94]**	**5.76 [1.37,10.15]**	**6.18 [2.49,9.86]**	4.69 [-0.92,10.30]	2.65 [-0.07,5.36]

Table B-1. (Continued)

Characteristics (at baseline)	10th Q_{PDC}	20th Q_{PDC}	30th Q_{PDC}	40th Q_{PDC}	50th Q_{PDC}	60th Q_{PDC}	70th Q_{PDC}
Good	2.47 [-7.01,11.96]	**6.38 [1.06,11.71]**	4.51 [-1.93,10.94]	5.55 [-1.54,12.65]	4.09 [-3.42,11.61]	2.34 [-6.61,11.30]	0.85 [-3.33,5.03]
Fair	**6.47 [0.27,12.66]**	**9.40 [6.61,12.18]**	**7.47 [3.07,11.87]**	**7.25 [1.35,13.16]**	5.89 [-0.63,12.40]	5.17 [-3.68,14.02]	2.34 [-3.09,7.77]
Poor	3.45 [-1.35,8.25]	2.26 [-2.58,7.09]	0.85 [-5.89,7.59]	-0.62 [-9.46,8.21]	-1.96 [-12.98,9.06]	-1.03 [-10.51,8.44]	-2.40 [-9.55,4.75]
Any Physical Limitation	1.32 [-5.75,8.39]	-1.46 [-6.24,3.32]	-0.25 [-1.68,1.18]	0.11 [-3.63,3.85]	0.50 [-3.61,4.62]	-0.00 [-4.17,4.16]	-0.14 [-2.49,2.20]
Any Cognitive Limitation	-6.10 [-17.12,4.93]	-1.48 [-13.39,10.42]	-1.86 [-10.93,7.21]	-0.68 [-9.27,7.92]	0.90 [-5.63,7.43]	-0.13 [-6.68,6.42]	-1.13 [-4.91,2.64]
Charlson Comorbidity Score Q3	-2.32 [-5.29,0.66]	**-2.33 [-4.17,-0.50]**	-0.44 [-4.96,4.09]	-0.40 [-4.67,3.87]	-1.24 [-6.67,4.20]	-1.92 [-7.05,3.21]	-0.51 [-3.12,2.11]
Charlson Comorbidity Score Q4	-1.23 [-7.94,5.48]	-2.07 [-13.74,9.61]	0.81 [-3.99,5.61]	1.35 [-0.20,2.90]	0.91 [-0.25,2.07]	-0.08 [-1.78,1.62]	-2.02 [-4.40,0.35]
Count of Comorbid Conditions	-0.93 [-2.10,0.25]	-0.85 [-2.13,0.43]	-0.99 [-2.07,0.09]	**-0.99 [-1.65,-0.33]**	**-1.12 [-1.92,-0.31]**	**-0.73 [-1.26,-0.21]**	-0.30 [-0.65,0.05]
Hypertension	6.06 [-1.52,13.64]	3.61 [-2.04,9.26]	4.55 [-2.28,11.38]	3.00 [-5.52,11.52]	2.47 [-5.86,10.80]	0.39 [-8.51,9.29]	-1.67 [-8.22,4.88]
Hyperlipidemia	2.01 [-3.18,7.21]	0.86 [-1.43,3.15]	0.61 [-0.76,1.98]	-0.27 [-3.95,3.40]	0.94 [-0.44,2.31]	-0.77 [-1.78,0.24]	**-1.27 [-2.44,-0.10]**
Angina/CHD	1.54 [-4.93,8.01]	2.54 [-0.69,5.77]	5.21 [-2.86,13.27]	3.21 [-3.30,9.73]	3.49 [-2.23,9.20]	2.17 [-1.39,5.72]	1.32 [-0.47,3.10]
CHF	3.15 [-5.30,11.59]	5.23 [-3.18,13.63]	1.04 [-12.90,14.98]	-0.84 [-9.83,8.14]	1.59 [-1.28,4.46]	2.62 [-1.16,6.41]	0.56 [-0.75,1.88]

Table B-1. (Continued)

Characteristics (at baseline)	10th Q_{PDC}	20th Q_{PDC}	30th Q_{PDC}	40th Q_{PDC}	50th Q_{PDC}	60th Q_{PDC}	70th Q_{PDC}
AMI	2.29 [-7.30,11.88]	0.61 [-8.62,9.83]	-2.67 [-26.58,21.25]	0.14 [-13.40,13.67]	-1.72 [-10.71,7.27]	-2.37 [-9.10,4.37]	-0.07 [-3.56,3.43]
Stroke	0.23 [-8.91,9.37]	0.02 [-14.07,14.10]	**-2.51 [-5.00,-0.01]**	-1.53 [-4.01,0.95]	-2.64 [-6.71,1.43]	0.95 [-6.51,8.40]	-0.64 [-5.64,4.36]
Depressive Symptoms	-6.25 [-17.08,4.58]	-4.77 [-10.55,1.00]	-3.11 [-9.44,3.23]	-3.44 [-8.53,1.64]	0.95 [-4.47,6.37]	-0.02 [-7.84,7.81]	-2.17 [-5.18,0.85]
More Likely to Take Risks	0.83 [-10.83,12.48]	1.51 [-4.88,7.89]	-1.08 [-9.03,6.87]	**-2.44 [-4.87,-0.01]**	-2.98 [-6.53,0.57]	**-2.60 [-4.02,-1.18]**	**-2.57 [-3.83,-1.30]**
Can overcome illness without medical care	0.09 [-5.69,5.88]	-0.36 [-4.54,3.81]	-1.08 [-9.98,7.81]	-1.98 [-8.60,4.63]	-0.80 [-6.33,4.74]	-0.19 [-6.01,5.62]	1.20 [-2.06,4.45]
Does not need health insurance	-3.93 [-12.50,4.64]	-8.31 [-18.45,1.83]	-7.05 [-15.39,1.29]	**-9.59 [-15.02,-4.16]**	-3.50 [-7.86,0.85]	**-4.71 [-8.52,-0.89]**	**-2.30 [-4.36,-0.25]**
Took 2-4 Drugs Concurrently	4.25 [-1.22,9.72]	4.56 [-2.16,11.27]	-0.32 [-3.17,2.54]	0.22 [-1.46,1.90]	-2.73 [-6.22,0.76]	-2.38 [-6.33,1.56]	**-2.67 [-4.62,-0.72]**
Took ≥5 Drug Concurrently	**11.51 [4.49,18.53]**	**10.90 [1.13,20.67]**	4.54 [-2.95,12.03]	**5.53 [1.88,9.17]**	2.03 [-0.03,4.09]	0.09 [-2.45,2.64]	-0.79 [-2.43,0.85]
Constant (Base Q_{PDC})	**30.35 [10.83,49.88]**	**48.45 [26.33,70.58]**	**63.22 [50.57,75.86]**	**73.95 [61.13,86.78]**	**82.15 [70.01,94.28]**	**94.53 [76.16,112.91]**	**100.17 [84.08,116.27]**
Sample Size				3,743			

Boldface estimates have P values <0.05. Q: Quantile, PDC: proportion of days covered, CHD: Coronary Heart Disease, CHF: Congestive Heart Failure, AMI: Acute Myocardial Infarction. Main models adjust race coefficient estimates for demographics and health status only, following the Institute of Medicine's framework on disparities. Standard errors underlying confidence intervals were estimated using 5,000 replications of a block bootstrap procedure.

Table B-2. Racial disparities in adherence across the PDC distribution by subgroup

Subgroup	10th Q_{PDC}	20th Q_{PDC}	30th Q_{PDC}	40th Q_{PDC}	50th Q_{PDC}	60th Q_{PDC}	70th Q_{PDC}
	Race Coefficient [95% Confidence Interval]						
Black-White Disparity in PDC among:							
Entire Sample (n=3,749)	-7.26 [-17.80,3.28]	-7.73 [-15.67,0.21]	**-9.05 [-14.32,-3.77]**	**-7.28 [-8.97,-5.59]**	**-5.55 [-7.60,-3.50]**	**-5.08 [-7.49,-2.67]**	**-3.28 [-4.29,-2.27]**
Men (n=1,569)	**-10.07 [-11.78,-8.36]**	**-11.31 [-14.55,-8.06]**	**-10.16 [-14.99,-5.33]**	**-4.83 [-9.47,-0.19]**	**-5.06 [-7.56,-2.56]**	**-3.78 [-6.90,-0.66]**	**-2.53 [-3.99,-1.07]**
Women (n=2,180)	-6.24 [-22.72,10.24]	-5.47 [-19.09,8.15]	**-9.24 [-16.76,-1.71]**	**-7.79 [-11.05,-4.53]**	**-3.75 [-6.62,-0.87]**	**-7.27 [-12.31,-2.24]**	**-3.89 [-6.35,-1.44]**
Auto Recipients of LIS (n=617)	**-15.70 [-22.18,-9.22]**	**-14.81 [-19.47,-10.16]**	**-8.35 [-12.33,-4.37]**	**-3.86 [-6.84,-0.88]**	0.94 [-4.55,6.42]	**-5.45 [-7.69,-3.21]**	-2.22 [-6.62,2.18]
Non-Auto. LIS Recipients (n=3,132)	-6.37 [-18.27,5.53]	-5.04 [-13.65,3.57]	**-9.23 [-15.38,-3.07]**	**-8.67 [-11.40,-5.93]**	**-7.25 [-10.41,-4.09]**	**-5.22 [-8.54,-1.89]**	**-4.10 [-5.31,-2.89]**
ACE Inhibitor /ARB Users (n=2,250)	**-7.13 [-13.43,-0.84]**	**-11.40 [-20.54,-2.27]**	-10.75 [-31.77,10.28]	-13.21 [-29.44,3.01]	-8.41 [-18.07,1.25]	-4.34 [-8.94,0.26]	**-3.30 [-6.08,-0.53]**
Statin Users (n=2,138)	-4.31 [-11.89,3.27]	-2.68 [-10.99,5.62]	-3.80 [-9.39,1.79]	**-4.55 [-7.92,-1.18]**	**-5.97 [-8.22,-3.72]**	**-2.70 [-3.97,-1.44]**	**-2.80 [-4.87,-0.74]**
β-Blocker Users (n=1,536)	**-6.13 [-8.18,-4.08]**	**-10.39 [-15.86,-4.92]**	**-10.18 [-14.21,-6.16]**	**-8.58 [-10.58,-6.58]**	**-8.84 [-10.11,-7.57]**	**-3.25 [-3.70,-2.80]**	**-2.23 [-2.82,-1.65]**
Ca Channel Blocker Users (n=872)	-6.17 [-12.54,0.20]	-5.25 [-13.45,2.95]	-2.99 [-13.73,7.75]	-3.96 [-8.76,0.85]	-3.46 [-9.87,2.95]	4.46 [-1.25,10.18]	0.90 [-2.33,4.13]
Diuretic Users (n=1,650)	**-4.48 [-8.83,-0.12]**	-12.71 [-29.40,3.99]	-7.33 [-17.95,3.28]	**-18.60 [-23.50,-13.69]**	**-15.55 [-21.52,-9.58]**	**-5.93 [-8.69,-3.16]**	**-4.91 [-5.98,-3.83]**

Table B-2. (Continued)

Subgroup	10th Q_{PDC}	20th Q_{PDC}	30th Q_{PDC}	40th Q_{PDC}	50th Q_{PDC}	60th Q_{PDC}	70th Q_{PDC}
Hispanic-White Disparity in PDC among:							
Entire Sample (n=3,749)	-2.09 [-5.44,1.26]	**-4.07 [-8.04,-0.10]**	-1.71 [-6.18,2.76]	**-1.40 [-2.48,-0.32]**	-1.98 [-5.42,1.47]	-1.12 [-3.48,1.24]	0.48 [-0.70,1.67]
Men (n=1,569)	-9.25 [-24.73,6.24]	-10.56 [-23.80,2.68]	-5.70 [-14.50,3.10]	-3.04 [-12.11,6.02]	-2.79 [-7.93,2.36]	-3.30 [-7.85,1.26]	-0.32 [-4.67,4.02]
Women (n=2,180)	4.01 [-4.09,12.11]	0.70 [-10.20,11.61]	0.64 [-8.99,10.28]	0.63 [-4.98,6.24]	0.33 [-5.16,5.82]	0.66 [-5.48,6.80]	0.71 [-1.61,3.04]
Auto Recipients of LIS (n=617)	-7.65 [-16.38,1.07]	**-8.03 [-12.42,-3.64]**	**-4.36 [-7.68,-1.05]**	0.44 [-4.39,5.27]	5.97 [-1.57,13.51]	1.49 [-2.88,5.85]	1.77 [-1.07,4.61]
Non-Auto LIS Recipients (n=3,132)	0.85 [-9.88,11.58]	-0.22 [-1.96,1.53]	0.72 [-2.15,3.60]	0.38 [-6.85,7.61]	-3.37 [-8.77,2.02]	-1.29 [-8.36,5.78]	-0.26 [-3.61,3.09]
ACE Inhibitor /ARB Users (n=2,250)	-5.84 [-14.18,2.51]	**-3.37 [-5.37,-1.38]**	**-3.38 [-5.38,-1.37]**	-6.36 [-13.84,1.12]	-2.46 [-12.59,7.67]	-0.28 [-5.49,4.93]	-2.69 [-8.80,3.41]
Statin Users (n=2,138)	-0.90 [-9.64,7.84]	-0.13 [-16.45,16.20]	0.87 [-9.02,10.75]	1.62 [-7.22,10.46]	1.99 [-11.21,15.19]	0.85 [-1.92,3.63]	**1.80 [0.56,3.04]**
β-Blocker Users (n=1,536)	3.58 [-4.31,11.48]	7.23 [-3.01,17.47]	**5.78 [3.36,8.21]**	6.06 [-4.56,16.68]	0.02 [-14.55,14.59]	-0.46 [-5.01,4.09]	-0.33 [-3.02,2.36]
Ca Channel Blocker Users (n=872)	-8.18 [-17.35,0.98]	-4.00 [-17.07,9.07]	-1.56 [-9.65,6.54]	-3.89 [-10.19,2.41]	**-6.69 [-12.92,-0.46]**	-2.15 [-7.09,2.78]	0.84 [-1.70,3.39]
Diuretic Users (n=1,650)	**-12.63 [-18.35,-6.91]**	**-13.58 [-23.32,-3.84]**	**-10.48 [-18.83,-2.14]**	**-15.42 [-24.39,-6.46]**	**-7.86 [-14.92,-0.80]**	**-4.55 [-6.76,-2.34]**	**-2.49 [-4.26,-0.71]**

Boldface estimates have P values <0.05. Q: Quantile, PDC: proportion of days covered, LIS: Low-income subsidy, ACE: Angiotensin-converting enzyme, ARB: Angiotensin II receptor blocker. Disparity estimates correspond to race coefficients estimated in the primary models adjusted for demographics and health status only, following the IOM framework on disparities. Standard errors underlying confidence intervals were estimated using 5,000 replications of a block bootstrap procedure.

Table B-3. Sensitivity of disparity estimates to various adjustments/definitions of racial disparity

Q_{PDC}	Demo	Demo+Health	Demo+Health +Rx	Demo+Geo +Health+Rx	Demo+Geo +Health +Rx +Beliefs "Main Analysis"	Fully Adjusted
			Race Coefficient [95% Confidence Interval]			
Black-White Disparity at Q_{PDC}:						
Q10	-8.33 [-16.99,0.34]	-8.46 [-18.30,1.37]	-8.18 [-17.93,1.57]	-7.26 [-17.96,3.44]	-7.26 [-17.80,3.28]	-7.37 [-17.85,3.11]
Q20	**-7.80 [-13.60,-2.00]**	**-8.60 [-16.62,-0.58]**	**-8.33 [-16.19,-0.46]**	-7.70 [-16.00,0.60]	-7.73 [-15.67,0.21]	**-9.57 [-16.99,-2.14]**
Q30	**-8.98 [-12.67,-5.29]**	**-10.18 [-14.55,-5.82]**	**-10.07 [-14.38,-5.77]**	**-8.92 [-14.23,-3.62]**	**-9.05 [-14.32,-3.77]**	**-11.36 [-16.00,-6.71]**
Q40	**-7.02 [-9.60,-4.44]**	-8.12 [-9.13,-7.10]	**-7.98 [-9.06,-6.90]**	**-7.06 [-8.13,-6.00]**	**-7.28 [-8.97,-5.59]**	**-8.97 [-12.00,-5.93]**
Q50	**-5.15 [-8.48,-1.83]**	-6.53 [-8.01,-5.04]	**-6.49 [-7.93,-5.06]**	**-5.42 [-7.18,-3.65]**	**-5.55 [-7.60,-3.50]**	**-7.04 [-9.86,-4.22]**
Q60	**-4.98 [-8.69,-1.27]**	-5.82 [-7.82,-3.82]	**-5.82 [-7.78,-3.87]**	**-4.97 [-7.32,-2.63]**	**-5.08 [-7.49,-2.67]**	**-6.40 [-9.59,-3.20]**
Q70	**-3.58 [-5.03,-2.13]**	-3.49 [-4.38,-2.60]	**-3.52 [-4.38,-2.67]**	**-3.26 [-4.25,-2.28]**	**-3.28 [-4.29,-2.27]**	**-4.07 [-5.46,-2.69]**
Hispanic-White Disparity at Q_{PDC}:						
Q10	**-4.32 [-6.98,-1.66]**	-4.25 [-8.71,0.21]	-3.68 [-7.77,0.40]	-2.15 [-5.60,1.30]	-2.09 [-5.44,1.26]	2.47 [-17.28,22.22]
Q20	**-4.89 [-7.44,-2.33]**	**-5.47 [-10.68,-0.27]**	**-4.96 [-9.63,-0.29]**	-4.16 [-8.40,0.09]	**-4.07 [-8.04,-0.10]**	-2.63 [-9.64,4.37]
Q30	-1.64 [-5.77,2.49]	-2.78 [-7.72,2.17]	-2.44 [-7.15,2.26]	-1.67 [-6.11,2.77]	-1.71 [-6.18,2.76]	-0.55 [-13.89,12.80]

Table B-3. (Continued)

Q_{PDC}	Demo	Demo+Health	Demo+Health +Rx	Demo+Geo +Health+Rx	Demo+Geo +Health +Rx +Beliefs "Main Analysis"	Fully Adjusted
Q40	-1.23 [-2.54,0.08]	**-2.16 [-2.91,-1.41]**	**-1.78 [-2.56,-1.00]**	**-1.28 [-2.23,-0.34]**	**-1.40 [-2.48,-0.32]**	-3.37 [-13.31,6.58]
Q50	-1.66 [-4.81,1.49]	-2.77 [-6.57,1.03]	-2.48 [-5.95,0.98]	-1.86 [-5.22,1.51]	-1.98 [-5.42,1.47]	-3.46 [-15.31,8.39]
Q60	-0.74 [-3.59,2.11]	-1.38 [-3.76,1.01]	-1.24 [-3.40,0.92]	-1.05 [-3.36,1.26]	-1.12 [-3.48,1.24]	-1.88 [-9.08,5.31]
Q70	0.15 [-1.25,1.56]	0.42 [-0.32,1.16]	0.51 [-0.36,1.38]	0.51 [-0.73,1.74]	0.48 [-0.70,1.67]	**-2.72 [-4.04,-1.39]**

Boldface estimates have P values <0.05. Q: Quantile, PDC: proportion of days covered. All analyses were conducted on the entire sample (n=3,749). As in **Table 2-1** in the text, demographics included age, gender, marital status, and urban residence. Health included self-reported health as well as diagnosed conditions. "Rx" included the number of other prescription drugs concurrently taken. Geography was represented by the Census Region. "Fully adjusted" estimates were adjusted for all covariates in **Table 2-1** as appropriate. Standard errors underlying confidence intervals were estimated using 5,000 replications of a block bootstrap procedure.

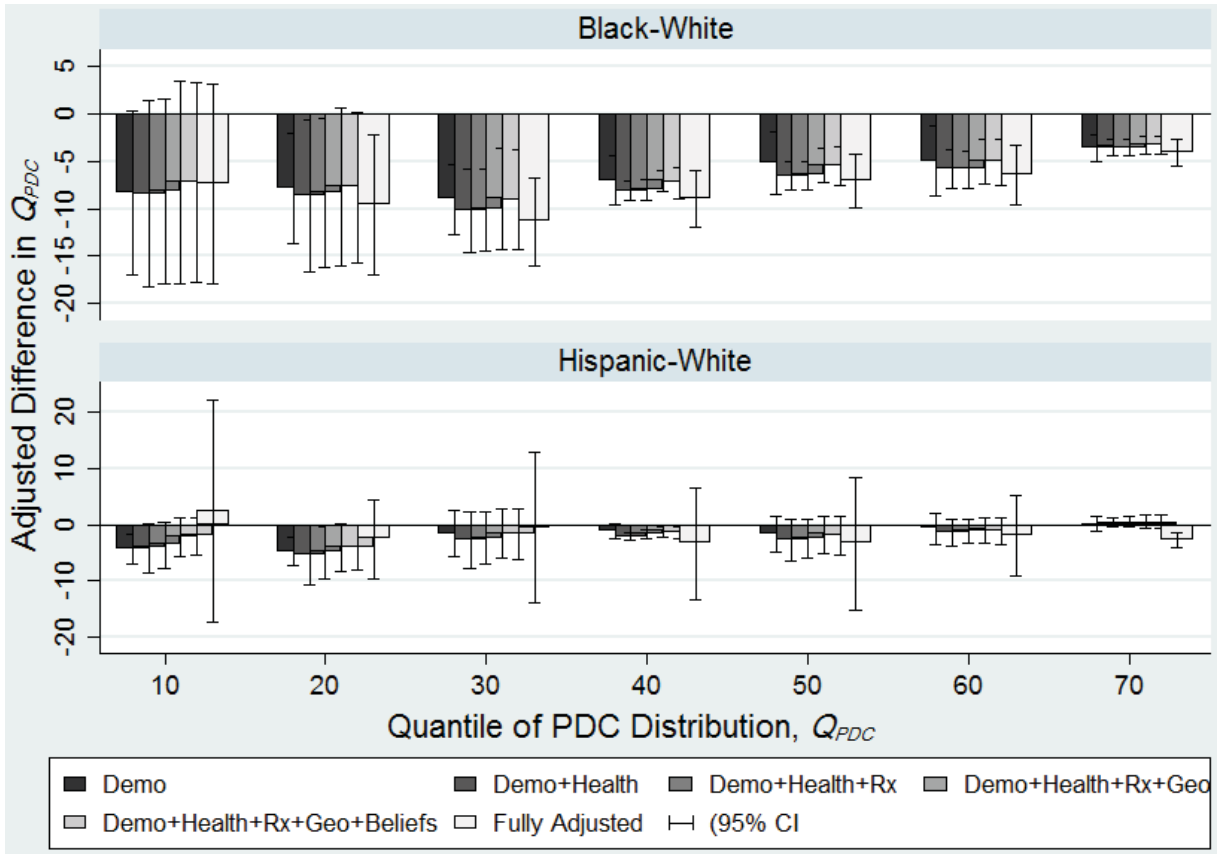

Figure B-1. Sensitivity of disparity estimates to various adjustments/definition of disparity
PDC: proportion of days covered. All analyses were conducted on the entire sample (n=3,749). As in **Table 2-1** in the text, demographics included age, gender, marital status, and urban residence. Health included self-reported health as well as diagnosed conditions. "Rx" included the number of other prescription drugs concurrently taken. Geography was represented by the Census Region. "Fully adjusted" estimates were adjusted for all covariates in **Table 2-1** as appropriate. Standard errors for confidence intervals were estimated using 5,000 replications in a block bootstrap procedure.

APPENDIX C. SUPPLEMENTAL MATERIALS FOR CHAPTER 4

Table C-1. Characteristics of sampled Medicare seniors by race across PDC quantile categories, Q10th-Q40th

Characteristics	Q_{PDC} 10th		Q_{PDC} 20th		Q_{PDC} 30th		Q_{PDC} 40th	
	White	Black	White	Black	White	Black	White	Black
	%, unless otherwise noted							
Demographics								
Female	56.70	57.13	54.12	63.48	57.44	67.61	57.64	74.69
Married	58.07	**28.60**	63.84	**26.86**	59.84	37.36	50.40	31.69
Urban/MSA	80.29	87.14	77.71	85.93	79.48	82.45	82.03	85.22
Census Region								
Northeast	16.82	23.86	22.04	15.90	23.19	14.00	20.45	28.90
Midwest	20.05	9.60	25.48	19.12	22.26	11.34	27.70	**10.31**
South	40.24	53.54	35.82	**59.45**	37.97	**69.64**	35.12	**53.91**
West	22.89	13.00	16.65	**5.52**	16.58	5.01	16.74	**6.88**
Self-Reported Health Status								
Excellent	18.91	10.21	15.51	9.83	11.38	3.89	15.58	10.67
Very Good	29.21	24.03	33.71	24.76	29.24	22.13	29.17	24.97
Good	33.81	32.02	28.27	43.85	34.52	40.13	31.35	37.08
Fair	12.36	**26.63**	15.71	17.57	18.64	26.86	17.24	20.69
Poor	5.71	7.12	6.80	3.99	6.22	7.00	6.66	6.59
Any Physical Limitation	59.60	63.68	64.03	60.45	64.84	51.00	63.15	51.97
Any Cognitive Limitation	11.89	**24.20**	9.83	8.31	10.80	13.71	9.82	15.86

Table C-1. (Continued)

Characteristics	Q_{PDC} 10th		Q_{PDC} 20th		Q_{PDC} 30th		Q_{PDC} 40th	
	White	Black	White	Black	White	Black	White	Black
				%, unless otherwise noted				
Depressive Symptoms	8.43	**21.23**	7.96	11.18	8.14	8.37	8.35	14.20
Cardiovascular Conditions & Comorbidity								
Hypertension	74.61	**89.29**	81.42	94.58	83.99	**96.40**	83.47	96.95
Lipidemia	63.12	53.77	66.63	55.93	67.45	62.69	67.39	52.28
Angina/CHD	19.17	14.18	20.80	12.78	18.59	17.21	24.51	19.26
CHF	3.28	2.57	2.69	3.24	6.62	**1.19**	4.51	5.03
AMI	5.69	8.33	9.63	5.92	10.50	9.32	7.39	5.99
Stroke	6.21	**2.78**	7.71	4.24	6.03	6.96	6.26	3.42
Count of Comorbid Conditions, Mean±SD	5.88 ±3.89	**3.85 ±2.61**	5.63 ±3.74	4.44 ±2.96	6.08 ±3.77	4.73 ±3.31	5.69 ±3.21	4.74 ±3.50
Charlson Comorbidity Score Q1-2	54.56	58.50	54.34	50.38	57.41	50.77	55.97	44.43
Charlson Comorbidity Score Q3	33.01	30.99	31.40	39.62	29.94	41.76	31.18	41.95
Charlson Comorbidity Score Q4	12.43	10.51	14.26	10.00	12.64	7.47	12.84	13.62

Table C-1. (Continued)

Characteristics	Q_{PDC} 10th		Q_{PDC} 20th		Q_{PDC} 30th		Q_{PDC} 40th	
	White	Black	White	Black	White	Black	White	Black
	%, unless otherwise noted							
Beliefs								
More Likely to Take Risk	16.15	10.35	17.90	18.38	17.74	22.79	21.10	10.90
Can Overcome Illness without Medical Care	12.02	9.11	11.67	6.84	11.91	14.22	13.93	5.40
No Need for Health Insurance	6.41	5.80	5.67	3.31	4.86	7.85	7.89	3.67
Behaviors								
Current Smoker	8.06	10.69	10.18	12.29	9.81	6.52	5.56	**16.06**
Moderate / Vigorous Exercise	50.71	39.70	53.42	44.42	48.66	43.95	46.70	36.11
Obese	26.71	22.52	24.37	37.46	28.40	33.72	24.62	**49.83**
Socioeconomic Status								
Income: Poor/Near Poor	14.72	**38.59**	14.32	**27.78**	13.90	**26.51**	14.87	**33.08**
Low-Income	15.95	18.30	14.24	25.49	17.08	23.99	14.69	21.20
Mid-Income	26.49	35.13	29.39	27.76	31.77	35.21	35.17	23.17
High-Income (Ref)	42.84	**7.98**	42.05	**18.97**	37.26	14.29	35.28	22.56
Education: Less than High School	18.81	**52.11**	15.97	**44.57**	20.94	**37.12**	18.49	**51.09**

Table C-1. (Continued)

Characteristics	Q_{PDC} 10th		Q_{PDC} 20th		Q_{PDC} 30th		Q_{PDC} 40th	
	White	Black	White	Black	White	Black	White	Black
				%, unless otherwise noted				
High School Diploma	52.65	41.24	58.78	**34.63**	49.25	51.50	52.83	40.56
Above High School (Ref)	28.54	**6.65**	25.25	20.80	29.81	11.37	28.68	8.35
Primary Drug Coverage at Baseline								
No Known Rx Coverage (Ref)	21.35	21.04	21.78	12.98	20.92	14.39	18.38	9.47
Part D: PDPs	31.71	39.89	34.43	**52.89**	34.26	42.69	38.67	41.44
Part D: MA-PD	22.78	33.00	20.42	22.80	21.43	32.70	20.09	34.60
Employer/Other Private	24.16	**6.07**	23.37	11.34	23.38	10.22	22.87	14.49
Auto Eligible for PD Low-Income Subsidy	3.46	**31.42**	5.29	**31.54**	5.47	9.51	7.00	18.49
Use of CV Drugs in Year 2								
ACEI/ARBs	49.45	53.82	57.32	67.08	60.55	70.84	58.00	59.69
Statins	52.69	**34.07**	62.16	63.59	62.03	54.38	64.55	**42.82**
Beta-Blockers	29.41	26.10	42.23	38.91	39.87	41.75	51.46	37.11
CCBs	13.92	**33.93**	24.46	26.38	24.68	38.96	23.69	40.48
Diuretics	33.57	**49.62**	41.60	**59.15**	48.47	59.08	47.08	**67.56**
Healthcare Use at Baseline								
No. of Concurrent CV Medications								
0-1	51.14	39.94	34.84	30.50	27.20	15.01	28.47	24.30

Table C-1. (Continued)

Characteristics	Q_{PDC} 10th		Q_{PDC} 20th		Q_{PDC} 30th		Q_{PDC} 40th	
	White	Black	White	Black	White	Black	White	Black
				%, unless otherwise noted				
2-3	42.90	53.21	56.44	60.61	63.28	64.19	59.08	59.54
≥4	5.96	6.85	8.72	8.89	9.52	20.81	12.45	16.16
No. of concurrent medications overall								
0-1	13.63	19.08	10.77	15.36	6.25	11.14	10.51	17.82
2-4	49.47	54.56	47.19	43.13	43.56	40.24	47.05	40.81
≥5	36.90	26.36	42.04	41.51	50.19	48.62	42.44	41.37
No. of Pharmacies Used	1.38 ±0.54	**1.14 ±0.45**	1.4 ±0.60	1.22 ±0.45	1.37 ±0.57	1.16 ±0.37	1.38 ±0.54	**1.15 ±0.48**
Average Copay for CV Drugs ($2010)	29.92 ±40.09	**16.01 ±32.39**	27.23 ±35.2	20.24 ±24.27	23.69 ±30.25	25.18 ±31.67	24.98 ±34.45	21.66 ±24.57
Had a Usual Source of Care	98.61	98.08	94.91	89.61	97.12	**99.65**	99.17	97.30
Had any Inpatient Stay?	16.91	22.15	19.52	12.73	20.82	14.87	16.27	14.16
Had any ER visit?	15.95	15.85	16.03	13.10	16.48	22.43	21.42	26.02
Quintiles of ambulatory physician visits (range)								
Q 1 (0-2)	17.85	**34.28**	16.56	26.28	18.74	30.66	18.67	25.31
Q 2 (3-4)	14.18	18.98	21.30	17.80	19.19	20.21	16.37	25.01
Q 3 (5-7)	21.12	24.68	16.62	28.41	17.20	21.00	18.98	17.39
Q 4 (8-12)	20.43	11.92	25.56	14.86	17.52	11.05	23.18	19.77
Q 5 (≥13)	26.42	10.14	19.97	12.64	27.36	17.08	22.79	12.52

Table C-1. (Continued)

Characteristics	Q_{PDC} 10th		Q_{PDC} 20th		Q_{PDC} 30th		Q_{PDC} 40th	
	White	Black	White	Black	White	Black	White	Black
	%, unless otherwise noted							
Experience with the Healthcare System								
Very Satisfied with Health Care	57.32	58.23	54.25	48.44	58.81	49.42	57.70	51.37
Provider Always Explained	53.37	67.46	53.23	58.59	60.55	52.42	57.12	55.27
Provider Always Listened	60.96	70.60	59.00	63.41	62.00	51.44	62.27	58.08
Provider Always Respected	63.66	72.88	62.28	66.80	58.46	54.91	64.99	64.09
Sample Size	259	95	269	90	225	63	256	72
Weighted Population	1,746,012	276,837	1,780,105	221,492	1,592,621	190,496	1,754,713	181,076

Boldface estimates have P<0.05 for pairwise comparisons relative to whites.
PDC: Proportion of Days Covered; MSA: Metropolitan Statistical Area; CHD: Coronary Heart Disease; CHF: Congestive Heart Failure; AMI: Acute Myocardial Infarction; SD: Standard Deviation; Q: Quantile; BMI: Body Mass Index; PD: Part D; PDP: stand-alone prescription drug plan; MA-PD: Medicare Advantage Prescription Drug plan; ACE: Angiotensin-Converting Enzyme; ARB: Angiotensin II Receptor Blocker

Table C-2. Characteristics of sampled Medicare seniors by race across PDC quantile categories, Q50th-Q80th

Characteristics	Q_{PDC} 50th		Q_{PDC} 60th		Q_{PDC} 70th		Q_{PDC} 80th	
	White	Black	White	Black	White	Black	White	Black
	%, unless otherwise noted							
Demographics								
Female	52.77	46.53	57.54	**74.43**	57.38	66.11	57.81	61.14
Married	53.57	41.01	52.30	**31.83**	57.30	**32.26**	55.25	**28.40**
Urban/MSA	78.71	84.13	78.71	83.27	74.50	84.95	80.62	81.48
Census Region								
Northeast	23.57	16.47	20.41	12.93	24.53	13.67	20.53	18.30
Midwest	22.10	**7.47**	32.31	20.33	28.15	20.66	26.26	19.26
South	35.88	**69.96**	31.09	**64.59**	28.42	**57.60**	33.50	**57.63**
West	18.45	6.10	16.19	**2.15**	18.90	8.08	19.71	**4.81**
Self-Reported Health Status								
Excellent	12.98	**5.66**	9.51	8.84	10.18	5.20	13.24	6.69
Very Good	26.28	21.77	32.42	20.55	28.53	21.55	34.79	26.14
Good	39.05	23.72	36.86	36.84	35.26	36.95	32.39	33.28
Fair	16.61	**41.91**	17.22	24.28	19.33	27.16	16.30	**24.55**
Poor	5.07	6.94	3.99	9.49	6.71	9.14	3.28	**9.35**
Any Physical Limitation	63.56	65.55	64.07	72.77	63.81	**78.57**	60.05	63.39
Any Cognitive Limitation	9.53	17.41	9.48	**24.63**	11.88	**29.50**	8.26	**15.04**
Depressive Symptoms	4.30	8.82	8.81	16.05	12.52	15.68	5.30	**16.33**

Table C-2. (Continued)

Characteristics	Q_{PDC} 50th		Q_{PDC} 60th		Q_{PDC} 70th		Q_{PDC} 80th	
	White	Black	White	Black	White	Black	White	Black
	%, unless otherwise noted							
Cardiovascular Conditions & Comorbidity								
Hypertension	85.28	84.63	85.88	95.86	88.22	97.50	81.01	**93.99**
Lipidemia	64.31	67.10	70.88	61.76	67.25	59.41	65.22	**52.18**
Angina/CHD	22.44	20.05	25.14	16.44	21.90	22.37	21.69	18.17
CHF	2.98	4.94	3.34	2.43	5.50	5.45	3.87	3.80
AMI	10.81	9.10	11.04	7.24	7.64	7.09	8.77	6.15
Stroke	6.67	7.00	2.94	**16.94**	8.95	**1.82**	5.08	6.73
Count of Comorbid Conditions, Mean±SD	5.99 ±3.56	5.00 ±2.87	5.47 ±3.34	4.81 ±2.95	5.48 ±3.53	5.09 ±3.01	5.31 ±3.40	4.45 ±3.44
CCI Q1-2	53.00	35.10	54.22	**31.84**	56.54	**33.40**	59.17	52.00
CCI Q3	34.56	44.64	34.03	48.81	25.97	**51.27**	31.66	32.00
CCI Q4	12.44	20.26	11.75	19.35	17.49	15.33	9.17	**16.00**
Beliefs								
More Likely to Take Risk	16.73	10.69	15.76	12.58	16.58	15.21	14.23	13.49
Can Overcome Illness without Medical Care	8.95	1.98	11.11	5.13	8.24	3.74	11.76	7.62
No Need for Health Insurance	0.52	**4.66**	4.62	8.36	2.98	0.00	3.90	5.51

Table C-2. (Continued)

Characteristics	Q_{PDC} 50th		Q_{PDC} 60th		Q_{PDC} 70th		Q_{PDC} 80th	
	White	Black	White	Black	White	Black	White	Black
	%, unless otherwise noted							
Behaviors								
Current Smoker	7.18	9.64	13.39	16.64	7.09	6.19	7.34	10.40
Moderate / Vigorous Exercise	46.35	37.00	43.66	27.91	42.26	27.79	47.48	38.79
Obese	28.45	35.80	29.09	**44.10**	34.10	33.12	29.87	39.59
Socioeconomic Status								
Income: Poor/Near Poor	18.07	**39.24**	15.67	**32.32**	19.25	**37.97**	14.30	**29.00**
Low-Income	16.69	14.98	13.96	20.41	17.20	22.06	16.59	19.90
Mid-Income	29.04	33.87	35.88	32.43	30.52	24.72	32.09	33.07
High-Income (Ref)	36.20	**11.91**	34.50	**14.85**	33.03	**15.25**	37.02	**18.02**
Education: Less than High School	19.48	**55.80**	21.59	**53.24**	20.78	**50.91**	20.47	**41.82**
High School Diploma	49.33	**29.97**	54.84	38.88	58.03	**34.62**	51.26	**39.16**
Above High School (Ref)	31.18	14.23	23.57	**7.88**	21.19	14.47	28.27	19.02
Primary Drug Coverage at Baseline								
No Known Rx Coverage (Ref)	18.58	**8.19**	24.01	9.20	23.71	13.48	16.70	12.08
Part D: PDPs	38.46	36.10	37.88	42.71	32.64	50.97	37.10	42.74

Table C-2. (Continued)

Characteristics	Q_{PDC} 50th		Q_{PDC} 60th		Q_{PDC} 70th		Q_{PDC} 80th	
	White	Black	White	Black	White	Black	White	Black
				%, unless otherwise noted				
Part D: MA-PD	20.01	**34.51**	19.51	**38.43**	25.49	25.50	26.67	27.03
Employer/Other Private	22.96	21.20	18.60	9.66	18.16	10.05	19.53	18.14
Auto Eligible for PD Low-Income Subsidy	7.38	**21.40**	5.09	**36.62**	6.85	**21.24**	5.55	**28.63**
Use of CV Drugs in Year 2								
ACEI/ARBs	66.78	58.45	63.08	59.07	64.96	**77.96**	53.96	48.06
Statins	60.42	55.63	68.42	61.36	64.28	47.11	55.66	46.69
Beta-Blockers	44.74	35.06	51.34	39.19	44.46	47.80	37.75	36.12
CCBs	21.63	**37.58**	20.65	**40.28**	20.77	**48.08**	15.96	**33.61**
Diuretics	44.77	54.73	54.69	53.48	50.65	58.09	39.48	47.69
Healthcare Use at Baseline								
No. of Concurrent CV Medications								
0-1	33.33	40.74	23.59	27.67	25.46	22.15	41.62	43.71
2-3	58.09	48.01	65.34	60.44	63.06	67.24	51.65	43.36
≥4	8.58	11.25	11.07	11.89	11.48	10.60	6.74	**12.93**
No. of concurrent medications overall								
0-1	5.80	3.27	8.43	17.03	7.10	9.40	12.24	14.96
2-4	44.24	55.42	39.53	37.14	46.81	34.91	42.39	45.70
≥5	49.95	41.30	52.04	45.83	46.09	55.69	45.37	39.34
No. of Pharmacies	1.28 ±0.48	1.26 ±0.5	1.26 ±0.52	**1.12 ±0.32**	1.29 ±0.53	1.22 ±0.49	1.30 ±0.52	**1.17 ±0.44**

Table C-2. (Continued)

Characteristics	Q_{PDC} 50th		Q_{PDC} 60th		Q_{PDC} 70th		Q_{PDC} 80th	
	White	Black	White	Black	White	Black	White	Black
				%, unless otherwise noted				
Average Copay for CV Drugs ($2010)	25.84 ±29.08	**17.45 ±19.39**	24.62 ±29.3	**12.68 ±15.64**	25.99 ±32.54	**14.09 ±15.74**	23.28 ±26.56	**15.04 ±24.05**
Had a Usual Source of Care	98.06	94.76	96.58	97.21	96.11	99.20	97.90	**92.80**
Had any Inpatient Stay?	16.84	17.66	17.74	20.90	18.69	18.07	15.31	19.18
Had any ER visit?	18.36	26.87	14.46	20.58	19.89	19.21	16.88	24.40
Quintiles of ambulatory physician visits (range)								
Q 1 (0-2)	14.37	16.43	17.94	**40.42**	15.78	27.35	20.03	27.50
Q 2 (3-4)	19.48	**33.01**	16.31	11.99	19.16	22.94	18.41	22.09
Q 3 (5-7)	21.41	19.63	23.75	21.44	20.80	23.94	21.52	18.77
Q 4 (8-12)	22.39	21.76	23.55	**5.91**	20.79	7.89	22.63	**13.56**
Q 5 (≥13)	22.35	9.17	18.45	20.24	23.47	17.88	17.41	18.08
Experience with the Healthcare System								
Very Satisfied with Health Care	55.06	50.55	64.39	**47.15**	59.09	59.10	60.08	58.46
Provider Always Explained	52.53	53.43	55.81	57.76	55.71	53.96	59.96	59.98
Provider Always Listened	58.50	60.41	60.64	55.46	60.16	61.63	62.96	67.01

Table C-2. (Continued)

Characteristics	Q_{PDC} 50th		Q_{PDC} 60th		Q_{PDC} 70th		Q_{PDC} 80th	
	White	Black	White	Black	White	Black	White	Black
	%, unless otherwise noted							
Provider Always Respected	59.33	58.31	63.26	51.04	61.90	68.09	65.59	68.78
Sample Size	274	59	264	74	264	72	774	178
Weighted Population	1,784,639	163,306	1,722,877	196,246	1,737,023	196,465	5,329,553	465,402

Boldface estimates have P<0.05 for pairwise comparisons relative to whites.
PDC: Proportion of Days Covered; MSA: Metropolitan Statistical Area; CHD: Coronary Heart Disease; CHF: Congestive Heart Failure; AMI: Acute Myocardial Infarction; SD: Standard Deviation; Q: Quantile; BMI: Body Mass Index; PD: Part D; PDP: stand-alone prescription drug plan; MA-PD: Medicare Advantage Prescription Drug plan; ACE: Angiotensin-Converting Enzyme; ARB: Angiotensin II Receptor Blocker

Table C-3. RIF unconditional quantile regressions for by race, Q10th-Q40th

Covariate	Q_{PDC} 10th		Q_{PDC} 20th		Q_{PDC} 30th		Q_{PDC} 40th	
	Whites	Blacks	Whites	Blacks	Whites	Blacks	Whites	Blacks
	Coefficient Estimate (Standard Error)							
Age 70-75	-2.78	**-10.67**	**-5.28**	-0.86	-4.11	1.61	-2.18	0.34
	(3.36)	**(2.89)**	**(1.71)**	(4.69)	(4.16)	(3.35)	(3.24)	(2.15)
Age 75-80	**-7.04**	**-14.19**	**-6.15**	-3.65	-2.68	0.48	-1.88	0.79
	(2.08)	**(3.30)**	**(1.43)**	(2.79)	(3.67)	(4.57)	(2.80)	(3.10)
Age ≥ 80	-6.95	**-8.29**	-5.80	-2.81	-5.21	3.40	-4.58	3.22
	(6.60)	**(3.79)**	(5.43)	(3.24)	(7.26)	(2.69)	(6.31)	(5.08)
Female	-1.55	-0.88	-1.39	**7.18**	-2.52	2.61	-2.68	-3.55
	(1.87)	(3.84)	(3.33)	**(3.01)**	(1.77)	(2.68)	(1.47)	(3.40)
Married	-1.74	-2.39	-4.46	3.12	-6.05	**7.34**	-3.28	3.77
	(3.09)	(7.74)	(3.70)	(3.08)	(4.37)	**(2.34)**	(3.54)	(4.39)
Urban Residence	-0.13	**4.79**	0.49	-2.95	-0.56	-3.59	-1.82	-0.98
	(7.20)	**(2.28)**	(8.92)	(2.73)	(10.30)	(2.94)	(5.67)	(2.06)
Census Region: Midwest	1.96	6.19	3.62	**15.01**	**6.20**	2.04	1.53	**8.28**
	(3.96)	(6.65)	(5.47)	**(4.18)**	**(2.54)**	(3.07)	(1.25)	**(3.03)**
South	**-6.14**	4.10	-1.83	7.78	-1.13	0.80	**-3.53**	3.58
	(1.28)	(9.17)	(3.20)	(7.28)	(2.07)	(4.25)	**(0.86)**	(2.66)
West	**-5.93**	-16.81	0.69	-7.59	2.02	-5.98	0.58	-6.00
	(1.81)	(10.94)	(3.85)	(14.78)	(1.89)	(9.84)	(1.52)	(6.49)
Health Status: Very Good	7.06	-0.32	6.03	2.12	4.52	5.27	**5.76**	-0.96
	(3.67)	(8.03)	(3.84)	(3.43)	(2.41)	(4.30)	**(1.95)**	(5.05)
Good	5.89	1.07	7.59	2.07	4.27	-1.42	5.79	-2.98
	(6.19)	(7.71)	(5.80)	(7.51)	(5.18)	(9.12)	(4.05)	(7.89)

Table C-3. (Continued)

Covariate	Q_{PDC} 10th		Q_{PDC} 20th		Q_{PDC} 30th		Q_{PDC} 40th	
	Whites	**Blacks**	**Whites**	**Blacks**	**Whites**	**Blacks**	**Whites**	**Blacks**
	Coefficient Estimate (Standard Error)							
Fair	**13.36 (6.18)**	-0.95 (10.68)	**12.14 (5.54)**	7.84 (6.68)	6.85 (4.29)	9.89 (6.54)	**7.54 (3.27)**	3.76 (3.54)
Poor	5.85 (8.26)	0.72 (21.52)	4.06 (6.16)	12.05 (10.88)	-0.99 (10.46)	10.36 (10.59)	-3.59 (5.88)	8.13 (7.64)
Any Physical Limitation	0.76 (4.51)	3.99 (3.79)	-3.51 (3.48)	1.65 (2.68)	-3.91 (3.29)	-4.46 (5.24)	-1.94 (2.60)	4.43 (5.84)
Any Cognitive Limitation	-5.59 (8.72)	-10.51 (6.02)	-4.71 (9.66)	0.62 (5.72)	-4.88 (8.85)	6.51 (3.88)	-2.55 (7.16)	**6.99 (2.13)**
Depressive Symptoms	-6.41 (8.14)	-10.10 (7.59)	-3.43 (7.87)	**-15.53 (7.35)**	-2.52 (11.54)	-7.71 (6.77)	-3.77 (5.42)	-5.53 (8.00)
Hypertension	4.49 (2.59)	**-7.29 (3.68)**	3.39 (3.55)	-5.58 (6.71)	**6.19 (2.25)**	**8.31 (2.49)**	5.06 (3.22)	**6.61 (2.46)**
Hyperlipidemia	1.87 (4.07)	**-12.56 (5.94)**	1.24 (2.51)	-4.10 (6.15)	1.65 (1.59)	0.85 (6.87)	1.06 (1.49)	5.54 (6.64)
Angina/CHD	-1.95 (2.59)	5.44 (3.39)	-1.30 (0.92)	7.44 (5.40)	2.35 (2.51)	4.65 (6.23)	1.29 (2.63)	4.32 (9.91)
CHF	2.57 (4.37)	-1.46 (15.31)	4.82 (4.01)	-7.70 (4.70)	-0.53 (5.51)	0.96 (4.14)	-0.66 (4.46)	6.12 (10.02)
AMI	4.58 (9.70)	1.65 (5.59)	1.76 (5.61)	**-12.12 (3.41)**	0.21 (13.32)	**-11.21 (2.10)†**	2.59 (9.29)	-6.52 (6.86)
Stroke	0.88 (4.62)	9.99 (9.19)	-4.31 (8.88)	5.73 (6.47)	**-4.67 (1.94)**	2.23 (12.39)	**-4.16 (0.84)**	-1.53 (16.26)

Table C-3. (Continued)

Covariate	Q_{PDC} 10th		Q_{PDC} 20th		Q_{PDC} 30th		Q_{PDC} 40th	
	Whites	**Blacks**	**Whites**	**Blacks**	**Whites**	**Blacks**	**Whites**	**Blacks**
	Coefficient Estimate (Standard Error)							
Count of Comorbid Conditions	0.05 (0.61)	**1.60 (0.54)**	0.11 (0.79)	1.04 (0.61)	-0.31 (0.71)	0.30 (0.36)	-0.18 (0.41)	0.14 (0.24)
Charlson Comorbidity Score Q3	-2.13 (1.26)	1.61 (4.15)	**-2.74 (1.33)**	**4.59 (1.89)**	-0.70 (1.88)	**6.72 (1.56)**	-0.59 (2.03)	**6.46 (3.15)**
Charlson Comorbidity Score Q4	-3.04 (5.97)	-0.03 (5.14)	-2.63 (6.36)	**5.10 (1.45)**	0.37 (3.29)	**9.59 (3.32)**	-0.63 (1.73)	**12.38 (3.86)**
More Likely to Take Risks	1.76 (5.19)	4.33 (4.08)	-1.18 (4.45)	8.14 (4.86)	-0.43 (4.45)	-1.45 (4.22)	-2.03 (1.49)	**-6.52 (2.78)**
Can overcome illness without medical care	0.60 (1.22)	-1.73 (12.84)	2.40 (1.44)	-3.29 (18.23)	-0.30 (1.54)	-12.41 (9.17)	-0.76 (1.11)	-11.41 (10.92)
Does not need health insurance	**-9.41 (1.50)**	-8.47 (19.76)	**-9.79 (3.53)**	-9.66 (22.38)	**-7.97 (2.08)**	1.76 (16.68)	**-12.93 (1.81)**	7.17 (15.42)
Current Smoker	-2.94 (1.56)	**5.42 (2.18)**	**-4.02 (2.02)**	0.60 (2.63)	-3.77 (7.31)	-1.08 (3.46)	0.34 (4.31)	1.91 (2.95)
Had Moderate / Vigorous Exercise	-0.93 (1.58)	0.60 (5.57)	**-3.88 (1.32)**	-4.60 (5.61)	**-4.66 (0.93)**	-1.55 (6.81)	-3.21 (1.93)	-1.31 (5.57)
Obese (BMI≥30)	-0.88 (1.02)	**14.91 (3.58)**	1.46 (1.12)	**11.96 (2.41)**	0.63 (0.88)	**12.83 (3.92)**	**1.67 (0.65)†**	**9.26 (2.22)**
Income: Poor/Near-Poor	-1.73 (4.45)	-5.58 (3.44)	-0.17 (1.32)	**-13.74 (6.00)**	0.75 (5.01)	-2.32 (5.54)	1.86 (2.80)	**-6.90 (2.25)**

Table C-3. (Continued)

Covariate	Q_{PDC} 10th		Q_{PDC} 20th		Q_{PDC} 30th		Q_{PDC} 40th	
	Whites	**Blacks**	**Whites**	**Blacks**	**Whites**	**Blacks**	**Whites**	**Blacks**
	Coefficient Estimate (Standard Error)							
Low-Income	-0.21 (1.85)	-5.21 (3.51)	**4.06** **(1.44)**	**-11.83** **(2.73)**	-0.50 (1.10)	-4.90 (3.37)	1.31 (0.84)	**-10.77** **(5.19)**
Middle-Income	4.16 (2.68)	-4.11 (5.38)	**4.71** **(1.70)**	-7.55 (7.61)	2.26 (2.68)	-3.24 (5.08)	1.42 (2.41)	**-7.59** **(3.21)**
Education: Less than High School	-2.23 (2.71)	-7.49 (8.38)	-2.14 (2.17)	3.68 (7.64)	-0.25 (2.87)	0.62 (5.86)	1.83 (2.79)	1.87 (4.31)
High School Diploma	-0.68 (2.67)	**-14.44** **(7.16)**	-4.16 (2.55)	-0.87 (7.61)	-1.80 (2.30)	-2.80 (3.15)	0.68 (2.78)	-2.12 (6.33)
Drug Coverage Plan: Part D: PDPs	1.49 (2.45)	**26.03** **(7.05)**	**2.47** **(0.93)**	**15.07** **(1.22)**	2.07 (2.65)	**8.27** **(3.82)**	-0.55 (1.58)	**10.94** **(4.48)**
Part D: MA-PD	1.95 (4.27)	**22.97** **(6.57)**	**3.61** **(1.42)**	**14.02** **(3.80)**	3.64 (1.88)	**13.38** **(5.46)**	2.93 (2.00)	14.43 (7.73)
Employer/Other Private	-1.61 (1.97)	**19.00** **(4.33)**	1.09 (0.98)	**18.36** **(3.02)**	0.68 (1.50)	**21.03** **(7.83)**	-1.83 (1.02)	**27.54** **(9.05)**
Auto Eligible for PD Low-Income Subsidy	6.80 (4.96)	-12.98 (7.23)	1.42 (2.39)	**-12.87** **(5.46)**	3.29 (3.87)	**-12.29** **(3.17)**	-0.21 (2.63)	-4.34 (3.27)
Average Copay for CV Drugs ($2010)	-0.07 (0.04)	**0.17** **(0.04)**	-0.07 (0.04)	-0.06 (0.07)	-0.04 (0.04)	-0.12 (0.08)	-0.05 (0.02)	**-0.18** **(0.09)**

Table C-3. (Continued)

Covariate	Q_{PDC} 10th		Q_{PDC} 20th		Q_{PDC} 30th		Q_{PDC} 40th	
	Whites	**Blacks**	**Whites**	**Blacks**	**Whites**	**Blacks**	**Whites**	**Blacks**
	Coefficient Estimate (Standard Error)							
Concurrently taking: 2-3 CV Drugs	10.44 (5.65)	**10.51 (3.41)**	6.51 (5.25)	**4.91 (1.12)**	0.67 (3.01)	-1.05 (2.33)	-1.54 (1.94)	**-9.49 (1.33)**
≥4 CV Drugs	12.98 (15.12)	**12.70 (2.93)**	6.61 (9.14)	5.49 (3.68)	3.21 (9.93)	1.60 (3.18)	-2.40 (5.88)	**-11.46 (4.31)**
Quantiles of Ambulatory Visits: Q 3 (5-7)	-1.47 (1.59)	-3.11 (9.26)	**3.16 (1.53)**	-6.55 (5.78)	**6.18 (2.44)**	-7.05 (6.03)	**5.00 (2.36)**	**-10.24 (2.69)**
Q 4 (8-12)	-2.22 (2.11)	-9.52 (11.90)	-1.39 (4.61)	-2.50 (7.37)	1.26 (2.78)	-9.17 (7.16)	0.58 (1.88)	**-11.63 (4.00)**
Q 5 (≥13)	-6.96 (5.36)	3.99 (7.44)	-1.31 (6.31)	-0.37 (3.62)	-1.40 (5.87)	2.18 (3.13)	-2.76 (4.56)	-0.78 (3.84)
Had a Usual Source of Care	-11.41 (10.66)	-13.49 (9.96)	3.64 (4.89)	-6.96 (12.11)	2.01 (6.08)	6.62 (4.59)	-6.02 (4.40)	1.59 (7.35)
Any Emergency Department Visit-Baseline Year	3.78 (3.82)	-1.03 (3.89)	3.23 (4.04)	**6.22 (2.78)**	**5.31 (2.58)**	**11.67 (5.08)**	1.98 (1.12)	10.09 (5.46)
No. of Pharmacies Used	-2.92 (3.04)	1.17 (5.15)	**-4.52 (1.67)**	-4.62 (6.06)	**-6.07 (2.71)**	-4.23 (4.03)	**-5.86 (2.69)**	-4.51 (4.93)
Very Satisfied with Received Healthcare	1.89 (2.07)	2.91 (6.35)	3.11 (1.74)	**14.35 (5.47)**	**3.95 (0.77)**	8.66 (6.26)	**4.32 (1.50)**	7.77 (4.04)

Table C-3. (Continued)

Covariate	Q_{PDC} 10th		Q_{PDC} 20th		Q_{PDC} 30th		Q_{PDC} 40th	
	Whites	**Blacks**	**Whites**	**Blacks**	**Whites**	**Blacks**	**Whites**	**Blacks**
	Coefficient Estimate (Standard Error)							
Provider Always Explained	3.41 (2.69)	-1.83 (5.73)	3.13 (3.94)	-3.21 (7.80)	-0.41 (0.89)	-3.71 (6.86)	**1.16 (0.52)†**	0.60 (5.93)
Provider Always Listened	-1.84 (3.42)	-3.84 (3.72)	-0.64 (1.72)	-6.17 (3.93)	-1.40 (3.30)	-2.23 (7.12)	**-3.16 (0.76)†**	3.11 (6.11)
Provider Always Respected	-1.42 (1.18)	-3.16 (7.00)	-2.46 (2.76)	-8.88 (7.79)	0.56 (3.32)	-4.97 (10.28)	0.96 (1.82)	-7.12 (9.19)
Constant (Base Q_{PDC})	**41.86 (13.73)**	31.83 (31.56)	**48.09 (11.90)**	**40.80 (12.60)**	**65.63 (9.32)**	**31.49 (12.29)**	**84.83 (8.00)**	**48.12 (11.74)**
Sample Size	2,585	703	2,585	703	2,585	703	2,585	703

Boldface estimates have P values <0.05. Standard errors were estimated by balanced repeated replications using MEPS-provided survey weights and half-sample identifiers.

Table C-4. RIF unconditional quantile regressions for by race, Q50th-Q80th

Covariate	Q_{PDC} 50th		Q_{PDC} 60th		Q_{PDC} 70th		Q_{PDC} 80th	
	Whites	**Blacks**	**Whites**	**Blacks**	**Whites**	**Blacks**	**Whites**	**Blacks**
	Coefficient Estimate (Standard Error)							
Age 70-75	-2.06 (1.10)	1.29 (7.79)	**-3.67** **(0.85)**	-0.79 (5.63)	-1.49 (1.73)	-2.96 (6.48)	-0.89 (1.17)	-0.18 (3.92)
Age 75-80	-2.54 (2.25)	0.57 (6.27)	**-5.74** **(2.41)**	1.23 (4.12)	**-4.45** **(1.54)**	3.59 (5.69)	**-2.53** **(0.65)**	4.92 (3.46)
Age ≥ 80	-5.80 (4.64)	0.09 (9.02)	**-6.86** **(2.71)**	0.15 (5.76)	-3.83 (3.03)	-0.49 (4.28)	-1.50 (1.59)	2.04 (3.60)
Female	0.68 (1.98)	-6.02 (4.13)	0.83 (1.15)	-0.42 (1.51)	0.21 (0.96)	-3.67 (2.42)	-0.08 (0.84)	-2.91 (2.85)
Married	-1.40 (3.19)	1.01 (3.50)	-0.89 (1.65)	-3.29 (3.11)	-1.26 (0.83)	-3.33 (2.67)	**-0.71** **(0.29)**	-2.60 (2.33)
Urban Residence	-1.57 (6.49)	0.79 (3.86)	-0.61 (5.42)	-1.12 (3.24)	1.59 (4.61)	-1.41 (3.46)	1.32 (4.31)	-0.07 (4.34)
Census Region: Midwest	**4.07** **(2.03)**	**15.25** **(6.92)**	1.78 (1.64)	9.13 (8.20)	0.91 (1.85)	7.39 (4.73)	0.09 (1.07)	2.96 (1.59)
South	**-2.00** **(0.62)**	7.76 (7.15)	-0.84 (1.49)	0.08 (7.53)	0.03 (0.94)	0.24 (3.88)	0.02 (1.38)	0.52 (1.40)
West	1.53 (1.29)	-1.55 (7.69)	1.94 (1.11)	-5.45 (5.94)	1.05 (1.03)	0.67 (3.90)	**1.16** **(0.44)**	-2.55 (2.52)
Health Status: Very Good	**6.61** **(1.90)**	**4.24** **(1.85)**	**4.19** **(2.12)**	5.37 (4.56)	**3.11** **(0.55)**	2.99 (2.59)	**1.23** **(0.28)**	4.94 (2.94)
Good	4.16 (3.94)	4.89 (3.27)	1.96 (2.86)	6.49 (5.34)	1.16 (1.89)	**6.01** **(1.30)**	0.67 (1.38)	3.52 (2.18)

Table C-4. (Continued)

Covariate	Q_{PDC} 50th		Q_{PDC} 60th		Q_{PDC} 70th		Q_{PDC} 80th	
	Whites	Blacks	Whites	Blacks	Whites	Blacks	Whites	Blacks
	Coefficient Estimate (Standard Error)							
Fair	7.27 (3.73)	9.30 (7.28)	4.41 (2.46)	9.23 (6.89)	2.70 (1.47)	7.18 (6.02)	**1.83** **(0.70)**	7.45 (5.46)
Poor	-2.18 (5.10)	**17.13** **(4.83)**	-1.80 (4.38)	**17.20** **(4.07)**	0.29 (3.14)	**14.05** **(2.89)**	1.43 (0.88)	**12.10** **(3.78)**
Any Physical Limitation	-1.21 (1.43)	**10.62** **(2.91)**	-1.19 (2.10)	**6.99** **(3.29)**	-0.55 (2.14)	1.37 (3.02)	-1.10 (1.40)	-0.95 (1.66)
Any Cognitive Limitation	-4.16 (4.10)	**5.25** **(1.85)**	-3.18 (6.20)	0.41 (3.21)	-2.32 (2.21)	**-3.85** **(1.42)**	-3.03 (1.76)	**-4.67** **(2.11)**
Depressive Symptoms	1.93 (5.15)	-6.19 (3.78)	-1.98 (3.38)	-1.53 (3.69)	-2.57 (1.86)	**2.88** **(1.33)**	-0.64 (0.97)	**4.60** **(0.80)**
Hypertension	3.08 (3.18)	**9.44** **(4.48)**	4.07 (3.58)	**14.64** **(3.47)**	1.39 (3.03)	7.81 (4.12)	0.39 (1.89)	**8.02** **(1.48)**
Hyperlipidemia	1.90 (1.43)	1.05 (7.95)	1.53 (0.92)	2.49 (5.63)	1.13 (0.93)	1.90 (2.40)	0.12 (0.79)	1.38 (1.44)
Angina/CHD	1.22 (2.63)	4.49 (7.53)	1.22 (1.53)	2.91 (4.95)	1.90 (1.47)	0.36 (2.31)	1.64 (1.47)	-0.00 (1.95)
CHF	3.60 (2.55)	-1.17 (7.12)	5.25 (3.20)	-1.02 (6.66)	-0.17 (2.63)	4.11 (2.53)	1.51 (4.55)	-2.53 (5.51)
AMI	2.10 (6.66)	**-7.88** **(3.53)**	0.58 (5.05)	-2.44 (4.05)	1.41 (4.41)	-2.02 (7.00)	-1.00 (3.65)	-3.61 (2.05)
Stroke	-3.57 (2.20)	3.72 (17.65)	0.95 (1.24)	2.21 (12.54)	-0.94 (1.89)	-4.20 (3.35)	0.74 (1.03)	1.24 (2.44)

Table C-4. (Continued)

Covariate	Q_{PDC} 50th		Q_{PDC} 60th		Q_{PDC} 70th		Q_{PDC} 80th	
	Whites	**Blacks**	**Whites**	**Blacks**	**Whites**	**Blacks**	**Whites**	**Blacks**
	Coefficient Estimate (Standard Error)							
Count of Comorbid Conditions	**-0.57 (0.29)**	-0.24 (0.31)	-0.53 (0.40)	-0.99 (0.55)	-0.08 (0.18)	-0.67 (0.43)	0.10 (0.20)	-0.34 (0.45)
Charlson Comorbidity Score Q3	-1.15 (2.50)	**8.15 (2.73)**	-2.16 (1.78)	2.67 (3.60)	0.24 (0.74)	-0.56 (3.94)	0.56 (0.55)	**-3.95 (0.88)**
Charlson Comorbidity Score Q4	0.19 (0.88)	**10.86 (2.38)**	-2.21 (1.69)	**4.06 (1.49)**	**-3.22 (1.64)**	5.58 (4.10)	-1.89 (2.66)	-1.12 (1.58)
More Likely to Take Risks	-2.50 (2.51)	-2.67 (1.61)	-2.07 (1.57)	-2.97 (2.83)	**-2.28 (0.98)**	0.12 (2.31)	-1.54 (1.58)	-1.63 (2.91)
Can overcome illness without medical care	0.87 (1.31)	-2.98 (12.17)	0.98 (1.02)	2.65 (8.98)	1.71 (2.13)	3.26 (8.17)	0.87 (1.89)	5.04 (7.53)
Does not need health insurance	-3.76 (4.09)	-3.57 (15.92)	-4.85 (2.86)	-1.72 (10.83)	-1.07 (2.45)	-2.34 (5.81)	-0.28 (2.58)	4.10 (4.64)
Current Smoker	0.12 (1.88)	-5.97 (5.46)	**-5.56 (1.92)**	-3.79 (3.35)	-2.56 (2.02)	-0.73 (3.48)	-0.43 (2.36)	1.92 (1.80)
Had Moderate / Vigorous Exercise	-3.21 (2.00)	-1.08 (2.86)	-2.33 (2.16)	3.20 (2.88)	-1.09 (1.76)	1.81 (4.37)	0.00 (0.84)	1.74 (2.51)
Obese (BMI≥30)	1.49 (2.01)	**4.10 (0.57)**	2.00 (1.76)	0.66 (0.96)	0.12 (0.82)	1.38 (1.03)	0.89 (0.97)	**3.12 (0.64)**
Income: Poor/Near-Poor	-0.07 (1.97)	**-7.81 (3.08)**	0.32 (1.68)	-6.44 (4.44)	-1.22 (1.37)	-3.41 (6.90)	-0.39 (0.82)	-5.48 (4.55)

Table C-4. (Continued)

Covariate	Q_{PDC} 50th		Q_{PDC} 60th		Q_{PDC} 70th		Q_{PDC} 80th	
	Whites	Blacks	Whites	Blacks	Whites	Blacks	Whites	Blacks
	Coefficient Estimate (Standard Error)							
Low-Income	0.63 (1.62)	**-9.15** **(4.36)**	1.09 (2.48)	-1.89 (6.98)	0.96 (1.37)	-1.85 (8.75)	-0.85 (0.85)	-1.64 (4.85)
Middle-Income	**1.24** **(0.61)**	-3.25 (3.70)	0.29 (1.01)	-3.30 (6.58)	0.02 (0.99)	0.58 (8.34)	-0.32 (0.84)	-1.36 (4.74)
Education: Less than High School	**2.81** **(1.40)**	-2.38 (4.45)	1.85 (1.30)	-4.77 (4.08)	0.33 (0.69)	**-4.49** **(2.01)**	**0.84** **(0.42)**	0.05 (1.75)
High School Diploma	0.77 (1.55)	-3.79 (3.60)	-0.03 (0.47)	-2.80 (3.20)	**-1.29** **(0.24)**	-3.12 (2.17)	**-0.76** **(0.37)**	0.50 (3.50)
Drug Coverage Plan: Part D: PDPs	-0.01 (1.23)	2.06 (4.59)	0.79 (1.61)	1.23 (4.28)	**2.34** **(0.93)**	1.60 (8.76)	1.10 (0.97)	-2.76 (6.28)
Part D: MA-PD	3.78 (3.53)	1.80 (8.80)	**5.75** **(1.08)**	-3.36 (4.74)	**4.12** **(0.81)**	-2.11 (6.43)	**2.97** **(0.70)**	-2.76 (3.42)
Employer/Other Private	-1.94 (2.01)	**12.79** **(3.33)**	0.21 (1.76)	**8.87** **(2.97)**	1.18 (1.07)	**9.70** **(2.43)**	-0.18 (0.95)	**8.15** **(2.34)**
Auto Eligible for PD Low-Income Subsidy	-2.22 (3.76)	1.29 (3.31)	-0.23 (2.24)	-0.18 (4.49)	-0.68 (0.93)	-0.12 (3.23)	-1.71 (0.99)	3.09 (2.49)
Average Copay for CV Drugs ($2010)	**-0.05** **(0.01)**	**-0.23** **(0.05)**	**-0.05** **(0.02)**	**-0.16** **(0.05)**	**-0.04** **(0.02)**	-0.06 (0.06)	-0.01 (0.01)	-0.04 (0.05)

Table C-4. (Continued)

Covariate	Q_{PDC} 50th		Q_{PDC} 60th		Q_{PDC} 70th		Q_{PDC} 80th	
	Whites	Blacks	Whites	Blacks	Whites	Blacks	Whites	Blacks
	Coefficient Estimate (Standard Error)							
Concurrently taking: 2-3 CV Drugs	-1.13 (1.30)	**-12.82 (3.63)**	**-5.27 (1.14)**	**-11.34 (3.45)**	**-4.97 (1.86)**	**-10.41 (1.66)**	**-3.09 (0.58)**	**-9.61 (1.87)**
≥4 CV Drugs	-2.00 (2.72)	**-13.34 (2.76)**	**-6.36 (2.29)**	**-11.61 (4.09)**	**-7.77 (3.18)**	**-8.89 (3.23)**	**-6.59 (1.51)**	**-4.75 (2.13)**
Quantiles of Ambulatory Visits: Q 3 (5-7)	3.89 (2.13)	**-5.33 (2.49)**	1.46 (2.42)	0.98 (4.24)	0.46 (1.49)	-1.08 (5.67)	0.47 (0.70)	-0.24 (2.66)
Q 4 (8-12)	1.47 (0.98)	**-15.69 (5.07)**	1.19 (1.54)	-0.74 (2.96)	0.18 (1.00)	0.60 (1.37)	-0.67 (0.64)	0.77 (0.84)
Q 5 (≥13)	-1.08 (2.29)	2.45 (3.95)	-0.92 (2.45)	6.62 (4.28)	-2.60 (1.67)	4.12 (4.96)	-0.88 (1.23)	-0.68 (3.34)
Had a Usual Source of Care	-5.55 (3.43)	-2.21 (10.25)	-0.10 (2.92)	-4.42 (10.52)	3.20 (3.53)	-6.90 (7.89)	-0.08 (3.99)	**-7.85 (2.52)**
Any Emergency Department Visit-Baseline Year	1.45 (0.81)	2.57 (4.29)	**2.76 (1.20)**	2.27 (3.88)	1.73 (1.55)	2.43 (3.23)	1.42 (1.12)	4.18 (2.47)
No. of Pharmacies Used	**-5.17 (1.46)**	**-6.76 (3.40)**	-1.66 (2.07)	-6.44 (6.26)	-0.90 (1.02)	-6.81 (4.40)	-0.40 (0.80)	**-5.30 (2.45)**
Very Satisfied with Received Healthcare	4.99 (2.69)	**7.85 (1.40**	1.40 (2.44)	2.68 (2.58)	0.20 (1.10)	**4.17 (0.96)**	**1.03 (0.50)**	3.96 (2.30)

Table C-4. (Continued)

Covariate	Q_{PDC} 50th		Q_{PDC} 60th		Q_{PDC} 70th		Q_{PDC} 80th	
	Whites	**Blacks**	**Whites**	**Blacks**	**Whites**	**Blacks**	**Whites**	**Blacks**
	Coefficient Estimate (Standard Error)							
Provider Always Explained	1.95 (2.37)	2.33 (3.96)	2.01 (1.92)	-0.16 (1.79)	2.02 (1.09)	-2.34 (3.32)	0.94 (0.98)	**-4.92 (1.79)**
Provider Always Listened	**-2.89 (1.27)**	0.19 (4.97)	**-1.60 (0.48)**	2.86 (3.47)	-0.95 (0.57)	1.84 (2.41)	-1.57 (1.13)	1.91 (1.78)
Provider Always Respected	0.33 (1.21)	-6.10 (7.32)	0.55 (1.25)	1.00 (7.13)	0.61 (1.01)	4.75 (3.70)	0.83 (0.54)	2.93 (2.41)
Constant (Base Q_{PDC})	**87.74 (8.13)**	**70.03 (27.98)**	**92.18 (6.40)**	**80.64 (14.34)**	**93.28 (7.27)**	**98.77 (15.40)**	**100.45 (9.46)**	**105.77 (6.75)**
Sample Size	2,585	703	2,585	703	2,585	703	2,585	703

Boldface estimates have P values <0.05. Standard errors were estimated by balanced repeated replications using MEPS-provided survey weights and half-sample identifiers.

Table C-5. Oaxaca-Blinder decomposition using coefficients from pooled RIF models, Q10th-Q40th

Outcome	Q_{PDC} 10th		Q_{PDC} 20th		Q_{PDC} 30th		Q_{PDC} 40th	
	Estimate (Standard Error)							
***Panel A*: Fitted Adherence Levels and Differences**								
Q_{PDC}, Blacks	**26.63 (3.33)**		**43.99 (2.52)**		**50.65 (2.68)**		**64.39 (2.37)**	
Q_{PDC}, Whites	**34.28 (1.22)**		**51.50 (1.11)**		**60.10 (1.28)**		**70.45 (1.14)**	
Difference	**-7.65 (3.77)**		**-7.51 (2.86)**		**-9.45 (3.06)**		**-6.05 (2.69)**	
***Panel B*: Portion of Adherence Difference Due to:**								
Characteristics	Difference in Characteristics	Difference in *Returns* to Characteristics	Difference in Characteristics	Difference in *Returns* to Characteristics	Difference in Characteristics	Difference in *Returns* to Characteristics	Difference in Characteristics	Difference in *Returns* to Characteristics
Aggregate Contribution	1.68 (2.00)	**-9.33 (3.80)**	2.23 (1.74)	**-9.73 (2.98)**	**3.77 (1.68)**	**-13.22 (3.20)**	**3.21 (1.37)**	**-9.26 (2.70)**
Age 70-75	-0.27 (0.30)	-2.60 (2.47)	-0.30 (0.28)	0.39 (2.44)	-0.26 (0.25)	2.38 (2.08)	-0.16 (0.22)	0.90 (1.99)
Age 75-80	0.13 (0.17)	-1.83 (1.95)	0.10 (0.14)	0.87 (1.46)	0.03 (0.07)	0.27 (1.41)	0.02 (0.07)	0.47 (1.35)
Age ≥ 80	0.47 (0.35)	0.84 (2.54)	0.33 (0.23)	1.46 (2.10)	0.29 (0.23)	1.69 (2.12)	0.29 (0.21)	1.01 (1.98)
Female	-0.02 (0.19)	2.67 (5.61)	-0.05 (0.17)	4.47 (4.39)	-0.16 (0.18)	0.73 (4.24)	-0.21 (0.18)	-2.55 (3.85)
Married	0.05 (0.71)	0.36 (2.97)	1.05 (0.57)	3.82 (2.35)	**1.35 (0.66)**	3.14 (2.35)	0.90 (0.59)	1.98 (2.13)
Urban Residence	-0.01 (0.21)	0.64 (7.88)	0.00 (0.17)	-3.40 (7.03)	-0.03 (0.17)	-0.52 (7.13)	-0.10 (0.15)	2.44 (6.72)
Census Region: Midwest	-0.39 (0.34)	1.88 (1.84)	-0.37 (0.27)	1.02 (1.53)	-0.57 (0.37)	0.08 (1.76)	-0.32 (0.33)	1.66 (1.56)
South	-0.89 (0.72)	7.25 (6.42)	-0.25 (0.60)	4.11 (4.59)	-0.45 (0.72)	2.13 (5.16)	-0.55 (0.72)	5.90 (4.52)
West	0.76 (0.50)	-0.43 (1.73)	0.12 (0.42)	-0.11 (1.07)	-0.09 (0.45)	-0.85 (1.03)	-0.11 (0.38)	-0.41 (0.88)
Health Status: Very Good	-0.48 (0.33)	-0.60 (4.54)	-0.45 (0.26)	-1.48 (3.02)	-0.34 (0.28)	-0.41 (3.34)	-0.45 (0.29)	-0.88 (2.67)
Good	0.04 (0.14)	1.18 (6.25)	0.07 (0.17)	-3.18 (3.95)	0.04 (0.13)	-1.70 (4.49)	0.07 (0.18)	-1.98 (3.49)

Table C-5. (Continued)

Characteristics	Q_{PDC} 10th		Q_{PDC} 20th		Q_{PDC} 30th		Q_{PDC} 40th	
	Estimate (Standard Error)							
	Difference in Characteristics	Difference in *Returns* to Characteristics	Difference in Characteristics	Difference in *Returns* to Characteristics	Difference in Characteristics	Difference in *Returns* to Characteristics	Difference in Characteristics	Difference in *Returns* to Characteristics
Fair	0.94 (0.50)	-1.25 (5.21)	**1.02 (0.48)**	-1.53 (3.35)	0.70 (0.50)	-0.17 (3.84)	0.87 (0.46)	-0.01 (2.94)
Poor	0.14 (0.21)	0.83 (1.62)	0.12 (0.18)	0.55 (1.24)	0.05 (0.17)	0.90 (1.42)	0.01 (0.16)	1.23 (1.11)
Any Physical Limitation	0.01 (0.10)	-0.54 (5.41)	-0.05 (0.11)	1.87 (4.35)	-0.04 (0.09)	5.66 (4.25)	-0.03 (0.08)	**7.70 (3.72)**
Any Cognitive Limitation	-0.47 (0.38)	-0.30 (1.83)	-0.20 (0.30)	0.77 (1.57)	-0.31 (0.33)	2.03 (1.46)	-0.15 (0.26)	1.15 (1.39)
Depressive Symptoms	-0.73 (0.41)	-1.88 (1.88)	-0.42 (0.33)	-0.77 (1.38)	-0.24 (0.31)	-0.43 (1.29)	-0.32 (0.26)	-0.68 (1.13)
Hypertension	0.26 (0.35)	-11.53 (14.21)	0.01 (0.31)	-2.36 (11.44)	0.59 (0.36)	0.29 (10.50)	0.61 (0.32)	-0.26 (9.42)
Hyperlipidemia	-0.10 (0.20)	-5.26 (4.49)	-0.00 (0.16)	0.13 (3.96)	-0.14 (0.19)	1.29 (3.77)	-0.12 (0.19)	2.43 (3.55)
Angina/CHD	0.06 (0.15)	0.48 (1.70)	0.00 (0.12)	1.42 (1.37)	-0.13 (0.12)	0.33 (1.22)	-0.07 (0.10)	0.43 (1.30)
CHF	-0.01 (0.04)	-0.03 (0.47)	-0.01 (0.04)	-0.26 (0.46)	0.00 (0.05)	0.22 (0.47)	0.00 (0.04)	0.05 (0.45)
AMI	-0.06 (0.10)	-0.53 (1.15)	-0.02 (0.09)	-0.72 (0.89)	0.01 (0.09)	-0.56 (0.89)	-0.04 (0.09)	-0.75 (0.75)
Stroke	0.00 (0.07)	0.86 (0.86)	-0.00 (0.06)	0.39 (0.66)	-0.01 (0.07)	0.11 (0.81)	-0.01 (0.07)	0.30 (0.80)
Count of Comorbid Conditions	-0.17 (0.57)	8.16 (6.58)	-0.11 (0.42)	3.04 (5.13)	0.41 (0.47)	1.31 (5.05)	0.23 (0.38)	-0.62 (4.32)
Charlson Comorbidity Score Q3	-0.01 (0.28)	3.48 (3.36)	-0.13 (0.24)	3.25 (2.54)	0.01 (0.23)	2.97 (2.30)	0.05 (0.22)	2.99 (2.25)

Table C-5. (Continued)

Characteristics	Q_{PDC} 10th		Q_{PDC} 20th		Q_{PDC} 30th		Q_{PDC} 40th	
	Estimate (Standard Error)							
	Difference in Characteristics	Difference in *Returns* to Characteristics	Difference in Characteristics	Difference in *Returns* to Characteristics	Difference in Characteristics	Difference in *Returns* to Characteristics	Difference in Characteristics	Difference in *Returns* to Characteristics
Charlson Comorbidity Score Q4	-0.04 (0.15)	0.92 (1.89)	-0.04 (0.13)	1.14 (1.58)	0.03 (0.11)	1.82 (1.62)	0.01 (0.10)	1.63 (1.41)
More Likely to Take Risks	-0.04 (0.10)	0.97 (1.22)	-0.04 (0.08)	0.43 (1.20)	0.02 (0.08)	-0.91 (1.42)	0.05 (0.09)	-0.48 (1.20)
Can overcome illness without medical care	0.04 (0.22)	-1.01 (1.07)	-0.00 (0.19)	-0.50 (0.80)	0.00 (0.24)	-0.87 (0.82)	0.07 (0.18)	-0.23 (0.71)
Does not need health insurance	-0.04 (0.10)	0.29 (0.77)	-0.06 (0.12)	0.51 (0.77)	-0.05 (0.11)	0.60 (0.82)	-0.10 (0.14)	0.87 (0.69)
Current Smoker	-0.00 (0.12)	0.70 (1.11)	-0.10 (0.13)	0.61 (0.87)	-0.10 (0.15)	0.84 (0.87)	-0.01 (0.12)	-0.53 (0.82)
Had Moderate / Vigorous Exercise	0.23 (0.25)	0.32 (3.29)	0.26 (0.21)	0.06 (2.39)	0.41 (0.25)	1.17 (2.82)	0.28 (0.22)	0.86 (2.40)
Obese (BMI≥30)	-0.00 (0.24)	**7.09 (2.91)**	0.16 (0.21)	4.05 (2.29)	0.14 (0.23)	3.83 (2.50)	0.15 (0.20)	1.14 (2.11)
Income: Poor/Near-Poor	-0.47 (0.64)	-4.53 (3.44)	-0.02 (0.59)	-3.39 (2.86)	0.11 (0.58)	-2.39 (3.21)	0.18 (0.55)	-1.41 (2.61)
Low-Income	-0.07 (0.22)	-2.63 (2.12)	0.18 (0.19)	-3.15 (1.77)	0.02 (0.23)	-2.44 (2.05)	0.03 (0.19)	-1.26 (1.91)
Middle-Income	-0.01 (0.13)	-4.04 (3.70)	-0.01 (0.14)	-3.07 (3.28)	-0.00 (0.10)	-3.69 (3.50)	-0.00 (0.08)	-0.42 (2.97)

Table C-5. (Continued)

Characteristics	Q_{PDC} 10th		Q_{PDC} 20th		Q_{PDC} 30th		Q_{PDC} 40th	
	Estimate (Standard Error)							
	Difference in Characteristics	Difference in *Returns* to Characteristics	Difference in Characteristics	Difference in *Returns* to Characteristics	Difference in Characteristics	Difference in *Returns* to Characteristics	Difference in Characteristics	Difference in *Returns* to Characteristics
Education: Less than High School	-0.98 (0.89)	-1.18 (3.78)	-0.42 (0.78)	3.58 (3.85)	-0.03 (0.86)	1.43 (3.86)	0.17 (0.76)	-1.67 (3.60)
High School Diploma	0.24 (0.39)	-4.94 (3.79)	0.32 (0.34)	1.99 (3.84)	0.26 (0.40)	-0.21 (4.07)	0.10 (0.34)	-1.21 (3.68)
Drug Coverage Plan: Part D: PDPs	0.40 (0.36)	**12.30 (6.27)**	0.24 (0.25)	2.80 (4.86)	0.33 (0.29)	3.23 (4.58)	0.00 (0.24)	1.92 (3.62)
Part D: MA-PD	0.16 (0.28)	5.80 (4.36)	0.26 (0.23)	2.16 (3.08)	0.31 (0.27)	3.05 (3.08)	0.18 (0.22)	0.94 (2.48)
Employer/Other Private	0.06 (0.34)	3.68 (2.23)	-0.21 (0.27)	2.15 (1.60)	-0.25 (0.30)	**3.52 (1.43)**	0.06 (0.26)	**2.67 (1.19)**
Auto Eligible for PD Low-Income Subsidy	0.59 (0.96)	**-4.90 (2.31)**	-0.23 (0.85)	**-4.08 (1.81)**	0.42 (0.94)	-2.42 (1.88)	0.16 (0.80)	0.09 (1.65)
Average Copay for CV Drugs ($2010)	0.54 (0.35)	2.16 (2.77)	0.35 (0.28)	-0.18 (2.13)	0.42 (0.29)	-2.41 (2.11)	0.41 (0.24)	-2.50 (1.85)
Concurrently taking: 2-3 CV Drugs	-0.04 (0.23)	-0.28 (5.29)	-0.03 (0.15)	-4.06 (3.63)	-0.00 (0.07)	-6.22 (3.70)	0.01 (0.10)	-5.76 (3.28)
≥4 CV Drugs	0.44 (0.30)	-0.01 (1.75)	0.31 (0.19)	-0.62 (1.35)	0.09 (0.16)	-1.62 (1.19)	-0.13 (0.16)	-1.49 (1.08)

Table C-5. (Continued)

Characteristics	Q_{PDC} 10th		Q_{PDC} 20th		Q_{PDC} 30th		Q_{PDC} 40th	
	Estimate (Standard Error)							
	Difference in Characteristics	Difference in *Returns* to Characteristics	Difference in Characteristics	Difference in *Returns* to Characteristics	Difference in Characteristics	Difference in *Returns* to Characteristics	Difference in Characteristics	Difference in *Returns* to Characteristics
Ambulatory Visit Quantiles:								
Q 3 (5-7)	-0.05 (0.15)	0.28 (2.27)	0.02 (0.09)	-2.60 (1.77)	0.07 (0.14)	-2.94 (1.58)	0.07 (0.14)	-2.10 (1.26)
Q 4 (8-12)	0.21 (0.29)	-0.13 (1.77)	0.21 (0.24)	-0.71 (1.36)	-0.12 (0.25)	-1.44 (1.35)	-0.03 (0.21)	-1.25 (1.24)
Q 5 (≥13)	0.46 (0.34)	2.04 (1.76)	0.18 (0.27)	1.00 (1.31)	0.12 (0.28)	0.36 (1.47)	0.18 (0.25)	0.37 (1.32)
Had a Usual Source of Care	0.18 (0.15)	-7.53 (13.74)	-0.07 (0.13)	2.72 (15.34)	-0.05 (0.13)	-2.38 (14.92)	0.09 (0.13)	2.13 (13.42)
Any ED Visit-Baseline Year	0.13 (0.15)	0.13 (1.57)	0.09 (0.12)	1.92 (1.43)	0.19 (0.15)	1.01 (1.29)	0.06 (0.10)	0.70 (1.03)
No. of Pharmacies	0.48 (0.37)	-1.10 (10.02)	0.62 (0.34)	-5.26 (7.86)	**0.89 (0.38)**	0.31 (8.33)	**1.07 (0.32)**	2.34 (7.17)
Very Satisfied with Healthcare	-0.01 (0.14)	3.79 (4.92)	-0.17 (0.17)	5.21 (4.20)	-0.18 (0.18)	4.15 (3.88)	-0.24 (0.19)	1.38 (3.56)
Provider Explained	0.06 (0.14)	-3.63 (6.47)	0.07 (0.14)	-5.14 (4.70)	-0.01 (0.10)	-1.62 (4.92)	0.00 (0.09)	-0.74 (4.40)
Provider Listened	-0.03 (0.10)	-3.77 (6.07)	-0.04 (0.11)	-1.61 (4.73)	-0.02 (0.10)	3.48 (5.69)	-0.04 (0.10)	5.32 (4.32)
Provider Respected	-0.01 (0.09)	-3.15 (5.55)	-0.05 (0.11)	-1.83 (5.18)	0.01 (0.09)	-5.65 (5.74)	0.00 (0.08)	-6.44 (5.20)
Constant (Base Q_{PDC})		-8.80 (32.31)		-17.62 (25.77)		-25.75 (30.57)		-26.61 (26.37)
Sample Size	3,288							

Boldface estimates have P values <0.05. Standard errors were estimated by balanced repeated replications using MEPS-provided survey weights and half-sample identifiers.

Table C-6. Oaxaca-Blinder decomposition using coefficients from pooled RIF models, Q50th-Q80th

Outcome	Q_{PDC} 50th		Q_{PDC} 60th		Q_{PDC} 70th		Q_{PDC} 80th	
	Estimate (Standard Error)							
***Panel A*: Fitted Adherence Levels and Differences**								
Q_{PDC}, Blacks	**73.83 (1.89)†**		**81.38 (1.60)†**		**89.54 (1.07)†**		**96.98 (0.60)†**	
Q_{PDC}, Whites	**77.86 (1.02)†**		**86.19 (0.95)†**		**93.22 (0.71)†**		**99.42 (0.41)†**	
Difference	-4.03 (2.15)		**-4.80 (1.88)†**		**-3.68 (1.37)†**		**-2.44 (0.76)†**	
***Panel B*: Portion of Adherence Difference Due to:**								
Characteristics	Difference in Characteristics	Difference in *Returns* to Characteristics	Difference in Characteristics	Difference in *Returns* to Characteristics	Difference in Characteristics	Difference in *Returns* to Characteristics	Difference in Characteristics	Difference in *Returns* to Characteristics
Aggregate Contribution	2.52 (1.30)	**-6.55 (2.29)**	1.64 (1.27)	**-6.45 (2.16)**	0.91 (0.88)	**-4.59 (1.53)**	0.20 (0.54)	**-2.64 (0.87)**
Age 70-75	-0.18 (0.19)	0.82 (1.73)	-0.26 (0.21)	0.38 (1.74)	-0.10 (0.14)	0.02 (1.14)	-0.06 (0.08)	0.13 (0.61)
Age 75-80	0.04 (0.07)	0.86 (1.22)	0.07 (0.10)	1.80 (1.20)	0.05 (0.08)	**1.88 (0.82)**	0.03 (0.04)	**1.12 (0.49)**
Age ≥ 80	0.37 (0.22)	1.42 (1.83)	0.39 (0.24)	2.01 (1.80)	0.25 (0.16)	1.42 (1.20)	0.08 (0.07)	0.88 (0.72)
Female	0.06 (0.14)	-0.32 (3.19)	0.03 (0.12)	-3.01 (2.93)	0.00 (0.11)	-1.76 (1.86)	-0.02 (0.06)	-0.46 (1.06)
Married	0.37 (0.52)	0.80 (1.85)	0.25 (0.48)	-0.79 (1.73)	0.41 (0.34)	-0.67 (1.10)	0.11 (0.20)	0.26 (0.61)
Urban Residence	-0.07 (0.15)	-0.65 (5.81)	-0.05 (0.15)	-0.13 (5.07)	0.05 (0.10)	-1.54 (3.66)	0.06 (0.07)	0.65 (1.99)
Census Region: Midwest	-0.48 (0.33)	1.79 (1.21)	-0.19 (0.26)	1.20 (1.11)	-0.11 (0.20)	0.34 (0.78)	0.01 (0.10)	0.46 (0.48)
South	-0.32 (0.57)	3.85 (3.57)	-0.31 (0.54)	0.51 (3.10)	-0.00 (0.41)	-0.35 (2.41)	-0.10 (0.25)	0.55 (1.34)
West	-0.14 (0.32)	-0.41 (0.79)	-0.22 (0.31)	-0.26 (0.81)	-0.14 (0.24)	-0.38 (0.51)	-0.07 (0.13)	0.03 (0.27)
Health Status: Very Good	-0.48 (0.27)	-1.06 (1.98)	-0.33 (0.24)	-0.10 (1.75)	-0.24 (0.18)	0.40 (1.27)	-0.11 (0.10)	-0.17 (0.75)

Table C-6. (Continued)

Characteristics	Q_{PDC} 50th		Q_{PDC} 60th		Q_{PDC} 70th		Q_{PDC} 80th	
	Estimate (Standard Error)							
	Difference in Characteristics	Difference in *Returns* to Characteristics	Difference in Characteristics	Difference in *Returns* to Characteristics	Difference in Characteristics	Difference in *Returns* to Characteristics	Difference in Characteristics	Difference in *Returns* to Characteristics
Good	0.04 (0.13)	-0.96 (2.81)	0.03 (0.10)	1.35 (2.69)	0.02 (0.07)	1.00 (1.94)	0.01 (0.04)	-0.64 (1.14)
Fair	0.63 (0.38)	-1.31 (2.30)	0.55 (0.38)	0.86 (2.17)	0.29 (0.28)	1.00 (1.58)	0.15 (0.16)	-0.36 (0.91)
Poor	-0.02 (0.15)	1.03 (0.90)	0.02 (0.13)	1.30 (0.87)	0.05 (0.08)	1.03 (0.62)	0.05 (0.05)	0.06 (0.33)
Any Physical Limitation	-0.00 (0.06)	5.47 (3.11)	-0.02 (0.06)	2.48 (2.90)	-0.01 (0.05)	-0.10 (1.98)	-0.02 (0.04)	0.88 (1.22)
Any Cognitive Limitation	-0.13 (0.27)	0.99 (1.15)	-0.25 (0.26)	0.94 (1.07)	-0.24 (0.16)	-0.16 (0.65)	-0.19 (0.10)	0.21 (0.35)
Depressive Symptoms	0.10 (0.25)	-0.50 (1.01)	-0.04 (0.22)	0.04 (0.98)	-0.20 (0.16)	0.68 (0.57)	-0.07 (0.09)	0.14 (0.30)
Hypertension	0.41 (0.27)	8.84 (8.11)	0.41 (0.27)	7.33 (8.34)	0.20 (0.18)	4.43 (6.25)	0.09 (0.12)	4.67 (2.71)
Hyperlipidemia	-0.17 (0.16)	-0.42 (3.24)	-0.11 (0.14)	-0.23 (2.82)	-0.09 (0.10)	0.31 (1.97)	-0.03 (0.06)	0.11 (1.12)
Angina/CHD	-0.08 (0.09)	0.13 (1.00)	-0.08 (0.10)	-0.14 (0.88)	-0.10 (0.08)	-0.16 (0.58)	-0.08 (0.05)	-0.04 (0.39)
CHF	-0.01 (0.04)	-0.23 (0.42)	-0.02 (0.05)	-0.11 (0.35)	-0.01 (0.03)	-0.18 (0.27)	-0.00 (0.02)	-0.08 (0.16)
AMI	-0.02 (0.07)	-0.43 (0.62)	0.01 (0.07)	-0.13 (0.66)	-0.02 (0.05)	-0.20 (0.44)	0.02 (0.03)	-0.05 (0.24)
Stroke	-0.01 (0.07)	0.52 (0.59)	0.00 (0.05)	-0.73 (0.59)	-0.00 (0.03)	0.06 (0.35)	0.00 (0.02)	-0.02 (0.20)
Count of Comorbid Conditions	**0.64 (0.31)**	0.10 (4.10)	0.42 (0.31)	-0.00 (4.36)	0.11 (0.23)	-2.87 (2.56)	-0.08 (0.15)	-0.59 (1.49)
Charlson Comorbidity Score Q3	-0.05 (0.20)	2.24 (2.01)	-0.18 (0.18)	0.53 (1.97)	-0.04 (0.12)	-1.25 (1.16)	0.06 (0.07)	-0.61 (0.66)

Table C-6. (Continued)

Characteristics	Q_{PDC} 50th		Q_{PDC} 60th		Q_{PDC} 70th		Q_{PDC} 80th	
	Estimate (Standard Error)							
	Difference in Characteristics	Difference in *Returns* to Characteristics	Difference in Characteristics	Difference in *Returns* to Characteristics	Difference in Characteristics	Difference in *Returns* to Characteristics	Difference in Characteristics	Difference in *Returns* to Characteristics
Charlson Comorbidity Score Q4	0.00 (0.08)	0.78 (1.31)	-0.03 (0.08)	0.75 (1.28)	-0.07 (0.08)	0.61 (0.66)	-0.03 (0.04)	0.33 (0.37)
More Likely to Take Risks	0.04 (0.08)	-0.05 (1.08)	0.04 (0.08)	0.46 (0.93)	0.06 (0.07)	0.42 (0.59)	0.03 (0.04)	0.20 (0.34)
Can overcome illness without medical care	-0.03 (0.15)	-0.02 (0.64)	-0.04 (0.13)	0.01 (0.68)	-0.11 (0.11)	-0.01 (0.47)	-0.06 (0.07)	-0.11 (0.24)
Does not need health insurance	-0.02 (0.06)	0.17 (0.61)	-0.04 (0.07)	-0.03 (0.53)	-0.01 (0.04)	0.19 (0.35)	-0.00 (0.02)	0.16 (0.22)
Current Smoker	0.01 (0.11)	-0.29 (0.71)	-0.17 (0.14)	0.08 (0.66)	-0.08 (0.08)	0.27 (0.46)	-0.00 (0.04)	0.27 (0.30)
Had Moderate / Vigorous Exercise	0.25 (0.20)	1.17 (2.19)	0.18 (0.19)	1.03 (2.07)	0.06 (0.13)	1.35 (1.26)	0.02 (0.07)	-0.17 (0.70)
Obese (BMI≥30)	0.18 (0.19)	0.29 (1.91)	0.19 (0.19)	-0.18 (1.76)	0.06 (0.12)	0.87 (1.19)	0.09 (0.08)	0.08 (0.73)
Income: Poor/Near-Poor	-0.09 (0.44)	-3.02 (2.39)	-0.01 (0.42)	-1.49 (2.48)	-0.27 (0.28)	-0.54 (1.71)	-0.12 (0.17)	-0.78 (0.92)
Low-Income	0.01 (0.17)	-1.75 (1.73)	0.07 (0.16)	-0.81 (1.80)	0.07 (0.11)	-0.43 (1.15)	-0.05 (0.06)	0.24 (0.64)
Middle-Income	-0.00 (0.07)	-2.06 (2.68)	-0.00 (0.06)	-0.45 (2.51)	-0.00 (0.04)	0.44 (1.53)	0.00 (0.03)	-0.54 (0.89)

Table C-6. (Continued)

Characteristics	Q_{PDC} 50th		Q_{PDC} 60th		Q_{PDC} 70th		Q_{PDC} 80th	
	Estimate (Standard Error)							
	Difference in Characteristics	Difference in *Returns* to Characteristics	Difference in Characteristics	Difference in *Returns* to Characteristics	Difference in Characteristics	Difference in *Returns* to Characteristics	Difference in Characteristics	Difference in *Returns* to Characteristics
Education:								
Less than High School	0.56 (0.67)	-1.73 (2.91)	0.39 (0.72)	-3.68 (2.71)	-0.01 (0.52)	-1.42 (2.02)	0.09 (0.32)	-1.24 (1.14)
High School Diploma	-0.05 (0.27)	-0.65 (2.88)	-0.02 (0.25)	-2.68 (2.87)	0.18 (0.18)	-0.47 (1.77)	0.11 (0.12)	0.07 (0.96)
Drug Coverage Plan:								
Part D: PDPs	0.03 (0.21)	0.28 (3.37)	0.13 (0.19)	0.34 (3.20)	0.24 (0.15)	-1.27 (2.29)	0.10 (0.09)	-0.32 (0.95)
Part D: MA-PD	0.22 (0.20)	-1.14 (2.37)	0.33 (0.21)	-2.49 (2.15)	0.25 (0.17)	-1.56 (1.53)	0.17 (0.11)	-0.59 (0.77)
Employer/Other Private	0.13 (0.22)	1.43 (1.04)	-0.07 (0.23)	1.32 (1.02)	-0.14 (0.18)	1.10 (0.72)	-0.00 (0.11)	0.70 (0.41)
Auto Eligible for PD Low-Income Subsidy	-0.11 (0.73)	1.06 (1.41)	-0.08 (0.63)	-0.33 (1.40)	0.11 (0.42)	0.89 (0.89)	-0.06 (0.23)	0.89 (0.52)
Average Copay for CV Drugs ($2010)	**0.43 (0.22)**	-2.25 (1.41)	0.39 (0.20)	-1.20 (1.31)	**0.35 (0.13)**	0.15 (0.87)	0.08 (0.08)	0.17 (0.53)
Concurrently taking:								
2-3 CV Drugs	0.01 (0.07)	-3.14 (2.91)	0.02 (0.14)	-2.74 (3.13)	0.03 (0.16)	-2.58 (1.96)	0.02 (0.09)	-2.15 (1.20)
≥4 CV Drugs	-0.10 (0.16)	-0.64 (0.98)	-0.24 (0.18)	-0.27 (1.07)	**-0.30 (0.15)**	0.26 (0.65)	**-0.24 (0.11)**	0.42 (0.39)

Table C-6. (Continued)

Characteristics	Q_{PDC} 50th		Q_{PDC} 60th		Q_{PDC} 70th		Q_{PDC} 80th	
	Estimate (Standard Error)							
	Difference in Characteristics	Difference in *Returns* to Characteristics	Difference in Characteristics	Difference in *Returns* to Characteristics	Difference in Characteristics	Difference in *Returns* to Characteristics	Difference in Characteristics	Difference in *Returns* to Characteristics
Ambulatory Visits Quantiles								
Q 3 (5-7)	0.06 (0.12)	-1.15 (1.27)	0.02 (0.08)	-0.20 (1.18)	0.00 (0.05)	-0.08 (0.80)	0.00 (0.03)	-0.30 (0.46)
Q 4 (8-12)	-0.13 (0.21)	-1.23 (1.01)	-0.03 (0.21)	-0.33 (0.95)	0.02 (0.14)	0.31 (0.61)	0.03 (0.09)	0.26 (0.42)
Q 5 (≥13)	0.01 (0.19)	1.19 (1.10)	0.10 (0.20)	0.81 (1.06)	0.16 (0.15)	0.76 (0.76)	0.07 (0.09)	-0.19 (0.42)
Had a Usual Source of Care	0.08 (0.11)	2.51 (12.50)	0.02 (0.09)	-4.97 (13.03)	-0.03 (0.06)	-12.36 (8.94)	0.01 (0.04)	-6.35 (5.24)
Any ED Visit-Baseline Year	0.05 (0.09)	0.08 (1.07)	0.08 (0.09)	0.13 (1.01)	0.05 (0.06)	0.27 (0.63)	0.05 (0.05)	0.15 (0.41)
No. of Pharmacies	**0.74 (0.28)**	-2.52 (5.76)	0.39 (0.26)	-4.20 (5.60)	0.16 (0.17)	-5.65 (3.64)	0.07 (0.12)	-1.80 (2.36)
Very Satisfied with Healthcare	-0.24 (0.19)	0.02 (2.91)	-0.10 (0.14)	1.69 (2.78)	-0.04 (0.09)	1.25 (1.79)	-0.04 (0.06)	0.26 (1.02)
Provider Explained	0.02 (0.08)	-0.69 (3.95)	0.02 (0.08)	-3.24 (3.85)	0.03 (0.06)	-3.33 (2.48)	0.01 (0.03)	-0.71 (1.33)
Provider Listened	-0.04 (0.09)	3.21 (3.90)	-0.02 (0.08)	2.58 (3.82)	-0.01 (0.06)	2.24 (2.35)	-0.03 (0.04)	2.09 (1.66)
Provider Respected	0.01 (0.06)	-3.42 (5.63)	0.01 (0.07)	1.82 (4.01)	0.01 (0.05)	2.13 (2.88)	0.02 (0.04)	-0.27 (1.54)
Constant (Base Q_{PDC})		-15.53 (22.44)		-3.28 (21.40)		8.68 (14.98)		-0.53 (8.67)
Sample Size	3,288							

Boldface estimates have P values <0.05. Standard errors were estimated by balanced repeated replications using MEPS-provided survey weights and half-sample identifiers.

Table C-7. Oaxaca-Blinder decomposition of mean differences in continuous PDC and in the probability of having PDC≥80%

Outcome	Linear Probability Model (PDC≥80%)		Logistic Model (PDC≥80%)		Ordinary Least Squares (Continuous PDC)	
	Estimate (Standard Error)					
	***Panel A*: Fitted Adherence Levels and Difference**					
	Average Probability of Adherence (PDC≥80%)				*Mean PDC*	
Blacks	**0.41 (0.02)**		**0.41 (0.02)**		**68.05 (1.42)**	
Whites	**0.47 (0.01)**		**0.47 (0.01)**		**73.09 (0.67)**	
Difference	**-0.06 (0.03)**		**-0.06 (0.03)**		**-5.04 (1.62)**	
	***Panel B*: Portion of adherence difference due to**					
Characteristics	Difference in Characteristics	Difference in *Returns* to Characteristics	Difference in Characteristics	Difference in *Returns* to Characteristics	Difference in Characteristics	Difference in *Returns* to Characteristics
Aggregate Contribution	0.03 (0.03)	**-0.09 (0.04)**	0.03 (0.03)	**-0.09 (0.04)**	0.95 (2.58)	-5.99 (3.09)
Age 70-75	-0.00 (0.00)	0.00 (0.02)	-0.00 (0.00)	0.00 (0.02)	-0.08 (0.21)	0.30 (0.93)
Age 75-80	-0.00 (0.00)	0.01 (0.02)	-0.00 (0.00)	0.01 (0.01)	0.01 (0.11)	0.56 (0.89)
Age ≥ 80	-0.00 (0.00)	0.03 (0.03)	-0.00 (0.00)	0.03 (0.03)	0.02 (0.25)	1.21 (1.38)
Female	-0.00 (0.00)	-0.01 (0.03)	-0.00 (0.00)	-0.01 (0.03)	-0.05 (0.26)	-0.19 (2.06)
Married	0.01 (0.01)	-0.01 (0.04)	0.01 (0.01)	-0.01 (0.03)	0.03 (1.01)	1.07 (2.37)
Urban Residence	0.00 (0.00)	0.01 (0.06)	0.00 (0.00)	0.01 (0.06)	-0.02 (0.23)	0.09 (3.57)
Census Region: Midwest	-0.01 (0.01)	0.03 (0.02)	-0.01 (0.01)	0.03 (0.02)	-0.68 (0.50)	1.23 (1.29)
South	0.01 (0.02)	0.02 (0.03)	0.01 (0.01)	0.02 (0.03)	0.60 (0.99)	1.45 (1.53)
West	0.01 (0.01)	-0.02 (0.02)	0.01 (0.01)	-0.01 (0.02)	0.52 (1.02)	-0.90 (1.64)

Table C-7. (Continued)

Characteristics	Linear Probability Model (PDC≥80%)		Logistic Model (PDC≥80%)		Ordinary Least Squares (Continuous PDC)	
	Estimate (Standard Error)					
	Difference in Characteristics	Difference in *Returns* to Characteristics	Difference in Characteristics	Difference in *Returns* to Characteristics	Difference in Characteristics	Difference in *Returns* to Characteristics
Health Status: Very Good	-0.00 (0.01)	-0.00 (0.03)	-0.00 (0.01)	0.00 (0.03)	-0.29 (0.50)	0.05 (2.04)
Good	0.00 (0.00)	0.01 (0.03)	0.00 (0.00)	0.01 (0.03)	0.03 (0.20)	-0.11 (2.13)
Fair	0.01 (0.01)	0.00 (0.02)	0.01 (0.01)	0.00 (0.02)	0.57 (0.65)	0.11 (1.22)
Poor	0.01 (0.00)	0.01 (0.01)	0.01 (0.00)	0.01 (0.01)	0.31 (0.26)	0.53 (0.44)
Any Physical Limitation	0.00 (0.00)	0.07 (0.04)	0.00 (0.00)	0.06 (0.03)	0.03 (0.12)	1.77 (2.21)
Any Cognitive Limitation	0.00 (0.01)	0.01 (0.01)	0.00 (0.00)	0.01 (0.01)	-0.02 (0.33)	0.29 (0.46)
Depressive Symptoms	-0.00 (0.01)	-0.01 (0.01)	-0.00 (0.01)	-0.01 (0.01)	-0.34 (0.37)	-0.15 (0.39)
Hypertension	0.02 (0.01)	0.12 (0.09)	0.02 (0.01)	0.12 (0.09)	0.46 (0.63)	1.57 (5.02)
Hyperlipidemia	-0.00 (0.00)	0.00 (0.04)	-0.00 (0.00)	0.00 (0.04)	0.04 (0.21)	-1.01 (2.20)
Angina/CHD	-0.00 (0.00)	-0.00 (0.01)	-0.00 (0.00)	0.00 (0.01)	-0.12 (0.15)	0.50 (0.80)
CHF	0.00 (0.00)	-0.00 (0.01)	0.00 (0.00)	-0.00 (0.00)	0.00 (0.06)	-0.09 (0.29)
AMI	0.00 (0.00)	-0.01 (0.01)	0.00 (0.00)	-0.00 (0.01)	0.08 (0.16)	-0.49 (0.57)
Stroke	0.00 (0.00)	0.00 (0.01)	0.00 (0.00)	0.00 (0.01)	0.00 (0.09)	0.19 (0.40)
Comorbid Conditions Count	0.01 (0.01)	-0.03 (0.07)	0.01 (0.01)	-0.03 (0.06)	-0.06 (0.53)	1.18 (3.29)
Charlson Comorbidity Score Q3	0.00 (0.01)	0.02 (0.02)	0.00 (0.00)	0.02 (0.02)	0.24 (0.28)	1.13 (1.04)

Table C-7. (Continued)

Characteristics	Linear Probability Model (PDC≥80%)		Logistic Model (PDC≥80%)		Ordinary Least Squares (Continuous PDC)	
	Estimate (Standard Error)					
	Difference in Characteristics	Difference in *Returns* to Characteristics	Difference in Characteristics	Difference in *Returns* to Characteristics	Difference in Characteristics	Difference in *Returns* to Characteristics
Charlson Comorbidity Score Q3	0.00 (0.01)	0.02 (0.02)	0.00 (0.00)	0.02 (0.02)	0.24 (0.28)	1.13 (1.04)
Charlson Comorbidity Score Q4	0.00 (0.00)	0.01 (0.01)	0.00 (0.00)	0.01 (0.01)	0.10 (0.15)	0.76 (0.78)
More Likely to Take Risks	0.00 (0.00)	-0.00 (0.01)	0.00 (0.00)	-0.00 (0.01)	0.01 (0.10)	0.12 (0.74)
Can overcome illness without medical care	-0.00 (0.01)	-0.00 (0.01)	-0.00 (0.00)	-0.00 (0.01)	0.10 (0.40)	-0.32 (0.79)
Does not need health insurance	-0.00 (0.00)	0.00 (0.01)	-0.00 (0.00)	0.00 (0.01)	-0.01 (0.09)	0.17 (0.37)
Current Smoker	-0.00 (0.00)	-0.00 (0.01)	-0.00 (0.00)	-0.00 (0.01)	-0.02 (0.13)	0.13 (0.34)
Had Moderate / Vigorous Exercise	-0.00 (0.01)	0.04 (0.03)	-0.00 (0.00)	0.03 (0.03)	0.05 (0.35)	0.66 (1.77)
Obese (BMI≥30)	0.00 (0.00)	-0.00 (0.02)	0.00 (0.00)	-0.00 (0.02)	0.54 (0.32)	1.49 (1.02)
Income: Poor/Near-Poor	-0.02 (0.01)	-0.01 (0.01)	-0.01 (0.01)	-0.01 (0.01)	-1.06 (0.84)	-0.95 (0.80)
Low-Income	-0.00 (0.00)	-0.01 (0.02)	-0.00 (0.00)	-0.01 (0.02)	-0.28 (0.28)	-0.97 (0.82)

Table C-7. (Continued)

Characteristics	Linear Probability Model (PDC≥80%)		Logistic Model (PDC≥80%)		Ordinary Least Squares (Continuous PDC)	
	Estimate (Standard Error)					
	Difference in Characteristics	Difference in *Returns* to Characteristics	Difference in Characteristics	Difference in *Returns* to Characteristics	Difference in Characteristics	Difference in *Returns* to Characteristics
Middle-Income	0.00 (0.00)	-0.02 (0.03)	0.00 (0.00)	-0.02 (0.03)	0.01 (0.15)	-1.59 (1.81)
Education:						
Less than High School	-0.01 (0.02)	-0.01 (0.02)	-0.01 (0.02)	-0.01 (0.01)	-0.41 (1.09)	-0.27 (0.82)
High School Diploma	0.00 (0.01)	-0.02 (0.04)	0.00 (0.01)	-0.02 (0.04)	0.43 (0.60)	-1.19 (2.72)
Drug Coverage Plan: Part D: PDPs	0.00 (0.01)	0.00 (0.03)	0.00 (0.01)	0.00 (0.03)	0.60 (0.61)	1.94 (2.11)
Part D: MA-PD	-0.00 (0.01)	-0.02 (0.02)	-0.00 (0.00)	-0.02 (0.02)	0.35 (0.37)	0.60 (1.39)
Employer/Other Private	-0.01 (0.01)	0.02 (0.02)	-0.01 (0.01)	0.02 (0.02)	**-1.10 (0.54)**	**2.78 (1.30)**
Auto Eligible for PD Low-Income Subsidy	-0.00 (0.01)	0.00 (0.00)	-0.00 (0.01)	0.00 (0.00)	-0.68 (0.85)	-0.21 (0.22)
Average Copay for CV Drugs ($2010)	**0.02 (0.01)**	-0.03 (0.02)	**0.02 (0.01)**	-0.04 (0.03)	0.47 (0.43)	-0.57 (1.47)
Concurrently taking:						
2-3 CV Drugs	0.00 (0.00)	-0.05 (0.03)	0.00 (0.00)	-0.05 (0.03)	0.02 (0.15)	-2.74 (2.12)
≥4 CV Drugs	-0.01 (0.00)	-0.01 (0.01)	-0.01 (0.00)	-0.01 (0.01)	-0.11 (0.19)	-0.26 (0.52)

Table C-7. (Continued)

Characteristics	Linear Probability Model (PDC≥80%)		Logistic Model (PDC≥80%)		Ordinary Least Squares (Continuous PDC)	
	Estimate (Standard Error)					
	Difference in Characteristics	Difference in *Returns* to Characteristics	Difference in Characteristics	Difference in *Returns* to Characteristics	Difference in Characteristics	Difference in *Returns* to Characteristics
Ambulatory Visits Quantiles						
Q 3 (5-7)	-0.00 (0.00)	-0.01 (0.02)	-0.00 (0.00)	-0.01 (0.01)	-0.05 (0.14)	-0.96 (0.83)
Q 4 (8-12)	0.00 (0.01)	-0.01 (0.02)	0.00 (0.01)	-0.01 (0.02)	0.37 (0.46)	-1.00 (1.17)
Q 5 (≥13)	-0.00 (0.00)	0.02 (0.02)	-0.00 (0.00)	0.02 (0.02)	-0.13 (0.32)	0.85 (1.06)
Had a Usual Source of Care	0.00 (0.00)	0.03 (0.15)	0.00 (0.00)	0.02 (0.14)	0.06 (0.16)	-2.65 (8.52)
Any ED Visit-Baseline Year	0.00 (0.00)	0.00 (0.01)	0.00 (0.00)	0.00 (0.01)	0.13 (0.14)	0.32 (0.59)
No. of Pharmacies	0.01 (0.01)	-0.03 (0.08)	0.01 (0.01)	-0.04 (0.08)	0.63 (0.56)	-1.58 (4.90)
Very Satisfied with Healthcare Provider	-0.00 (0.00)	0.01 (0.03)	-0.00 (0.00)	0.01 (0.03)	-0.27 (0.25)	2.39 (2.26)
Explained	0.00 (0.00)	-0.02 (0.05)	0.00 (0.00)	-0.02 (0.04)	-0.03 (0.16)	-2.10 (2.64)
Provider Listened	0.00 (0.00)	0.02 (0.05)	0.00 (0.00)	0.02 (0.05)	-0.00 (0.10)	0.59 (2.45)
Provider Respected	-0.00 (0.00)	-0.01 (0.06)	-0.00 (0.00)	-0.01 (0.06)	-0.03 (0.14)	-1.58 (2.76)
Constant		-0.23 (0.28)		-0.21 (0.26)		-10.18 (15.41)
Sample Size	3288					

Boldface estimates have P values <0.05. Standard errors were estimated by balanced repeated replications using MEPS-provided survey weights and half-sample identifiers.

VITA

I was born in 1986 to Hussein Muhammad Hussein and Sabah Erfan, both school teachers in Al-Bayho, a small rural village in Al-Minya, a province in Northern Upper Egypt. I was then blessed with two younger sisters: Marwa and Aya. In 1997, after finishing 5th grade, my family and I moved to the capital city, Al-Minya, where I also received my college degree in Pharmacy at Al-Minya University (officially: Minia University) in 2008. Shortly after graduation, I wed to Fatma Elzahraa and later that year moved together to the United States to start graduate school. I enrolled in the chemistry PhD program at Washington State University (WSU) in Pullman, WA in the spring of 2009. Later in 2009, I rediscovered myself and what I was truly passionate about: broadly, health and social wellbeing of vulnerable populations. In May 2011, I graduated with an MS in chemistry from WSU and three months later, in August of 2011, started in the PhD program in Health Outcomes and Policy Research at the University of Tennessee Health Science Center in Memphis. Two years later, I finished coursework and defended a dissertation proposal in May 2012. At that time, I was awarded a Summer Fellowship with residence at Mathematica Policy Research in Princeton, NJ to "pursue independent, self-directed research on economic or social problems that affect minority groups and individuals with disabilities." Early phases of my dissertation research were completed at Mathematica headquarters in Princeton, with their financial and technical support. After returning from Mathematica in September 2012, I became a PhD candidate and in November I received a one-year Pre-Doctoral Fellowship award from the American Heart Association to fund my dissertation research activities. I have published two articles in peer-reviewed journals, and gave oral and poster presentation in a few scientific meetings. The American Heart Association also prepared a press release featuring the results of this dissertation research. In July 2014, my family and I will move to Philadelphia, PA for a postdoctoral research fellowship in social epidemiology and health disparities under Professor Ana Diez-Roux, Dean of the Drexel School of Public Health.