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Essays in Health Economics

By

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Professor Benjamin R. Handel, Co-Chair
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Professor Jonathan T. Kolstad
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Abstract

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The influence of individual healthcare providers on healthcare utilization has important implications for healthcare systems and cost savings policies. Primary care physicians may be particularly influential because they have central, coordination roles in medicine, yet little is known about their impacts on healthcare utilization. This dissertation provides new empirical evidence on two fundamental questions. First, to what extent do differences in practice styles of individual primary care physicians, as measured by their patients' spending, explain variation in healthcare utilization? Second, do patients incur switching costs in the form of temporarily higher healthcare utilization when they switch PCPs? Specifically, I study the long-run and short-run effects of switching to different primary care physicians on patient healthcare utilization among traditional fee-for-service Original Medicare patients who are ages 65-99 in the United States.

In the first chapter, I show that patients who switch from a primary care physician whose other patients have low utilization to one whose other patients have high utilization experience increases in long-run utilization, whereas patients who switch in the opposite direction experience decreases. Regardless of the direction of the change, patients experience short-run increases in utilization around the switch. Using a model that includes both patient and physician fixed effects, I find that differences in primary care physician practice styles, as measured by spending, explain about 2% of the variation in long-run total utilization and about 13% of the variation in long-run primary care utilization within regional markets.

In the second chapter, I estimate the short-run effects of switching primary care physicians on patient utilization. I focus on patients who involuntarily switch because their physicians relocate or retire, such that the timing of the switches is exogenous. Each primary care physician switch leads to approximately \$500-725 in additional total utilization, and 20-30% comes from temporary increases in primary care utilization. Combining my findings from these two chapters, I construct counterfactuals and find that policies that reallocate patients across primary care physicians could potentially be counterproductive due to modest long-run savings and substantial short-run switching costs. Finally, I discuss potential mechanisms that could generate these switching costs and their welfare implications.

To my family –
my parents, Lily and Thomas,
my sister, Angela,
my husband, Vincent, and
my daughter, Katherine.

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Chapter 1

Influence of Primary Care Physician Practice Styles in Healthcare Utilization

1.1 Introduction

A defining feature of the healthcare industry is the outsized role played by suppliers in determining the overall demand for services (Arrow 1963, McGuire 2000). Differences in physician agency and productivity are widely interpreted as key drivers of the wide regional and local variation in U.S. healthcare utilization (see Chandra, Cutler, and Song 2011 and Skinner 2011 for reviews). Among physicians, primary care physicians (PCPs) may be particularly important because they hold information on patient medical history, informally coordinate care, and in some cases, formally manage access to specialists. Though existing research shows that PCP practice styles are correlated with differences in regional healthcare variation (Sirovich et al. 2005; Sirovich et al. 2008), a major challenge that remains is identifying the causal effects of PCPs on patient-level utilization.

Understanding the influence of individual physicians, particularly PCPs, on healthcare utilization has important policy implications. Supply-side polices rely on healthcare providers to regulate and reduce spending using mechanisms such as clinical guidelines, performance-based metrics, and monetary incentives. Demand-side policies induce patients to switch to lower-cost healthcare providers using mechanisms such as high deductibles, price transparency, and narrow provider networks. If PCP practice styles, as measured by spending, explain relatively little of variation in healthcare utilization, then the potential savings from changing PCP practice styles or reallocating patients across PCPs may be small. Moreover, if switching between PCPs has non-trivial costs, then policies that reallocate patients across PCPs may actually be counterproductive. Despite the central roles of PCPs, little empirical evidence exists on the influence of individual PCP practice styles or the effects of switching PCPs on patient-level utilization.

I investigate the influence of PCPs using administrative claims data for patients ages 65 and over in Original Medicare, commonly known as traditional fee-for-service Medicare, between 1999 and 2012. Original Medicare is an ideal setting for my study because it covers a large number of patients in a relatively uniform insurance environment and provides rich administrative data on physician visits and other forms of healthcare utilization. Medicare patients have relatively frequent primary care visits, which allows me to match patients to PCPs.[1] During the sample period, PCPs were generally simply paid fee-for-service, which means that I can measure PCP spending that is not affected by differences in direct monetary incentives across PCPs.[2] Though my findings cannot be directly extrapolated to private insurance settings, the results serve as a benchmark for measuring PCP practice styles. Furthermore, the policy implications even within Medicare are economically important because Medicare accounts for 20% of U.S. national health expenditures and 3.6% of gross domestic product.[3]

In a descriptive event study, I show that patients who switch from a PCP whose other patients have low utilization to a PCP whose other patients have high utilization experience increases in long-run utilization, whereas patients who switch from a PCP whose other patients have high utilization to a PCP whose other patients have low utilization experience decreases. Regardless of the direction of the change in PCP utilization, patients experience short-run increases in utilization around the time of the PCP switch.

In my main analysis, I estimate the contribution of differences in PCP practice styles, as measured by spending, to within-market variation in healthcare utilization.[4] My empirical strategy uses patients who switch PCPs to identify the components of utilization attributable to patient characteristics (e.g., health, preferences) and the components attributable to PCP practice styles. Specifically, I use a "two-way fixed effects" model that includes a patient fixed effect, a PCP fixed effect, and a time-varying component that reflects changing patient and market-level factors. This class of models has been recently used by Finkelstein, Gentzkow, and Williams (2016) to examine regional variation in healthcare utilization and is widely used in labor economics to separate effects of employer and employee characteristics in wage determination (e.g., Abowd, Kramarz, and Margolis 1999; Card, Heining, and Kline 2013). The key identifying assumption in this setup is that switches between different types of PCPs are unrelated to any patient-specific trends in healthcare utilization. My event study tests for such trend-related switching patterns, and I find no evidence that patients who switch to higher- or lower-spending PCPs systematically have rises or falls in utilization prior to or after their switches in the long run.

Estimating the model separately for each of 306 hospital referral region (HRR) markets, I find that differences in individual PCP practice styles contribute to approximately 2.4% of variation in total healthcare utilization and 12.6% of variation in primary care utilization within markets on average. Differences in time-invariant patient characteristics account for approximately 28.4% of the variation in total healthcare utilization and 11.1% of the variation in primary care utilization.[5] As in most healthcare settings, a large share of utilization

[1] I assign a PCP to 72% of patients in each quarter among patient-quarters eligible for PCP assignment (as discussed in Sections 1.2.4 and 1.2.5).

[2] Under fee-for-service, services are unbundled and PCPs are paid for separately for each service they provide. Original Medicare more recently introduced performance-based incentives through Accountable Care Organizations (ACOs), such as in the Medicare Shared Savings Program, in which some PCPs participate.

[3] Source: Centers for Medicare and Medicaid Services (CMS) National Health Expenditure Data (https://www.cms.gov/Research-Statistics-Data-and-Systems/Statistics-Trends-and-Reports/NationalHealthExpendData).

[4] My markets are Hospital Referral Regions (HRRs) as defined by the Dartmouth Atlas of Health Care (http://archive.dartmouthatlas.org/data/region).

[5] The variance of patient-specific factors can be estimated on samples of only patients who switch PCPs

variation cannot be explained by time-invariant PCP and patient factors due to time-varying patient chronic conditions, health shocks, and other factors (e.g., clinical situation, see Chandra, Cutler, and Song 2011). The influence of PCP practice styles estimated in this Original Medicare setting is likely an approximate lower bound for the older U.S. population. Original Medicare patients do not require referrals from their PCPs to see specialists, whereas PCPs may have more influential roles as gatekeepers for Medicare Advantage health maintenance organization (HMO) patients who do require referrals.

This chapter makes a few key contributions to the literature. First, this chapter is among the first to estimate the influence of individual primary care physicians (PCPs) – who are an central yet understudied part of healthcare – on healthcare utilization while accounting for unobservable patient characteristics in a large U.S. population. The most closely related paper on PCPs is one by Koulayev, Simeonova, and Skipper (2017), who estimate the contribution of individual PCPs to drug adherence variation in Denmark using a two-way fixed effects model. More broadly, my research relates to the estimation of the effects of individual healthcare providers, including emergency department physicians (Gowrisankaran, Joiner, and Léger 2017; Silver 2019; Van Parys 2016), emergency department triage nurses (Chan and Gruber 2019), hospital physicians (Fletcher, Horwitz, and Bradley 2014; Tsugawa et al. 2017), cardiac surgeons (Kolstad 2013), cardiologists (Currie, MacLeod, and Van Parys 2016), specialist physicians (Tu 2017), physician teams (Doyle, Ewer, and Wagner 2010), and hospitals (Doyle et al. 2015). The existing literature generally relies on pseudo-random assignment of patients to healthcare providers, often in emergency settings, to separately identify provider effects from unobservable patient characteristics. Such pseudo-random assignment is rarely observed in primary care settings. As a result, I use a long panel of administrative data and estimate the variance of PCP effects in a model that allows for unobservable patient characteristics, allows for patient sorting across PCPs, and makes limited assumptions on the patient to PCP assignment process.

Second, this chapter complements the existing literature on healthcare variation and supplier-induced demand (e.g., Chandra, Cutler, and Song 2011; Cooper et al. 2019; Cutler et al. 2019; Fisher 2003a, 2003b; Gruber and Owings 1996; Johnson and Rehavi 2016; Skinner 2011; Wennberg and Gittelsohn 1973, 1982; Zhang et al. 2012). My study is most similar in spirit to the seminal contribution by Finkelstein, Gentzkow, and Williams (2016) in that I also use a two-way fixed effects model to separately identify the contribution of patient-specific factors and supply-specific factors to variation in healthcare utilization. In contrast to Finkelstein, Gentzkow, and Williams (2016), who decompose the contribution of patients and places *across* healthcare markets, I estimate the contribution of primary care physicians (PCPs) and patients to healthcare variation *within* each healthcare market (i.e., within each place). My within-market estimates enable me to construct policy-relevant counterfactuals that represent altering physician practice styles or reallocating patients across physicians within the broader context of a fixed regional healthcare market.

Finally, this chapter relates to the broad literature that uses changes in locations or institutions to separate individual characteristics from other (location/institutional-related) factors. In health economics, studies use patient migration across healthcare markets (Agha, Frandsen, and Rebitzer 2019; Finkelstein, Gentzkow, and Williams 2016, 2019; Song et al.

(which exclude patients who never switch PCPs in the sample).

2010) and counties (Finkelstein, Gentzkow, and Williams 2018), patient changes in health insurance providers (Handel et al. 2018), and physician migration across healthcare markets (Molitor 2018).[6] In this chapter, I separate primary care physician (PCP) practice styles from patient factors by using patient changes in PCPs and explicitly estimate the effects associated with the switches. I also apply recently available econometric methods (Kline, Saggio, and Sølvsten 2018) to provide unbiased estimates of the variance in PCP fixed effects given a setting and dataset in which the networks of PCPs and patients are weakly connected and standard ordinary least squares regressions produce biased variance estimates (Andrews et al. 2008). From a methodological perspective, I provide an empirical approach to estimate both long-run effects and short-run effects of changes in locations or institutions in a single, consistent framework that could be applied in other settings in which there may be substantial switching costs (e.g., reallocation of employees across worksites or students across schools).

This chapter proceeds with the following sections. Section 1.2 describes the context of my study, the data, and the sample. Section 1.3 provides a descriptive analysis that motivates my empirical framework. Section 1.4 describes the econometric model. Section 1.5 presents my methodology for estimating the contribution of differences in physician practice styles to healthcare variation, and Section 1.6 presents the results. Section 1.7 concludes with a discussion of significance, limitations, and policy implications.

1.2 Context, Data, and Sample

1.2.1 Primary Care in Medicare

The context of my study is primary care for individuals ages 65 and older in Original Medicare, commonly known as traditional or fee-for-service Medicare. Original Medicare provides an ideal setting for my study for several reasons. First, Original Medicare is national in its coverage and is the predominant health insurance plan for individuals ages 65 and older in the U.S. Over 90% all individuals age 65 or older are enrolled in Medicare, and 75-86% had public Original Medicare rather than private Medicare Advantage during my study period (Jacobson, Damico, et al. 2017; Smith and Medalia 2014). Original Medicare insurance is nearly uniform across the U.S. in basic patient cost-sharing requirements.[7,8]

Second, Medicare beneficiaries – who I henceforth refer to as "patients" – generally have primary care providers who they consider their usual sources of medical care, so PCPs are

[6] Other literatures also use this empirical strategy, such as worker employment switches across firms in labor economics (e.g., Abowd, Kramarz, and Margolis 1999; Card, Cardoso, Heining, and Kline 2018; Card, Heining, and Kline 2013) and changes in various other settings (e.g., Bronnenberg, Dube, and Gentzkow 2012; Chetty, Friedman, and Rockoff 2014).

[7] See the Medicare "Medicare Costs at a Glance" webpage for an overview (https://www.medicare.gov/your-medicare-costs/medicare-costs-at-a-glance).

[8] Some Original Medicare patients also have Medicaid dual-eligibility, primary payers (payers who have primary responsibility for the payment, e.g., employer group health plan, Department of Veteran Affairs), or secondary payers (e.g., Medigap supplemental insurance). In ongoing work, I examine the influence of these additional insurance factors in the context of my analysis. In the Medicare administrative claims data, I observe Medicaid dual-eligibility and primary payers (both type of payer and payments), but not secondary payers.

very relevant to this population. Primary care includes disease prevention, health maintenance, the diagnosis and treatment of acute and chronic illnesses, and the coordination and integration of medical care.[9,10] Nearly all Medicare patients have usual sources of care that they visit if they are sick or need advice about their health, and most of the individual providers are PCPs.[11,12] Medicare patients have relatively frequent primary care visits, so I am able to match patients to PCPs.[13]

Patients in Original Medicare do not require referrals to see specialists and have access to a relatively large network of physicians.[14] In contrast, patients in private Medicare Advantage Health Maintenance Organizations (HMOs) require referrals to see specialists, and in some cases, have more limited networks of physicians, so they may be more influenced by their PCPs. I would interpret the influence of PCPs estimated in this study's Original Medicare context to be an approximate lower bound of the influence of PCPs on older patients because PCPs have relatively small roles as coordinators and gatekeepers of care in Original Medicare.

Third, during the sample period, physicians were generally simply paid fee-for-service in physician practice groups across the U.S., which means that I can measure PCP spending that is not affected by differences in direct monetary incentives across PCPs.[15] The Centers for Medicare and Medicaid Services (CMS) sets prices that are paid to physicians for services, so unlike in private insurance markets, prices are not negotiated between healthcare providers and insurers.[16] Though some variation exists in the CMS administratively set prices that are paid to healthcare providers, this price variation primarily exists across regions, so spending differences are reflective of variation in utilization rather than variation in prices in my within-region analyses (Gottlieb et al. 2010).[17]

Finally, Medicare patients have chronic conditions and relatively high health care costs,

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[9] "Primary care is the level of a health services system that provides entry into the system for all new needs and problems, provides person-focused (not disease-oriented) care over time, provides care for all but very uncommon or unusual conditions, and coordinates or integrates care, regardless of where the care is delivered and who provides it." Source: https://www.jhsph.edu/research/centers-and-institutes/johns-hopkins-primary-care-policy-center/definitions.html.

[10] "Primary care includes health promotion, disease prevention, health maintenance, counseling, patient education, diagnosis and treatment of acute and chronic illnesses in a variety of health care settings." Source: https://www.aafp.org/about/policies/all/primary-care.html.

[11] The Medical Expenditure Panel Survey defines a usual source of care as "a particular doctor's office, clinic, health center, or other place that the individual usually goes to if he/she is sick or needs advice about his/her health" (Medical Expenditure Panel Survey 2009).

[12] Ninety-six percent of beneficiaries report having a usual source of care, primarily a doctor's office or doctor's clinic (Boccuti et al. 2013). When patients report that they regard individual professionals, rather than facilities, as their usual source of care, about 90% of the individual professionals are primary care physicians (Mold et al. 2002). Patients who report a clinic, health center, or other place may still see a PCP at that facility.

[13] I assign a PCP to 72% of patients in each quarter among patient-quarters eligible for PCP assignment (as discussed in Sections 1.2.4 and 1.2.5).

[14] Ninety-one percent of non-pediatric physicians accept new Medicare patients (Boccuti et al. 2013).

[15] Under fee-for-service, services are unbundled and PCPs are paid for separately for each service they provide. Original Medicare more recently introduced performance-based incentives through Accountable Care Organizations (ACOs), such as in the Medicare Shared Savings Program.

[16] See the Medicare Physician Fee Schedule "Documentation and Files" webpage for details (https://www.cms.gov/apps/physician-fee-schedule/documentation.aspx).

[17] My within-region estimates could be interpreted as including any remaining price differences. Within regions, some price adjustments are made for providers designated to be in Health Professional Shortage Areas

which make them an economically important population. Many Medicare patients have chronic conditions that may lead them to seek regular medical care. For example, 58% have high blood pressure, 45% have high cholesterol, 31% have heart disease, 29% have arthritis, and 28% have diabetes (Centers for Medicare and Medicaid Services 2012). In 2012, total healthcare spending per person over age 65 was $18,988 per year on average.[18]

1.2.2 Medicare Administrative Claims Data

As noted above, my primary data source is the 20% random sample of Medicare beneficiaries ("patients") from 1999 through 2012 from the Centers for Medicare and Medicaid Services (CMS). I measure patient-quarter outcomes for the period from 2002 through 2011 (for reasons I discuss in the sample selection in Section 1.2.5), which includes approximately 9.3 million patients. These administrative data provide patient demographic information (e.g., date of birth, sex, race, zip code of residence), and for patients in Original Medicare, their medical claims for inpatient care, outpatient care, and physician services.[19]

Each claim has information on the date of service, the types and quantities of services provided, the physician (or other provider/facility) performing the service, the diagnoses, and the dollar values of payments by Medicare, the beneficiary, and any primary payer.[20] The physician services claims list the specialty of the physician performing each service and the Tax Identification Number (TIN) of the physician/entity to whom the payment for each service is made.[21] The specialty of the physician performing the service allows me to identify the primary specialty of each physician over a given time period. The TIN of the physician/entity allows me to identify each physician practice group in which physicians share the TIN of the entity.

In addition to the Medicare claims, I use several secondary data sources for physician characteristics, such as medical school graduation year and gender. These data sources include the American Medical Association (AMA) Physician Masterfile, the CMS Medicare Data on Provider Practice and Specialty (MD-PPAS), the CMS National Plan and Provider Enumeration System (NPPES), the Unique Physician Identification Number (UPIN) Directory, the UPIN Group File, and the UPIN Member File. Appendix C.3.1 provides additional information on these datasets.

(HPSAs), cancer hospitals, children's hospitals, rural hospitals, and sole community hospitals (Finkelstein, Gentzkow, and Williams 2016). In ongoing work, I am constructing utilization measures that remove price adjustments.

[18]Source: Centers for Medicare and Medicaid Services (CMS) National Health Expenditure Data (https://www.cms.gov/Research-Statistics-Data-and-Systems/Statistics-Trends-and-Reports/NationalHealthExpendData).

[19]The Medicare claims include Part A (hospital and other facility care), and Part B (medical services (e.g., office visits, surgeries, lab tests) and supplies). I do not include Part D (drugs) in my main analysis, since patients have Medicare Part D only from 2006 onward.

[20]In the physician services claims, these variables are available at the line item level, which is more detailed than the claim level. In the outpatient claims, these variables are available at the revenue center level, which is more detailed than the claim level.

[21]My use of the "performing physician" identifiers, CMS (formerly Health Care Financing and Administration (HCFA)) provider specialty codes, and TINs follows the literature (e.g., Pham et al. 2009).

1.2.3 Level of Analysis

My level of observation for analysis is at the patient and quarterly calendar date level. I use data at the quarterly level to more precisely measure the timing of patients' PCP switches than I could with yearly level data.[22]

I conduct my estimations within geographic healthcare markets, Hospital Referral Regions (HRRs), defined by the Dartmouth Atlas of Health Care.[23] I assign patients to an HRR if both any of the patient's reported zip codes and any of their main PCP's reported zip codes are within the HRR over the past year.[24,25] I estimate my model within each HRR to hold fixed features of the broader healthcare market.[26] The healthcare variation within a healthcare market is relevant for policies that change PCP practice styles without changing other features of the healthcare market or that reallocate patients across PCPs within the patients' geographic regions.

In my analysis, I aggregate within-market estimates by weighting them by the HRR Original Medicare population in 2007, approximately the midpoint of the sample.[27] In cases in which I report estimates for markets by spending categories (e.g., above median, below median), I classify markets based on the HRR-level 2007 Medicare reimbursements adjusted for price, age, gender, and race.[28]

1.2.4 Primary Care Physician Definition

I define a primary care physician (PCP) as a healthcare provider with a Doctor of Medicine (MD) or Doctor of Osteopathic Medicine (DO) degree with a specialty in family medicine, general internal medicine, general practice, or geriatrics.[29] I define a physician's specialty as the modal specialty associated with their claims over the past year and exclude physicians who might temporarily be classified as PCPs but actually practice as specialist physicians.[30]

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[22] I present main results with outcomes aggregated to the yearly level where applicable. In ongoing work, I also aggregate the quarterly level data to the yearly level across my analysis for comparison.

[23] See the Dartmouth Atlas of Health Care definitions at: http://archive.dartmouthatlas.org/data/region.

[24] Zip codes are occasionally reassigned to different HRRs during the sample period, so I assign each zip code to the modal HRR (and in the case of ties, the most recent modal HRR) over the sample period.

[25] The past year is defined as the current and past three quarters, which are the four quarters I consider for the main PCP assignment described in Section 1.2.4.

[26] A number of factors vary across HRRs, including hospitals, specialist practice styles, and regional prices. In ongoing work, I am estimating the relationships among PCP practice styles across HRRs. These relationships are identified off of patients who move across HRRs, PCPs who move across HRRs, or patients and PCPs located near HRR borders.

[27] Source: Centers for Medicare and Medicaid Services (CMS) "HRR Table - Beneficiaries 65 and older" (https://www.cms.gov/Research-Statistics-Data-and-Systems/Statistics-Trends-and-Reports/Medicare-Geographic-Variation/GV_PUF.html).

[28] Source: Dartmouth Atlas of Healthcare "General Atlas Rates - Medicare Spending" (https://atlasdata.dartmouth.edu/static/general_atlas_rates#spending).

[29] I discuss how I identify unique physicians using Unique Provider Identification Numbers (UPINs), National Provider Identifiers (NPIs), and names from a number of physician datasets in Appendix C.3.2.

[30] I exclude PCPs who are fewer than six years from medical school graduation or who become specialist physicians within one year to exclude PCPs who further subspecialize (e.g., physicians may complete cardiology fellowships after general internal medicine residency) and practice as specialist physicians rather than as PCPs. In ongoing work, I am examining different restrictions on whether a primary care physician should

Following the literature, I assign each patient to at most one "main PCP" per quarter based on the PCP with whom they have the greatest number of evaluation and management (E&M) visits in the past year (i.e., the current quarter and the previous three quarters) (Pham et al. 2007; duGoff et al. 2018).[31,32,33] Some patient-quarters will not be assigned main PCPs. These patient-quarters consist of patients without any E&M visits with PCPs in the past year and patients who do not meet sample restrictions for all quarters of the past year.

I define a switch in a main PCP as change in the main PCP assignment. In the context of switches, I refer to the main PCP a patient switches from as the "origin" PCP and the main PCP a patient switches to as the "destination" PCP.[34]

An important feature of the one-year retrospective main PCP definition is that there will be some lag in the timing of measured switches between PCPs. For example, consider a patient who visits a PCP for an E&M visit once per quarter, stops visiting the origin PCP in quarter $t-1$, and starts visiting the destination PCP in quarter t. Using the main PCP definition, the patient would switch from the origin PCP to the destination PCP at quarter $t+1$, since at that point the majority of visits over the current and previous three quarters (with the most recent visit to break the tie) will switch from the origin PCP to the destination PCP.[35]

I illustrate the actual empirical relationship between the main PCP assignment and primary care utilization patterns in Figures 1.1 and 1.2.[36] For clarity, I identify a subsample of patients who are consistently matched with their origin PCPs for at least 13 quarters (12 quarters before the switch and the quarter of the switch) and then switch to and remain matched with their destination PCPs for at least 12 quarters. I refer to this subsample as the "consistent matches" sample. I define time zero for the PCP switch event as the last quarter that a patient is assigned their origin PCP. Column (4) of Table 1.5 reports the descriptive statistics for this "consistent matches" sample. I also present the primary care utilization patterns for an "all matches" sample of switching patients, who must be matched

be excluded because they may become a specialist.

[31]I define a visit as a unique patient, PCP, and line item date combination.

[32]In my main analysis sample, which I discuss in Section 1.2.5, I require that patients have 75% of visits in the past year with their main PCPs. When I do not impose this requirement, I break ties by selecting the PCP with visit(s) in the most recent quarter and then by greatest utilization in the most recent quarter with visit(s).

[33]In ongoing work, I am also using alternative definitions, such as more restrictive classifications of PCPs visits (e.g., to focus on patient-PCP relationships formed through office-based visits rather than all E&M visits).

[34]In my switching cost analysis, I distinguish among four types of switches: (a) switching from one PCP to another PCP in the same practice group, (b) switching from a PCP to a PCP in a different practice group, (c) switching from a PCP to no main PCP, and (d) from no main PCP to a PCP. I also distinguish between voluntary and involuntary PCP switches. I define involuntary switches as cases in which the patients' main PCPs leave their states or leave Medicare (e.g., due to retirement) within one year before or after the main PCP switches.

[35]The transition in influence from the origin PCP to the destination PCP may indeed be gradual (e.g., a patient may be referred to a specialist by their origin main PCP but have changed to seeing their destination PCP exclusively by the time of the specialist appointment months later). I account for these main PCP assignment timing features in my analysis in Section 2.3.

[36]I restrict the sample in the figures to PCPs and patients in my analysis, specifically those in Columns (2)-(3) of Table 1.4.

with PCPs over the same quarters but the matches can be with any PCP. Column (3) of Table 1.5 reports the descriptive statistics for this "all matches" sample.

Figure 1.1 plots whether a patient has any claim with any PCP, any claim with their origin PCP, and any claim with their destination PCP on average across patient-quarters. Figure 1.1 has several key features. First, the main PCP definition is a rolling window, and on average patients gradually stop seeing their origin PCPs and begin seeing their destination PCPs – even though the PCP switch may be discrete for individual patients. Second, because the PCP switch is defined based on PCP visits, patients are mechanically more likely to have (a) claims with their origin PCP at three quarters before their last matched quarter with their origin PCP (event time -3) and (b) claims with their destination PCP the first quarter they are matched with their destination PCP (event time 1).[37]

Figure 1.2 plots the share of claims a patient has with their origin PCP and the share of claims a patient has with their destination PCP (conditional on having any claim with any PCP) on average across patient-quarters. As previously shown in Figure 1.1, on average patients gradually stop visiting their origin PCPs and begin visiting their destination PCPs. Also, on average, even patients in the "all matches" sample have an over 60% claim share with their origin PCPs for the 12 quarters before the switch and an over 60% claim share with their destination PCPs for the 12 quarters after the switch. This persistently high claim share suggests that the main PCP definition accurately identifies the PCP who has the greatest influence on patient healthcare utilization in the sample.

The utilization patterns in these figures motivate the specification decisions in my analysis, which I discuss in Sections 1.5 and 2.3.

1.2.5 Sample Selection and Descriptive Statistics

To construct my sample, I first restrict the observations to patient-quarters during which patients are 65-99 years old, are enrolled in Original Medicare, and have Medicare Parts A and B coverage in all three months.[38]

My definitions of a main PCP and a main PCP switch restrict the quarters that I can use for outcomes to the period from quarter 3 of year 2000 through quarter 4 of year 2011.[39] I further restrict the patient-quarters I use for outcomes to the period from quarter 1 of year 2002 through quarter 4 of year 2011 because the Medicare claims utilization data are much more consistent in the 2002-2012 period. I refer to this restricted sample in years 2002-2011

[37] For example, a patient who visits a PCP in the first quarter of every calendar year is defined as switching from their origin PCP to their destination PCP upon visiting their destination PCP for the first time (event time 1), exactly four quarters after visiting their origin PCP for the last time (event time -3).

[38] I exclude Medicare Advantage patients because I do not observe Medicare Advantage claims. I also exclude a small number of patients for whom I do not observe gender, which I use as a demographic control in addition to age.

[39] First, a PCP is defined by physician specialties using the current and past three quarters of claims as discussed in Section 1.2.4. With data starting quarter 1 of year 1999, I first have PCPs defined in quarter 4 of year 1999. Second, a patient's main PCP is defined using the current and past three quarters of claims as discussed in Section 1.2.4. With PCPs defined starting in quarter 4 of year 1999, I first assign main PCPs to patients in quarter 3 of year 2000. Third, in order to check whether a patient is in the process of switching PCPs in a given quarter, I need to observe four following quarters. This means that I can last confirm whether a patient is in the process of switching PCPs in quarter 4 of year 2011.

as my *selected population sample*.

Column (1) of Table 1.1 reports the descriptive statistics for this *selected population sample*. In this sample, I identify patient-quarters that are eligible for main PCP assignment – patients who meet the sample restrictions for the current and past three quarters – and assign main PCPs to eligible patient-quarters.[40]

The patient population in Column (1) is split into Columns (2)-(4) to compare three groups of patients. Column (2) consists of patients who are never assigned a main PCP.[41] Column (3) consists of patients who are ever assigned only one main PCP. Column (4) consists of patients who switch main PCPs at least once (i.e., they are ever assigned two or more main PCPs). Approximately 89% of patients ever have a main PCP. Of these patients who ever have a main PCP, approximately 62% switch PCPs at least once, so switching PCPs is quite common.[42]

For my *main analysis sample*, I further restrict the selected population sample to patient-quarters during which the patient is assigned a main PCP in the same HRR who they visit for at least 75% of PCP visits over the past year. This restriction excludes 6% of patient-quarters during which the patient is assigned a main PCP.[43] For patient-quarters during the main PCP switch, visits with both their origin PCPs and their destination PCPs may count toward the 75% of PCP visits requirement. I require that patients visit their main PCP for at least 75% of PCP visits to accurately attribute patient utilization to their main PCP and avoid attenuation bias in my estimates.[44] Figure B.1 illustrates the relationships among the samples used in this dissertation.

Column (5) of Table 1.1 reports the descriptive statistics for my *main analysis sample*.[45] Among patients in my main analysis sample, 58.5% are female and 87.4% are white. They have an average of 2.51 main PCPs and an average age of 76.9 years. Average yearly total utilization is about \$8,200 with a standard deviation of about \$16,000. Average yearly primary care utilization is about \$500 with a standard deviation about \$670.

Table 1.2 reports the descriptive statistics of main PCPs associated with patient-quarters in my main analysis sample. On average, in the 20% sample of Original Medicare patients, PCPs are assigned 20 patients per quarter (with a standard deviation of 23), ever have 69 patients in the sample (with a standard deviation of 73), and are observed and classified as

[40] I allow the past three quarters to be in year 2001.

[41] These may be patients who (a) meet the sample restrictions for only a short period of time, (b) visit primary care providers who I do not use in the main PCP assignment (e.g., nurse practitioners, physician assistants), and/or (c) do not receive primary care (e.g., they are healthy, visit specialist physicians only, or reside in facilities).

[42] The patients who switch PCPs have more patient-quarter observations (37.4 versus 24.7), which is partially mechanical because they would have more opportunities to switch PCPs. On average, the patients who switch PCPs are more female, are more white, are older, have higher total utilization, and have higher primary care utilization. The differences in these characteristics may, in part, come from the longer panel lengths of patients who switch PCPs.

[43] In ongoing work, I am examining the sensitivity of my results to this 75% of visits requirement.

[44] For example, the restriction excludes patients who split their visits between two PCPs, which could occur due to institutional features (e.g., practice group policies) or patient choices (e.g., "snowbirds" who live in colder climates in the summer and warmer climates in the winter).

[45] My main analysis sample in Column (5) is a subset of the patient-quarters in Columns (3) and (4) in that Column (5) includes patients who do not switch main PCPs and patients who do switch main PCPs but not patients who are never assigned any main PCP.

PCPs for 6 of 10 years in the sample period. Weighted by patient-quarter observations, on average, PCPs are assigned 51 patients per quarter (with a standard deviation of 35), ever have 159 patients in the sample (with a standard deviation of 100), and are observed and classified as PCPs for 9 of 10 years in the sample period.

1.2.6 Outcome Measures

My outcome measures are payment-based utilization, which I define to be total payments in dollars from Medicare, the patient, and any primary payer (a payer who has primary responsibility for the payment, e.g., employer group health plan, Department of Veteran Affairs).[46,47]

My two main outcome measures are (a) total utilization, which is important for cost savings and policy, and (b) primary care utilization, which is the category in which PCPs likely have the most influence. Total utilization includes all physician claims, inpatient claims, and outpatient claims.[48] Primary care utilization includes evaluation and management (E&M) claims in which the provider is a broadly defined primary care provider, including primary care physicians, nurse practitioners, and physician assistants. Primary care utilization includes but is not limited to services provided by main PCPs.

I repeat my analyses with other categories of utilization – including tests, imaging, emergency department visits, and inpatient hospitalizations – to examine the influence of PCPs on other medical care and investigate potential mechanisms through which PCPs influence total utilization. Examples of tests include bacterial cultures, blood counts, cardiovascular stress tests, electrocardiograms, glucose, and urinalysis. Examples of imaging include cardiac catheterization, contrast gastrointestinal, computed tomography (CT or CAT) scan, mammogram, magnetic resonance imaging (MRI), nuclear medicine, ultrasound, and X-ray.

Table 1.3 provides examples of common claims and their associated utilization. One of the most common primary care services, a 15-minute office visit, is \$35 on average. A 30-minute office visit for a new patient is \$90 on average. Longer office visits of about 40-45 minutes are about \$120. Among diagnostic tests and imaging, a blood test to measure lipids (including cholesterol) is \$14, a hemoglobin A1c test to measure blood sugar is \$14, and a mammography screening is \$48 on average. Appendix C.3.3 provides additional information on the classification of claims and how I construct the outcome measures.

In additional to these payment-based utilization measures, I am including claim-based utilization measures (e.g., counts, indicators) in ongoing work. Claim-based utilization results are relevant for interpreting the extent to which PCP influence is on the extensive margin (e.g., whether a patient has an emergency department visit) versus the intensive margin (e.g., whether a patient visits an emergency department that is associated with

[46]I include year-by-quarter fixed effects in my estimations, which accounts for inflation and other increases healthcare prices.

[47]In some cases Medicare is the primary payer and there is a secondary payer (e.g., Medigap supplemental insurance), but I do not observe the payments made by the secondary payer versus the patient or the identity of the secondary payer.

[48]My measure of total utilization excludes skilled nursing facility, home health care, hospice, and durable medical equipment claims, which is consistent with other studies (e.g., Finkelstein, Gentzkow, and Williams 2016). In ongoing work, I am estimating a version of the analysis that includes these categories.

greater utilization).

1.3 Descriptive Analysis

1.3.1 Descriptive Event Study Analysis

To examine the long-run and short-run changes in healthcare utilization with switches in main PCPs, I construct descriptive event study graphs that illustrate the effects I more precisely identify in the following sections.

First, if the variation in healthcare utilization is driven entirely by patients (e.g., general health status, preferences) and patient time-invariant factors (e.g., patient neighborhoods), then patients who switch main PCPs will not experience systematic changes in healthcare utilization. If variation in healthcare utilization is driven entirely by PCP practice styles, as measured by spending, then patients who switch main PCPs will see their healthcare utilization change to be the same as that of the other patients at their destination PCPs. If PCP practice styles explain part of the variation in healthcare utilization, patients who switch from PCPs with low-spending practice styles to PCPs with high-spending practice styles would on average experience increases in healthcare utilization, and vice versa.

Second, I consider whether switching main PCPs is associated with temporary effects on healthcare utilization. If switching costs are positive (e.g., due to information acquisition or temporarily lower productivity at new PCPs), the short-run increases in utilization would most likely be concentrated after patients begin to visit their destination PCPs, which may be either before or in the quarter of the main PCP switch (as discussed in Section 1.2.4).

As in Section 1.2.4, I define the main PCP a patient switches from as the "origin" PCP, the main PCP a patient switches to as the "destination" PCP, and event time zero as the last quarter that a patient is assigned their origin PCP. I use the "consistent matches" sample of patients who are consistently matched with their origin PCPs for at least 13 quarters (12 quarters before the switch and the quarter of the switch) and then switch to and remain matched with their destination PCPs for at least 12 quarters.

In this descriptive analysis, I classify the PCP practice style for each patient's PCP based on the demographics-adjusted log utilization of that PCP's other patients (i.e., based on a leave-out mean).[49] For each patient who switches, I first identify their origin PCP's other patients – who I refer to as "copatients" (as with "coworkers" of workers) – in a pre-switch period (year -1, where year 0 is the year of the switch) and their destination PCP's copatients in a post-switch period (year 2).[50] For these copatients, I classify (a) the origin PCP based

[49] I adjust utilization for patient age, gender, and cohort/date by controlling for gender interacted with second and third order polynomials in yearly age (discretized at the month level) and year-by-quarter fixed effects. I normalize the fixed effect for quarter 1 of year 2007, approximately the midpoint of the sample, to zero. I measure age in years at the monthly level relative to age 75 (the monthly level is consistent with Medicare enrollment and eligibility). I set female to one for the gender indicator. I do not adjust for time-varying patient chronic conditions because their diagnosis and coding may be correlated with PCP practice styles. Log utilization is defined as log(1 + dollar spending), such that patients who have zero utilization in the quarter are effectively assigned one dollar of utilization.

[50] Year -1 consists of quarters -7 to -4, year 0 consists of quarters -3 to 0, and year 2 consists of quarters 5 to 8.

on the within-market quartile of utilization in the associated pre-switch period and (b) the destination PCP based on the within-market quartile of utilization in the associated post-switch period.[51] I then assign patient switchers to 16 groups based on quartiles of copatient utilization at the origin PCPs and at the destination PCPs.[52] For the patient switchers, I calculate the mean demographics-adjusted log quarterly utilization in the quarters before and after the PCP switch event in each of the 16 quartile-to-quartile switching groups.

In Figures 1.3a and 1.3b, I plot the healthcare utilization profiles for patient switches for total utilization and primary care utilization, respectively. For clarity, I plot only switches between quartile 1 and quartile 4, and I bin quarters into years before the switch and after the switch, such that year 0 includes a patient's last 4 quarters with their origin PCP. I separate a patient's first quarter with their destination PCP from the remainder of the year to more precisely show the utilization patterns. Figure B.2 displays additional quartile-to-quartile switches, and Figure B.3 plots utilization profiles at quarterly intervals.

Figures 1.3a and 1.3b show several key features. I first focus on the periods outside of the switch period (i.e., the non-shaded area of year -2 to year -1 and quarters 2-4 to year 3), and then I discuss the patterns during the switch period (i.e., the shaded area of year 0 to quarter 1).

First, the figures suggest that different patient quartile-to-quartile switching groups have different utilization levels both before and after switching PCPs. The patients who switch from quartile 4 origin PCPs to quartile 4 destination PCPs have both (a) higher utilization before a switch than the patients who switch from quartile 4 origin PCPs to quartile 1 destination PCPs and (b) higher utilization after a switch than the patients who switch from quartile 1 origin PCPs to quartile 4 destination PCPs. This pattern suggests that the patients who switch from quartile 4 to quartile 4 PCPs may be systematically different (e.g., they have worse health status or preferences for more medical care). A similar pattern holds for patients who switch from quartile 1 origin PCPs to quartile 1 destination PCPs.

Second, patients do change their utilization when they switch PCPs and these changes are relatively symmetric relative to any overall trend. Changes in log utilization are approximately symmetric for patients who switch from quartile 1 origin PCPs to quartile 4 destination PCPs and for patients who switch from quartile 4 origin PCPs to quartile 1 destination PCPs. The gaps between these two groups are roughly the same before the switch and after the switch. Similarly, the gaps between these two groups and the patients who switch from quartile 4 origin PCPs to quartile 4 destination PCPs or from quartile 1 origin PCPs to quartile 1 destination PCPs are also roughly the same before the switch and after the switch.

Third, healthcare utilization is fairly stable in the pre-switch period and in the post-switch period.[53] The trends across the groups are roughly parallel and there appears to be no switching to different quartiles of PCPs based on pre-trends.

Finally, turning to the period around the time of the PCP switch (in the shaded area), Figures 1.3a and 1.3b show both a gradual adjustment and a temporary increase in uti-

[51] I define the quartile of copatient utilization among patients who switch PCPs in this sample within each market.

[52] I drop patient-quarter observations if the patient is only patient of their main PCP in the sample (i.e., if the patient has no copatients).

[53] There is a slight upward trend in total healthcare utilization across all quartile groups.

lization. Utilization begins to adjust during the last year a patient is assigned their origin PCP (year 0) toward the long-run, steady-state utilization at their destination PCP, which reflects the retrospective main PCP assignment. Healthcare utilization is higher during the period of the switch. This increase appears across all quartile-to-quartile switching groups. The utilization increase appears to be temporary and very concentrated in the first quarter a patient is assigned their destination PCP. The spike in the first quarter a patient is assigned their destination PCP does not seem to be driven by substitution from either the previous year (year 0) or the next three quarters in the same year (quarters 2-4). The temporarily higher utilization is similar in magnitude across quartile-to-quartile switching groups (relative to long-run, steady-state utilization at the destination PCP), which suggests that a single set of switch-based indicators (i.e., pre-switch leads and post-switch lags) could fairly accurately capture the switching costs across all quartile-to-quartile switching groups.

These event study graphs illustrate the long-run and short-run effects of switching to different PCPs that I estimate in Sections 1.5 and 2.3, respectively. The short-run effect is a temporary increase in utilization that is concentrated during the switch period. The long-run effect is a shift in steady-state utilization from the origin PCP's practice style to the destination PCP's practice style.

The symmetry and stability of healthcare utilization in the periods outside of the switch suggests that a simple additive model with a patient-specific component, a PCP-specific component, vectors of switch-based indicators, and a time-varying residual component that is uncorrelated with the other components would approximate the patterns of healthcare utilization. Furthermore, I examine the patterns of utilization around the shaded region of the PCP switch in additional detail in Section 2.3.

1.3.2 Log Utilization Outcome Measure

The descriptive event study analysis from Section 1.3.1 shows that a simple additive model that includes a patient-specific component, a PCP-specific component, and vectors of switch-based indicators would approximate the patterns of log utilization. In addition to approximating the observed patterns, a log utilization outcome models utilization to be additive in logs and multiplicative in levels for the patient-specific component and the PCP-specific component.

From an economic perspective, I prefer a log specification because it allows PCP practice styles to generate a larger impact in levels for sicker patients than for healthier patients. Office-based physicians, including PCPs, often adjust their patients' utilization by choosing follow-up visit frequency. No definitive guidelines exist on follow-up visit frequency for different types of patients, and the follow-up visit frequency is generally dictated as the number of months or weeks between visits (Ganguli, Wasfy, and Ferris 2015; Javorsky, Robinson, and Kimball 2014).[54,55] Each primary care visit may be associated with other

[54]In the *Washington Post*, Ishani Ganguli, a internal medicine/primary care physician, states: "The timing of follow-up visits...has tended to fall under the art, rather than the science, of medicine. While studies suggest that connecting with a doctor is generally a good way to build a trusting relationship and to promote health, we don't really know the right frequency of visits" (Ganguli 2015).

[55]Van De Graff, a cardiologist, states: "Is there some textbook somewhere, some set of guidelines that tells us how often patients with particular medical problems need routine follow-up? The answer: Nope....So,

categories of utilization, including tests, imaging, and referrals for specialist visits. This pattern of physician behavior generates a model that is multiplicative in levels.[56,57]

In addition, healthcare has a right-skewed cross-sectional distribution, and similar outcomes of log utilization have been used with models of physician and patient behavior (e.g., Finkelstein, Gentzkow, and Williams 2016). One potential disadvantage is that some patient-quarter observations in the sample have zero utilization, such that I add one to dollar payments before the log transformation. In the long-run practice styles analysis, I present analyses with yearly outcomes data such that all observations have non-zero utilization in my main outcome categories of total utilization and primary care utilization.[58] The log specification implicitly gives more weight to the lower-utilization part of the distribution than a specification that is additive in levels would.[59]

1.4 Model

1.4.1 Econometric Model

Based on the utilization patterns in the descriptive analysis, I use an econometric framework that combines (a) a two-way fixed effects model to capture time-invariant patient characteristics and PCP practice styles with (b) an event study model to capture PCP switching utilization patterns. I draw upon the methodology from two-way fixed effects models in the firm-worker literature (e.g., Abowd, Kramarz, and Margolis 1999; Abowd, Creecy, and Kramarz 2002; Card, Heining, and Kline 2013; Card, Cardoso, Heining, and Kline 2018).

In healthcare contexts, Finkelstein, Gentzkow, and Williams (2016) also use a two-way fixed effects model to separate components of utilization attributable to patient factors versus supply-side factors, and they show that it can be derived from a micro-founded model of patient demand and physician supply. In Appendix C.1, I extend their micro-founded model with a parameter that explicitly captures the effect of switching PCPs on utilization and derive my econometric model under the same main assumptions.

The dataset I construct includes an observation for each patient i and quarter t. The function $j(i,t)$ gives the identity of the unique main PCP of patient i in quarter t. I assume

routine follow-up will most likely fall somewhere between 'less often than weekly' and 'at least once yearly or more frequently.' But within those limits, as a doctor I'm pretty much free to choose whatever I like....Sadly, I've known doctors who use the unquestioning obedience of some patients to their own financial advantage. Does a stable patient really need to come in for visits every two months or need a stress test and echocardiogram every six?" (Van De Graaff 2011).

[56]For example, suppose a low-utilization PCP asks patients to visit every 12 months, and a high-utilization PCP ask patients to visit every 6 months. Suppose also that a healthy patient spends \$100 per visit and a sick patient spends \$300 per visit (e.g., due to billing codes for higher complexity, associated tests/imaging, associated specialist visits). The healthy patient would have either \$100 or \$200 of yearly utilization, whereas the sick patient would have either \$300 or \$600 of yearly utilization.

[57]What the log utilization specification does not accurately capture is if PCPs vary based on some fixed utilization amount that is nearly the same across patients (e.g., if high-utilization PCPs always do preventive care for all patients but low-utilization PCPs never do).

[58]Fewer than 1% of observations have negative dollar payments due to Medicare billing procedures, and I recode these values to be log of zero dollar payments plus one.

[59]In ongoing work, I am using other outcome measures without this log specification, such as counts and indicators for claim-based utilization measures.

that the log utilization outcome y_{it} of patient i in quarter t is the sum of a patient component α_i, a PCP component $\gamma_{j(i,t)}$, an index of time-varying observable characteristics $x_{it}\beta$, effects of switching PCPs $\Sigma_g \Sigma_k \theta^{g,k} D_{it}^{g,k}$ (where $D_{it}^{g,k}$ are indicators for k time periods relative to PCP switches of type g, which I discuss below), and an error component ε_{it}:

$$y_{it} = \alpha_i + \gamma_{j(i,t)} + x_{it}\beta + \sum_g \sum_k \theta^{g,k} D_{it}^{g,k} + \varepsilon_{it}. \tag{1.1}$$

I interpret α_i as the healthcare patient i would receive at all PCPs, which includes patient i's time-invariant health status and preferences as well as other time-invariant factors, such as patient i's neighborhood. I interpret physician $\gamma_{j(i,t)}$ as PCP j's practice style, the healthcare PCP j would choose for all patients. This term includes the general frequency at which the PCP asks patients to return for follow-up visits and the general propensity of the PCP to refer patients to specialists rather than attempting to diagnose and treat them directly. I include in x_{it} an unrestricted set of year-by-quarter indicators as well as quadratic and cubic terms in age interacted with gender.[60]

To capture temporary utilization patterns associated with PCP switches, I include indicators $D_{it}^{g,k}$ for whether patient has a specific type of switch g for any $k \in [-8, 12]$ quarters relative to event time $k = 0$, the last quarter a patient is assigned a given main PCP. I define the leads to be whether the patient switches away from their current main PCP and the lags to be whether the patient switched to their current main PCP.[61] I allow for four switch types g to capture utilization patterns that may vary across the different types of switches. The four switch types g are: (a) between two main PCPs in the same physician practice group, (b) between two main PCPs in different physician practice groups, (c) from no main PCP to a main PCP, and (d) from a main PCP to no main PCP.[62,63]

The PCP fixed effects and patient fixed effects are only separately identified within a "connected set" of PCPs and patients who are linked by patients who switch PCPs (Abowd, Creecy, and Kramarz 2002). In my estimation, I restrict my analysis to the largest connected set within each market, and I discuss the sample in Section 1.5.1. The identification also requires normalization, and I normalize the mean of PCP fixed effects and mean of patient fixed effects in each market to zero.

[60] I measure age in years at the monthly level relative to age 75 (the monthly level is consistent with Medicare enrollment and eligibility). I set female to one for the gender indicator. The year-by-quarter indicators control for market-level factors, which are different across dates/cohorts, and I normalize their mean to zero. See Card, Cardoso, Heining, and Kline (2018) for a discussion of normalizations.

[61] As an alternative specification, I could include leads and lags for additional switches (e.g., leads for whether a patient switches away from their next main PCP, lags for whether a patient switched to their previous main PCP).

[62] I define PCPs to be in the same physician practice group if they have a common tax number with up to a one-year gap relative to the PCP switch date. The one-year gap captures cases in which a PCP leaves a practice group and another (potentially replacement) PCP subsequently, but not immediately, joins the practice group.

[63] Specifically, $D_{it}^{g,k}$ consists of 63 indicators, three for each of the 21 event time quarters $k \in [-8, 12]$. Each of the two types of switches between PCPs has indicators for 21 event time quarters $k \in [-8, 12]$. The switch from a PCP to no PCP has indicators for 9 event time quarters $k \in [-8, 0]$. The switch from no PCP to a PCP has indicators for 12 event time quarters $k \in [1, 12]$.

1.4.2 Assumptions on the Physician Switching Process

For my estimation to identify the parameters of interest as defined, I assume that the error term ε_{it} has $E[\varepsilon_{it}|, i, t, x_{it}] = 0$, has $Var[\varepsilon_{it}|i, t, x_{it}] < \infty$, and is orthogonal to other terms in the model as described in Abowd, Creecy, and Kramarz (2002).[64] There are three forms of "endogenous" switching that would violate these assumptions and cause biases in my approach.

The first type would be patient sorting based on some idiosyncratic match of physician and patients. This form of sorting could be generated by the models from Roy (1951) and Chandra and Staiger (2007). I check for this sorting in two ways. First if patients select PCPs based on this match component, then I would expect the increases in utilization for patients who move from one PCP to another PCP to be different from the decreases in utilization for patients who move in the opposite direction. Under my assumptions, the expected utilization changes between pairs of PCPs, $(\gamma_j - \gamma_{j'})$ and $(\gamma_{j'} - \gamma_j)$, would be symmetric. As described in Section 1.3.1, the increase in average utilization for patients switching from quartile 1 PCPs to quartile 4 PCPs is roughly equal to the decrease in average utilization for patients switching in the opposite direction. Also, aside from the switch period, the average utilization among patients who switch from quartile 4 PCPs to other quartile 4 PCPs remains roughly constant, and the average utilization among patients who switch from quartile 1 PCPs to other quartile 1 PCPs remains roughly constant.[65] Second if match effects are important, a fully saturated model that includes a separate indicator for each matched patient-PCP pair should fit the data much better than the additively separable model in Equation 1.1. The model with the patient-PCP matches yields slightly higher R-squared values, but the increases are small. I present the results on the fit of the model in Section 1.6.

The second type of endogenous switching would be if the drift in the expected utilization a patient would have at all PCPs predicts PCP-to-PCP switches. This form of sorting would occur if a patient who receives a health shock with persistent effects is systematically more likely to switch to a PCP with a high-spending practice style or to a PCP with a low-spending PCP practice style. This type of behavior could be patient driven (e.g., if a patient who has declining health seeks a PCP who has greater appointment availability and generally allows for more frequent follow-up visits) or PCP-driven (e.g., if a PCP refers a patient with a new diagnosis to another PCP who may have more expertise in the disease). Though these switches may occur idiosyncratically for individual matched patient-PCP pairs, there is no evidence of systematic switching based on the drift in expected utilization. The figures do not exhibit systematic trends in the healthcare utilization prior to the year of the switch (years -1 and -2) or after the switch (years 2 and 3) across patients who make different quartile-to-quartile switches. Also, this type of switching might be more likely to occur for patients who receive negative health shocks (e.g., who may choose to switch to higher-spending PCPs), but the symmetry in the transitions of patients between quartile 1 PCPs and quartile 4 PCPs suggests that this type of switching would be limited.

The third type of endogenous switching would be if fluctuations in the transitory error (e.g., period-specific health shocks) are associated with switching to systematically high-

[64] See Card, Heining, and Kline (2013) for a detailed discussion of the assumptions.

[65] There is some narrowing of the distribution in total utilization, but not for primary care utilization, which would be easier for patients to sort on than total utilization.

spending PCPs or low-spending PCPs. I do not observe pre-trends or post-trends outside the period of the switch. In my estimation of the variance of PCP fixed effects, which I discuss further in Section 1.5, I exclude periods during the switch to accurately estimate the variance of PCP effects on long-run, steady-state utilization.

1.5 Methodology: Physician Practice Styles

1.5.1 Variance of Physician Fixed Effects and Estimation

In the first part of my analysis, I estimate the contribution of differences in individual PCP practice styles, as measured by spending, to variation in healthcare utilization within markets. I decompose the variance of healthcare utilization within each of the 306 Hospital Referral Region (HRR) markets.

I return to my econometric model from Section 1.4.1 with patient i, quarter t, and main PCP $j\,(i,t)$. My main parameter of interest is the variance of the PCP fixed effects $\gamma_{j(i,t)}$ in the econometric model

$$y_{it} \quad = \quad \alpha_i + \gamma_{j(i,t)} + x_{it}\beta + \sum_g \sum_k \theta^{g,k} D_{it}^{g,k} + \varepsilon_{it} \tag{1.2}$$

where y_{it} is the log utilization outcome, α_i are patient fixed effects, $\gamma_{j(i,t)}$ are main PCP fixed effects, x_{it} are controls, and $D_{it}^{g,k}$ are indicators for time relative to PCP switches as discussed in Section 1.4.1.[66]

My goal is to estimate the contribution of differences in individual PCP practice styles, as measured by spending, to variation in a demographics-adjusted measure of patient long-run, steady-state utilization. Patient gender, patient age, and market-level factors drive much of healthcare utilization but are essentially predetermined for individual PCPs and patients, so I exclude the contributions of these factors from healthcare variation. Similarly, I exclude the temporary effects of switching PCPs from healthcare variation given the utilization patterns discussed in Section 1.3.1.

In my estimation, I partial out the effects of the controls x_{it} and the effects of the switching indicators $D_{it}^{g,k}$ estimated from a first-stage ordinary least squares regression of Equation 1.2. Specifically, I calculate an adjusted measure of utilization

$$\widetilde{y_{it}} \quad = \quad y_{it} - x_{it}\hat{\beta} - \sum_g \sum_k \hat{\theta}^{g,k} D_{it}^{g,k} \tag{1.3}$$

where $\hat{\beta}$ and $\hat{\theta}^{g,k}$ are estimated from the first-stage ordinary least squares regression of Equation 1.2.[67] The intuition is that I adjust utilization for these factors in a way that is

[66] Controls x_{it} include an unrestricted set of year-by-quarter indicators as well as quadratic and cubic terms in age interacted with gender.

[67] Equation 1.2 could be rewritten and estimated in a second-stage ordinary least squares regression $\widetilde{y_{it}} = \alpha_i + \gamma_{j(i,t)} + \varepsilon_{it}$ for a standard variance decomposition. When estimated in ordinary least squares regressions, the estimated fixed effects $\hat{\alpha}_i$ and $\hat{\gamma}_{j(i,t)}$ in this equation are identical to those estimated from Equation 1.2. Note that this setup does not require the Frisch-Waugh-Lovell Theorem because all of the regressors (including patient fixed effects α_i and PCP fixed effects $\gamma_{j(i,t)}$) are in the first-stage regression of Equation 1.2.

consistent with the econometric model, including the patient fixed effects α_i and the PCP fixed effects $\gamma_{j(i,t)}$. I then decompose the variance of the adjusted measure of utilization as

$$Var\left(\widetilde{y_{it}}\right) = Var\left(\alpha_i\right) + 2Cov\left(\alpha_i, \gamma_{j(i,t)}\right) + Var\left(\gamma_{j(i,t)}\right) + Var\left(\varepsilon_{it}\right). \tag{1.4}$$

To obtain unbiased estimates of $Var\left(\gamma_{j(i,t)}\right)$ based on the variance decomposition in Equation 1.4, I cannot use the standard ordinary least squares approach. A key empirical challenge is that sampling errors lead to biases in variance decompositions (Andrews et al. 2008).[68] The biases are larger in datasets in which there are fewer movers, or switchers, such that this bias is also known as "limited mobility bias" (Andrews et al. 2008).[69] In the primary care setting, and particularly in a dataset that includes only a 20% sample of Original Medicare patients, there are few patient switchers between PCPs. Standard ordinary least squares estimation would lead to a positive bias in the variance of PCP fixed effects, a positive bias in the variance of patient fixed effects, and a negative bias in the covariance of PCP fixed effects and patient fixed effects.

I apply a recently available econometric method by Kline, Saggio, and Sølvsten (2018) that constructs unbiased estimators of variance and covariance. The estimators allow for heteroskedastic errors, and the estimation procedure allows for autocorrelation within a patient-PCP match by leaving out matched patient-PCP pairs.[70]

1.5.2 Estimation Outcome Measures and Samples

In my estimation, I use two sets of outcome measures. First, I estimate the variance of PCP fixed effects in yearly utilization – defined as utilization over the past year – for results that are directly interpretable and comparable to existing literature.[71] My outcome measure is, therefore, a rolling sum across patient-quarter observations. The intuition in interpreting this specification is that it is similar to one in which I would use *patient-year* observations and weight the observations by the number of quarters each patient is assigned each main PCP during the year, except that in my specification with *patient-quarter* observations, the utilization and the controls (e.g., patient age, cohort/date) are more precisely measured.

For my estimation sample, I omit patient-quarters during the main PCP switches based on the utilization patterns discussed in Section 1.2.4. Specifically, I omit any observation

[68] Sampling errors in the estimated PCP fixed effects and patient fixed effects leads to positive biases in the variance of PCP fixed effects and in the variance of patient fixed effects. The correlation in the sampling errors in the estimated PCP fixed effects and patient fixed effects often leads to a negative bias in the covariance of PCP fixed effects and patient fixed effects.

[69] Andrews et al. (2008) offer a correction that would require an assumption of normality in the sampling distribution of the estimated variance of PCP effects, but my data likely have non-normality in the sampling distribution of the estimated variance of PCP effects due to few movers in my connected set of PCPs and patients (Kline, Saggio, and Sølvsten 2018).

[70] Kline, Saggio, and Sølvsten (2018) also provide a method to compute standard errors on the variance and covariance estimates. Specifically, I compute homoskedastic standard errors (which I can compute in all of my markets), with a modification to the Kline, Saggio, and Sølvsten (2018) estimation procedure written by Saggio (2018) that computes heteroskedastic standard errors (which I cannot compute in all of my markets using the current estimation procedure).

[71] I use yearly utilization such that y_{it} is defined as the log of sum of the current quarter of utilization, the previous three quarters of utilization, and one.

that could include part of a switch period, which consists of event times -3 to 0 (the last four quarters with the origin PCP) and event time 1 (the first quarter with the destination PCP), in its outcome measure. In this analysis with yearly utilization, I omit eight quarters of outcomes (i.e., event times -3 to +4, where 0 is defined as the last quarter a patient is assigned their origin PCP, such that the outcome at event time +5 is the sum of utilization from event time +2 to event time +5). I also omit patient-quarter observations that are not followed by four quarters in the sample because patients might have switched main PCPs if their data were not censored.[72]

I exclude the switch period from the variance decomposition because patients are likely influenced by both their origin PCP and their destination PCP, on average, during the switch. Assignment to one PCP or another would lead to measurement error and attenuation bias in the estimates of the variance of PCP fixed effects.[73]

My main PCP definition and omission of switch period observations affect the utilization that I attribute to PCPs. I do not attribute utilization associated with the onset of Medicare eligibility at age 65 (as described in Card, Dobkin, and Maestas 2009) to PCPs because a patient is not assigned a main PCP until their fourth quarter of Medicare eligibility. I also do not attribute end-of-life utilization to PCPs because I omit the last four quarters of patient lives.[74]

My estimation allows for the mechanical autocorrelation in my outcome measure. The estimation procedure I use by Kline, Saggio, and Sølvsten (2018) accounts for any autocorrelation *within* a matched patient-PCP pair, so I can allow for this mechanical autocorrelation in outcomes *within* patient-PCP pairs. I omit more than four patient-quarter observations between matched patient-PCP pairs, so there is no mechanical autocorrelation in outcomes *between* patient-PCP pairs.

Column (4) of Table 1.4 reports the descriptive statistics for this sample.[75] Figure B.1 illustrates the relationship of this sample to others used in this dissertation. Compared with the *main analysis sample*, the patients in my connected set have lower average yearly total utilization of about \$5,000 (versus \$8,200) with a standard deviation about \$9,600 (versus \$16,000) and lower average primary care utilization of about \$380 (versus \$500) with a standard deviation of about \$390 (versus \$670).

Second, for simplicity and for consistency with my estimation of switching costs in Chapter 2, I estimate the variance of PCP fixed effects with contemporaneous quarterly utilization outcome measures.[76] I describe the sample and the results in Appendix C.2.

[72]For example, patients who plan to switch to Medicare Advantage might be in the process of switching to PCPs in the provider networks of their new Medicare Advantage plans.

[73]The omission of these observations in which a patient cannot be fully attributed to a PCP is consistent with similar variance decompositions in previous literature (e.g., Finkelstein, Gentzkow, and Williams (2016), who omit the year of the move in patient migration).

[74]Patients might have switched PCPs in the absence of death. In an alternative specification, I could allow for these periods and assume the patients do not switch when their data are censored.

[75]The estimation procedure further restricts the sample to the largest connected set within each market that remains connected when each patient-PCP pair is separately omitted from the sample, and this sample is referred to as the "leave-out" connected sets sample. Column (3) of Table A.1 reports the descriptive statistics for this sample. This leave-out connected sets sample is very similar to the full connected sets estimation sample in Column (2) of Table A.1 and Column (4) of Table 1.4.

[76]I use quarterly utilization such that y_{it} is defined as the log of sum of the current quarter of utilization

1.6 Results: Physician Practice Styles

Table 1.6 reports the variance decomposition results for yearly total utilization, and Table 1.7 reports the results for yearly primary care utilization. In both Tables 1.6 and 1.7, Column (3) reports the results for all 306 hospital referral region (HRR) markets weighted by their Original Medicare population.[77,78] The mean variance of PCP fixed effects is 2.4% of the total variance in total utilization, and the mean variance of PCP fixed effects is 12.6% of the total variance in primary care utilization.

Figure 1.4 plots the distribution of the estimated variances across markets. Some of the estimated variances of PCP fixed effects are negative and imprecisely estimated, and these are concentrated among smaller markets.[79]

In both Tables 1.6 and 1.7, Columns (4) and (5) report the estimates for markets with above median spending and below median spending, respectively. Column (1) reports the results for Miami, which is a high-spending market, and Column (2) reports the results for Minneapolis, which is a low-spending market.[80]

Due to the leave-out estimation that leaves out patient-PCP matches, the variance of *patient* fixed effects cannot be estimated for non-switchers.[81] To obtain estimates of the variance of patient fixed effects, I restrict the estimation to patients who switch PCPs at least once. Table A.7 reports the total utilization results for switchers, and Table A.8 reports the primary care utilization results for switchers. Among this switchers subsample, the mean variance of patient fixed effects is 28.4% of the total variance in total utilization, and the mean variance of patient fixed effects is 11.1% of the total variance in primary care utilization.

Bringing these results together, differences in PCP practice styles, as measured by spending, explain a small and significant 2.4% of total utilization variation. Differences across time-invariant patient factors contribute about 11 times more than differences in PCP practice styles to variance in total utilization. As one would expect, PCPs have substantially greater influence in primary care utilization. Differences in PCP practice styles explain 12.6% of primary care utilization variation. Differences across time-invariant patient factors explain slightly less than differences in PCP practice styles do in primary care.

A feature of my specification is that it does not capture time-varying patient characteristics. I do not include time-varying patient chronic conditions in my main analysis because their diagnosis and coding may be correlated with PCP practice styles. As a result, the contribution of differences across patients to variation in healthcare that I estimate is a lower bound.[82]

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and one.

[77] I compute the weighted means of the point estimates, means, and counts. I compute the standard errors that correspond to the weighted point estimates.

[78] Results are similar with an unweighted average across HRRs, and I present these estimates in Table A.6.

[79] Negative point estimates of the variance in PCP fixed effects occur for 71 of 306 markets in total utilization and for 12 of 306 markets in primary care utilization.

[80] The U.S. mean price, age, sex, and race-adjusted total Medicare reimbursements per beneficiary was $8,507 in 2007. Miami ranked highest in spending with $14,611, and Minneapolis ranked 259th of 306 HRRs in spending with $6,992.

[81] For non-switchers, all observations of a patient are left out when the estimation procedure leaves out its only patient-PCP match.

[82] In ongoing analysis, I am examining the contribution of time-varying patient chronic conditions.

I compare the total utilization and primary care utilization results to other categories of healthcare utilization, including tests and imaging, which PCPs often use for diagnosis, monitoring of chronic conditions, and preventive care. Table 1.8 reports the results for tests utilization and imaging utilization. The mean variance of PCP fixed effects is 5.9% of the total variance in tests utilization, and the mean variance of PCP fixed effects is 2.7% of the total variance in imaging utilization. Differences in PCP practice styles explain less of the variance in tests utilization (e.g., for diagnosis or monitoring of blood sugar or cholesterol) than in primary care utilization but more than in total utilization or in imaging utilization. Differences in PCP practice styles explain about the same amount of the variation in imaging utilization as they do in total utilization. I also report results for emergency department and hospital inpatient utilization in Table 1.9. The mean variance of PCP fixed effects is 1.6% of the total variance in emergency department utilization, and the mean variance of PCP fixed effects is 2.1% of the total variance in hospital inpatient utilization.

1.7 Discussion

1.7.1 Significance and Limitations

This chapter provides some of the first evidence on the influence of individual PCPs on healthcare utilization, while accounting for unobservable patient characteristics, in a large U.S. population. I first show that utilization patterns generated by PCP practice styles, patient characteristics, and patients switching PCPs can generally be explained in an event study framework with PCP fixed effects and patient fixed effects. In this model, I estimate the unbiased variance of PCP fixed effects within each of the 306 hospital referral region (HRR) markets. I find that differences in PCP practice styles, as measured by spending, explain 2.4% of the variation in total utilization and 12.6% of the variation in primary care utilization within healthcare markets.

This study has a few main limitations. First, I estimate the contribution of only two components of health production to healthcare utilization: PCPs and patients. The research design and econometric model do not enable me to separate out other supply-side factors – such as specialist physicians and hospitals – that influence healthcare utilization through PCPs, patients, and other channels.

Second, my sample is limited by the research design and methodology. My definitions of a main PCP and a main PCP switch affect the utilization that I attribute to PCPs. I do not attribute utilization associated with the onset of Medicare eligibility at age 65 to PCPs because patient are not assigned main PCPs until their fourth quarter of Medicare eligibility. I also do not attribute end-of-life utilization to PCPs because I omit the last four quarters of patients' lives. The requirement for connected sets further limits the sample of patient-quarters in the estimation samples.

Third, my main aggregate results likely mask heterogeneity both across PCPs and across patients. Some groups of PCPs and some groups of patients may be more influential than others in determining their healthcare utilization. For example, patients who are most familiar with the healthcare system (e.g., current and former healthcare professionals) likely exert greater influence on their healthcare utilization.

1.7.2 Policy Implications

My findings are relevant for policies that seek to alter physician practice styles for the purposes of increasing efficiency or reducing costs. PCPs have important roles as coordinators and gatekeepers of care in Accountable Care Organizations (ACOs), Health Maintenance Organizations (HMOs), and Point of Service (POS) health plans. PCPs are a central component of Medicare ACO programs.[83] Medicare has several ACO programs and started the Medicare Shared Savings Program (MSSP) in Original Medicare, the context of my study, in April 2012. The initial savings in Medicare ACOs, even not accounting for shared-savings bonuses paid, have been modest or insignificant (McWilliams et al. 2015; McWilliams et al. 2016). My findings indicate that differences in PCP practice styles explain a small, though significant, 2.4% of within-market healthcare variation, so the findings of modest savings in Medicare ACOs are not surprising. If MSSP or other ACOs could change PCPs at the 60th percentile of spending to become like PCPs at the 40th percentile of spending the savings would be only $231 per year for a representative patient, based on counterfactual calculations in Chapter 2. In practice, altering PCP practices styles by an amount equivalent to the difference across 20% of the distribution may be challenging in the short run. Physician training, institutional features, and other characteristics determine PCP practice styles, so policymakers would need to assess to what degree policies could feasibly alter PCP practice styles for substantial cost savings.

1.7.3 Conclusion

This chapter examines one dimension of PCP practice styles – utilization as measured by spending – and finds that differences across PCPs contributes to 2.4% of the variation in total healthcare utilization within markets. Given that I find significant variation across PCPs, understanding drivers of this variation would be important for PCP-targeted policies. For example, if less productive PCPs incur greater utilization, then forcing high-spending PCPs to reduce utilization could have adverse consequences on patient health outcomes. On the other hand, if productivity is the same across PCPs and some PCPs are just operating on the "flat of the curve" then incentivizing high-spending PCPs to reduce utilization could potentially lead to cost savings without adverse consequences. Future research could study variation in PCP practice styles across additional dimensions, such as productivity, expertise, and discretion, to develop informed policy recommendations.

[83] In Medicare ACOs, "primary care physicians are encouraged to join together with other providers to take responsibility for the full continuum of their primary care patients' care. They must commit to reporting comprehensive measures of the quality and – eventually – outcomes of care. If they are able to improve quality and thereby reduce costs, they will receive a share of the savings achieved." Source: Dartmouth Atlas of Health Care "Accountable Care" webpage (http://archive.dartmouthatlas.org/keyissues/issue.aspx?con=2943).

Table 1.1: Descriptive Statistics: Patient Selected Population and Main Analysis Samples

	Selected Pop.	Selected Population by Any Switch			Main Analysis Sample
		No PCP	No Switch	Switch(es)	
	(1)	(2)	(3)	(4)	(5)
A. Patients (millions)	9.32	1.06	3.12	5.15	7.51
Female (%)	56.7	46.3	55.3	59.6	58.5
White (%)	86.3	79.2	86.5	87.6	87.4
# main PCPs ever (mean)	2.14	0	1	3.28	2.51
# quarters in sample (mean)	30.5	14.0	24.7	37.4	33.9
B. Patient-Qtrs. (millions)	210.3	10.8	54.9	144.6	133.5
Age (years, mean)	75.9	71.6	74.7	76.5	76.9
Main PCP eligible (%)	93.5	79.7	90.6	95.6	100.0
Assigned main PCP (%)	72.1	0.0	69.4	78.5	100.0
Quarterly Utilization					
Total util. mean ($)	1,927	647	1,546	2,167	2,247
Total util. std. dev. ($)	6,741	4,612	6,134	7,070	7,032
Any total util. (%)	81.9	36.4	80.5	85.8	90.6
Primary care util. mean ($)	106	10	93	118	136
Prim. care util. std. dev. ($)	259	127	214	279	281
Any primary care util. (%)	53.9	4.1	55.0	57.1	69.9
Past Year Utilization					
Total util. mean ($)	6,872	1,938	5,361	7,815	8,151
Total util. std. dev. ($)	15,352	8,972	13,536	16,237	16,122
Any total util. (%)	93.7	52.4	93.3	96.9	100.0
Primary care util. mean ($)	381	24	333	426	500
Prim. care util. std. dev. ($)	627	227	519	673	666
Any primary care util. (%)	78.1	7.4	77.3	83.7	100.0

Notes: This table reports the descriptive statistics for the *selected population sample* and the *main analysis sample* described in Section 1.2.5. In Column (1), the *selected population sample* is restricted to (a) years 2002-2011 and (b) patient-quarters during which patients are 65-99 years old and are enrolled in traditional fee-for-service (Original) Medicare Parts A and B coverage in all three months. Columns (2)-(4) split the patients in Column (1). Column (2) consists of patients who are never assigned a main primary care physician (PCP). Column (3) consists of patients who are ever assigned only one main PCP. Column (4) consists of patients who are ever assigned to two or more PCPs. In Column (5), the *main analysis sample* is restricted to patient-quarters during which the patient is assigned a main PCP in the same market who they visit for at least 75% of PCP visits over the past year. For patient-quarters during main PCP switches, both origin PCPs and destination PCPs count toward the 75% of PCP visits requirement. Column (5) is a subsample of patient-quarters in Columns (3) and (4). Patients are eligible for main PCP assignment if they meet the selected population sample restrictions for the current and past three quarters. The reported percentages of patient-quarters with assigned main PCPs are calculated among those eligible for main PCP assignment.

Table 1.2: Descriptive Statistics: Primary Care Physicians (PCPs) of Main Analysis Sample

	Unweighted		Patient-Quarter Weighted	
	Mean / SD	Obs. (thousands)	Mean / SD	Obs. (millions)
	(1)	(2)	(3)	(4)
# Patients/Quarter	20	229.2	51	133.5
	(23)		(35)	
# Patients Ever	69	229.2	159	133.5
	(73)		(100)	
# Patient-Quarters	582	229.2	1787	133.5
	(837)		(1316)	
# Quarters	24	229.2	36	133.5
	(14.2)		(7.4)	
Med School Grad Year	1986	226.7	1983	133.4
	(12.35)		(10.26)	
Gender Female (%)	31.2	210.8	18.4	131.1

Notes: This table reports descriptive statistics of the main primary care physicians (PCPs) of the patients in the *main analysis sample* (see Table 1.1, Column (5)). Columns (1) and (2) report the unweighted statistics for PCPs with standard deviations in parentheses. Columns (3) and (4) report the patient-quarter weighted statistics for PCPs with standard deviations in parentheses. Main PCPs are defined in Section 1.2.4.

Table 1.3: Utilization Outcome Measure Examples

	Mean ($)	Freq.(thousands)	HCPCS
	(1)	(2)	(3)
A. Evaluation and Management Outpatient Visits			
Established patient visit (10 mins)	35.44	681	99212
Established patient visit (15 mins)	58.05	3323	99213
Established patient visit (40 mins)	120.75	243	99215
New patient visit (20 mins)	59.98	72	99202
New patient visit (30 mins)	90.01	148	99203
New patient visit (45 mins)	137.79	91	99204
Consultation (40 mins)	119.95	153	99243
Consultation (60 mins)	177.32	183	99244
B. Tests			
Blood lipids test (lipid panel)	14.21	642	80061
Hemoglobin A1c test	13.53	342	83036
C. Imaging			
Mammography (bilateral)	47.83	135	77057

Notes: This table reports mean utilization in dollars and frequency for several common physician services for patients in the *main analysis sample* (see Table 1.1, Column (5)) in quarter 1 of year 2007, approximately the midpoint of the sample. Column (1) reports the utilization in dollars of spending, which is the sum of Medicare payments, patient payments, and any primary payer payments, as defined in Section 1.2.6. Column (2) reports the frequency among patients. Column (3) reports the Healthcare Common Procedure Coding System (HCPCS) or Current Procedural Terminology (CPT) code that defines each service.

Table 1.4: Descriptive Statistics: Connected Sets Samples

	Main Analysis Sample	Connected Sets Samples: Quarterly Outcome w/o Switch	Connected Sets Samples: Quarterly Outcome w/ Switch	Connected Sets Samples: Yearly Outcome w/o Switch
	(1)	(2)	(3)	(4)
A. Patients (millions)	7.51	5.18		4.46
Female (%)	58.5	59.9		60.4
White (%)	87.4	88.9		89.4
# main PCPs ever (mean)	2.51	2.56		2.53
# quarters in sample (mean)	33.9	38.4		40.0
B. Patient-Qtrs. (millions)	133.5	73.4	81.3	61.6
Age (years, mean)	76.9	76.6	76.7	77.1
Quarterly Utilization				
Total util. mean ($)	2,247	1,297	1,313	1,292
Total util. std. dev. ($)	7,032	4,050	4,091	3,999
Any total util. (%)	90.6	90.1	90.0	90.6
Primary care util. mean ($)	136	96	95	97
Prim. care util. std. dev. ($)	281	146	147	144
Any primary care util. (%)	69.9	69.8	69.1	70.7
Past Year Utilization				
Total util. mean ($)	8,151	5,107	5,133	5,032
Total util. std. dev. ($)	16,122	9,879	9,939	9,649
Primary care util. mean ($)	500	379	375	378
Prim. care util. std. dev. ($)	666	399	398	392

Notes: This table reports the descriptive statistics for the connected sets samples (sets of patients and PCPs linked by patients who switch PCPs), which I use for analysis in Sections 1.5 and 2.3. Column (1) reports the *main analysis sample* from Column (5) of Table 1.1. Columns (2) and (4) report the patient-quarter samples that omit the quarters during PCP switches, which I use for analysis in Section 1.5. Column (3) reports the patient-quarter samples that may include the quarters during PCP switches, which I use for analysis in Section 2.3. The patient-quarter observations in Column (2) are a subset of those Column (3), and the patients are identical. The patients and patient-quarter observations in Column (4) are subsets of those in Column (2).

Table 1.5: Descriptive Statistics: Switchers Balanced Panel Around PCP Switch

		Connected Sets	Switchers Balanced Panel	
	Main Analysis Sample	Yearly Outcome w/o Switch	All Matches	Consistent Matches
	(1)	(2)	(3)	(4)
A. Patients (thousands)	7,512	4,464	540	156
Female (%)	58.5	60.4	65.2	66.7
White (%)	87.4	89.4	90.4	90.2
# main PCPs ever (mean)	2.51	2.53	3.59	2.79
# quarters in sample (mean)	33.9	40.0	49.2	50.4
B. Patient-Qtrs. (millions)	133.52	61.63	13.53	3.77
Age (years, mean)	76.9	77.1	77.6	78.2
Quarterly Utilization				
Total util. mean ($)	2,247	1,292	1,695	1,608
Total util. std. dev. ($)	7,032	3,999	5,092	4,527
Any total util. (%)	90.6	90.6	91.2	94.6
Primary care util. mean ($)	136	97	116	126
Prim. care util. std. dev. ($)	281	144	203	180
Any primary care util. (%)	69.9	70.7	69.6	79.1
Past Year Utilization				
Total util. mean ($)	8,151	5,032	6,502	6,227
Total util. std. dev. ($)	16,122	9,649	11,982	10,746
Primary care util. mean ($)	500	378	444	489
Prim. care util. std. dev. ($)	666	392	519	496

Notes: This table reports the descriptive statistics for a balanced panel of patients who switch PCPs that includes 12 quarters before the switch and 12 quarters after the switch, where event time zero for the switch is defined as the last quarter a PCP is assigned to a patient. Column (1) includes the *main analysis sample* from Column (5) of Table 1.1. Column (2) includes the connected sets sample from Column (4) of Table 1.4, which I use for analysis in Section 1.5. Columns (3) and (4) include the switchers balanced panel, which I restrict to the connected sets sample for quarterly utilization in Column (2) of Table 1.4. Column (3) includes all patient-PCP matches, i.e., patients who have *any* assigned main PCP in every quarter for 12 quarters before the switch through 12 quarters after the switch. Column (4) includes only consistent patient-PCP matches, which I define as patients who are *consistently* matched with their origin PCPs for 12 quarters before the switch and *consistently* matched with their destination PCPs for 12 quarters after the switch. Column (4) is a subset of Column (3). The number of patient-quarter observations is not exactly 25 times the number of patients because (a) a patient can appear in the sample for more than one switch and (b) a patient-quarter observation can appear in the post-period for one switch and in the pre-period for another switch.

Table 1.6: Practice Styles Results: Variance in Yearly Total Utilization

	Example Markets			Markets by Spending	
	Miami	Minne-apolis	All Markets	Above Median	Below Median
	(1)	(2)	(3)	(4)	(5)
# of within-market estimations	1	1	306	153	153
A. Variance and Covariance Estimates (market/multi-market mean, SE in parentheses)					
Variance of PCP FEs	0.217	2.200	**2.449**	2.617	2.212
as % share of total variance	(1.488)	(2.198)	(0.136)	(0.131)	(0.271)
Cov. of patient & PCP FEs	2.681	-0.007	0.011	0.156	-0.193
as % share of total variance	(1.611)	(2.103)	(0.134)	(0.129)	(0.266)
B. Other Statistics & Results (market or multi-market mean)					
# of PCP fixed effects	1,011	1,261	726	867	526
# of patient-qtr. obs.	239,060	345,977	361,421	433,553	259,626
Mean of log util.	8.232	7.422	7.735	7.791	7.655
Std. dev. of log util.	1.219	1.318	1.270	1.271	1.269
Var. of log util.	1.486	1.737	1.616	1.618	1.614
Var. of PCP FEs	0.003	0.038	0.040	0.043	0.036
Std. dev. of PCP FEs	0.057	0.195	0.180	0.189	0.168

Notes: This table reports the results of the 306 within-market estimations of (a) the variance of primary care physician (PCP) fixed effects (FEs) and (b) the covariance of the PCP fixed effects and the patient fixed effects in a two-way fixed effects model. The estimation uses patient-quarter level observations in the leave-out patient-PCP match procedure described in Section 1.5.1. The outcome variable is the *log of yearly total utilization* in the past year. Column (1) reports the results for Miami (a high-spending market), and Column (2) reports the results for Minneapolis (a low-spending market). Column (3) reports the estimates for all 306 markets weighted by the number of Original Medicare beneficiaries in each market. Columns (4)-(5) report the weighted estimates of the above median and below median markets by spending. Columns (1) and (2) of Panel A report estimates of the shares of utilization that are the variance of PCP fixed effects and the covariance of PCP fixed effects and patient fixed effects along with their corresponding standard errors (SEs). In Columns (3)-(5) of Panel A, the PCP fixed effects share and the covariance of PCP fixed effects and patient fixed effects share are the weighted means of the corresponding estimates, and the standard errors are computed accordingly. The standard deviation of the PCP fixed effects is imputed to be zero in markets where the point estimate of the variance of PCP fixed effects is negative. The sample is the connected set for yearly utilization that omits the switch period in Column (4) of Table 1.4 that remains connected when each patient-PCP pair is excluded. Markets are hospital referral regions (HRRs).

Table 1.7: Practice Styles Results: Variance in Yearly Primary Care Utilization

	Example Markets			Markets by Spending	
	Miami	Minne-apolis	All Markets	Above Median	Below Median
	(1)	(2)	(3)	(4)	(5)
# of within-market estimations	1	1	306	153	153
A. Variance and Covariance Estimates (market/multi-market mean, SE in parentheses)					
Variance of PCP FEs	18.960	6.675	**12.626**	13.757	11.030
as % share of total variance	(1.253)	(2.604)	(0.131)	(0.138)	(0.249)
Cov. of patient & PCP FEs	0.678	0.257	0.173	0.254	-0.059
as % share of total variance	(1.183)	(2.500)	(0.124)	(0.126)	(0.239)
B. Other Statistics and Results (market or multi-market mean)					
# of PCP fixed effects	1,011	1,261	726	867	526
# of patient-qtr. obs.	239,060	345,977	361,421	433,553	259,626
Mean of log util.	5.987	5.288	5.599	5.653	5.537
Std. dev. of log util.	0.878	0.847	0.791	0.798	0.781
Var. of log util.	0.770	0.717	0.628	0.639	0.612
Var. of PCP FEs	0.146	0.048	0.080	0.089	0.067
Std. dev. of PCP FEs	0.382	0.219	0.275	0.292	0.250

Notes: This table reports the results of the 306 within-market estimations of (a) the variance of primary care physician (PCP) fixed effects (FEs) and (b) the covariance of the PCP fixed effects and the patient fixed effects in a two-way fixed effects model. The estimation uses patient-quarter level observations in the leave-out patient-PCP match procedure described in Section 1.5.1. The outcome variable is the *log of yearly primary care utilization* in the past year. Column (1) reports the results for Miami (a high-spending market), and Column (2) reports the results for Minneapolis (a low-spending market). Column (3) reports the estimates for all 306 markets weighted by the number of Original Medicare beneficiaries in each market. Columns (4)-(5) report the weighted estimates of the above median and below median markets by spending. Columns (1) and (2) of Panel A report estimates of the shares of utilization that are the variance of PCP fixed effects and the covariance of PCP fixed effects and patient fixed effects along with their corresponding standard errors (SEs). In Columns (3)-(5) of Panel A, the PCP fixed effects share and the covariance of PCP fixed effects and patient fixed effects share are the weighted means of the corresponding estimates, and the standard errors are computed accordingly. The standard deviation of the PCP fixed effects is imputed to be zero in markets where the point estimate of the variance of PCP fixed effects is negative. The sample is the connected set for yearly utilization that omits the switch period in Column (4) of Table 1.4 that remains connected when each patient-PCP pair is excluded. Markets are hospital referral regions (HRRs).

Table 1.8: Practice Styles Results: Variance in Yearly Tests and Imaging Utilization

	Tests			Imaging		
		Markets by Spend.			Markets by Spend.	
	All Markets	Above Median	Below Median	All Markets	Above Median	Below Median
	(1)	(2)	(3)	(4)	(5)	(6)
# of within-market estimations	306	153	153	306	153	153
A. Variance and Covariance Estimates (multi-market mean, SE in parentheses)						
Variance of PCP FEs	**5.916**	6.527	5.053	**2.730**	2.921	2.460
as % share of total variance	(0.142)	(0.141)	(0.277)	(0.129)	(0.132)	(0.250)
Cov. of patient & PCP FEs	0.788	0.669	0.956	0.438	0.673	0.107
as % share of total variance	(0.137)	(0.134)	(0.272)	(0.127)	(0.129)	(0.247)
B. Other Statistics and Results (multi-market mean)						
# of PCP fixed effects	726	867	526	726	867	526
# of patient-qtr. obs.	361,421	433,553	259,626	361,421	433,553	259,626
Mean of log util.	5.118	5.188	5.020	4.561	4.646	4.440
Std. dev. of log util.	1.482	1.478	1.489	2.609	2.596	2.628
Var. of log util.	2.206	2.192	2.225	6.815	6.746	6.912
Var. of PCP FEs	0.130	0.143	0.113	0.185	0.195	0.171
Std. dev. of PCP FEs	0.347	0.365	0.320	0.396	0.422	0.359

Notes: This table reports the results of the 306 within-market estimations of (a) the variance of primary care physician (PCP) fixed effects (FEs) and (b) the covariance of the PCP fixed effects and the patient fixed effects in a two-way fixed effects model. The estimation uses patient-quarter level observations in the leave-out patient-PCP match procedure described in Section 1.5.1. The outcome variable is the *log of yearly utilization*. Columns (1)-(3) report results for *log of yearly tests utilization*, and Columns (4)-(5) report results for *log of yearly imaging utilization*. Columns (1) and (4) report the estimates for all 306 markets weighted by the number of Original Medicare beneficiaries in each market. Columns (2)-(3) and (5)-(6) report the estimates of the above median and below median markets by spending, weighted by the number of Original Medicare beneficiaries in the market. Panel A reports estimates of the shares of utilization that are the variance of PCP fixed effects and the covariance of PCP fixed effects and patient fixed effects as the weighted means of the corresponding estimates across the within-market estimations, and the standard errors (SEs) are computed accordingly. The standard deviation of the PCP fixed effects is imputed to be zero in markets where the point estimate of the variance of PCP fixed effects is negative. The sample is the connected set for yearly utilization that omits the switch period in Column (4) of Table 1.4 that remains connected when each patient-PCP pair is excluded. Markets are hospital referral regions (HRRs).

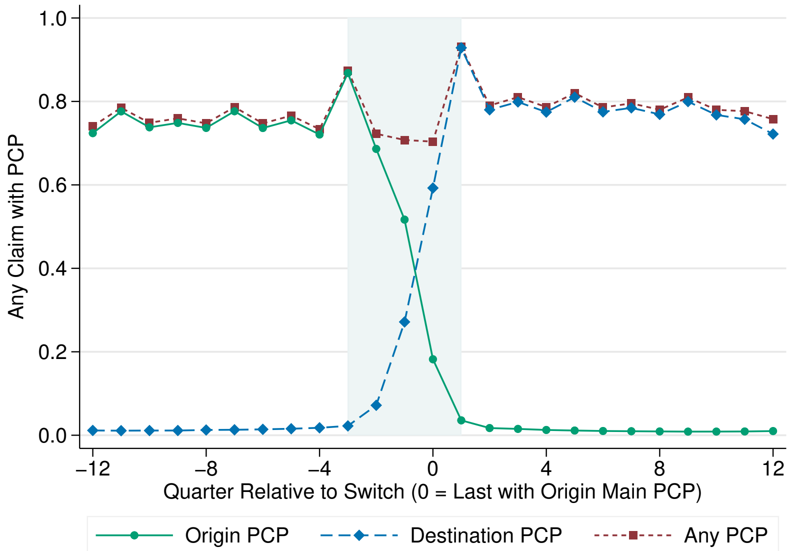
Table 1.9: Practice Styles Results: Variance in Yearly Emergency Department and Hospital Inpatient Utilization

	Emergency Department			Hospital Inpatient		
		Markets by Spend.			Markets by Spend.	
	All Markets	Above Median	Below Median	All Markets	Above Median	Below Median
	(1)	(2)	(3)	(4)	(5)	(6)
# of within-market estimations	306	153	153	306	153	153
A. Variance and Covariance Estimates (multi-market mean, SE in parentheses)						
Variance of PCP FEs	**1.571**	1.626	1.493	**2.055**	2.585	1.307
as % share of total variance	(0.151)	(0.161)	(0.284)	(0.176)	(0.158)	(0.361)
Cov. of patient & PCP FEs	-0.205	-0.085	-0.375	0.013	-0.160	0.257
as % share of total variance	(0.149)	(0.159)	(0.280)	(0.172)	(0.153)	(0.354)
B. Other Statistics and Results (multi-market mean)						
# of PCP fixed effects	726	867	526	726	867	526
# of patient-qtr. obs.	361,421	433,553	259,626	361,421	433,553	259,626
Mean of log util.	1.350	1.383	1.305	1.062	1.107	0.999
Std. dev. of log util.	2.930	2.976	2.864	2.747	2.803	2.667
Var. of log util.	8.601	8.875	8.215	7.581	7.890	7.146
Var. of PCP FEs	0.137	0.147	0.123	0.164	0.208	0.102
Std. dev. of PCP FEs	0.351	0.362	0.335	0.383	0.422	0.329

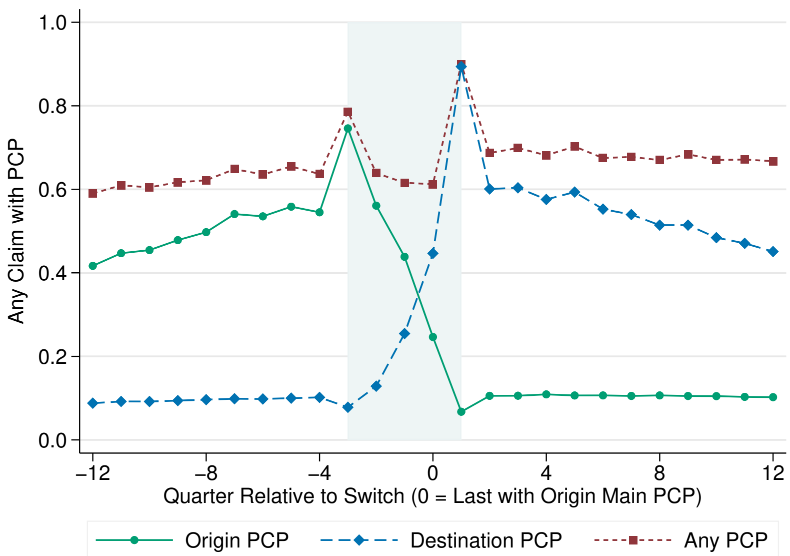
Notes: This table reports the results of the 306 within-market estimations of (a) the variance of primary care physician (PCP) fixed effects (FEs) and (b) the covariance of the PCP fixed effects and the patient fixed effects in a two-way fixed effects model. The estimation uses patient-quarter level observations in the leave-out patient-PCP match procedure described in Section 1.5.1. The outcome variable is the *log of yearly utilization*. Columns (1)-(3) report results for *log of yearly emergency department utilization*, and Columns (4)-(5) report results for *log of yearly hospital inpatient utilization*. Columns (1) and (4) report the estimates for all 306 markets weighted by the number of Original Medicare beneficiaries in each market. Columns (2)-(3) and (5)-(6) report the estimates of the above median and below median markets by spending, weighted by the number of Original Medicare beneficiaries in the market. Panel A reports estimates of the shares of utilization that are the variance of PCP fixed effects and the covariance of PCP fixed effects and patient fixed effects as the weighted means of the corresponding estimates across the within-market estimations, and the standard errors (SEs) are computed accordingly. The standard deviation of the PCP fixed effects is imputed to be zero in markets where the point estimate of the variance of PCP fixed effects is negative. The sample is the connected set for yearly utilization that omits the switch period in Column (4) of Table 1.4 that remains connected when each patient-PCP pair is excluded. Markets are hospital referral regions (HRRs).

Figure 1.1: Any Claim with Primary Care Physicians (PCPs) Around PCP Switch

(a) Consistent Matches, Balanced Panel



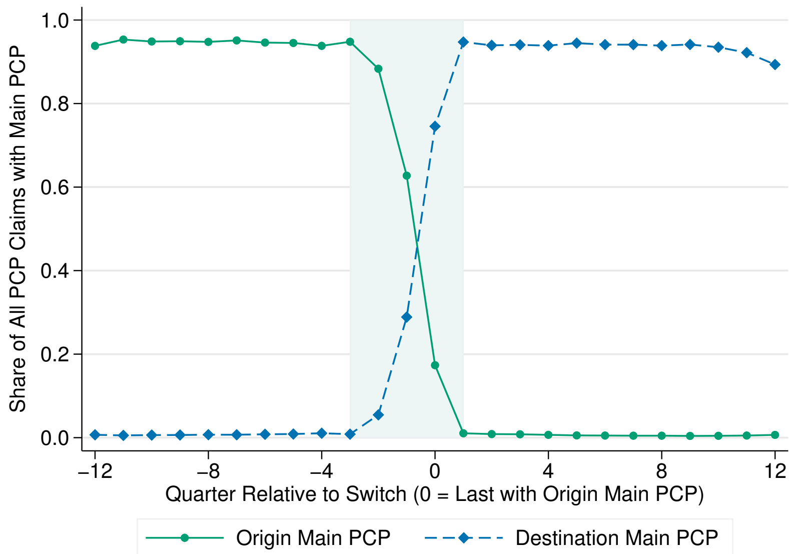
(b) All Matches, Balanced Panel



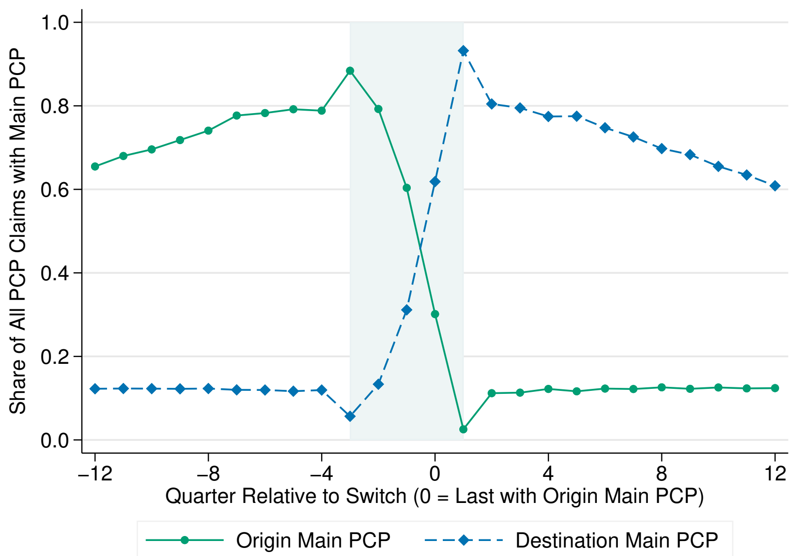
Notes: These figures present the patterns of having any PCP claim with any PCP, the origin PCP, and the destination PCP around the time of a PCP switch. The vertical axis plots whether a patient has a claim with a PCP in the quarter. The sample for Panel (a) includes only consistent patient-PCP matches, which I define as patients who consistently assigned the origin PCP for 12 quarters before the switch and consistently assigned the destination PCP for 12 quarters after the switch as described in Table 1.5 Column (3). The sample for Panel (b) is a balanced panel of all patient-PCP matches, i.e., patients who have *any* assigned main PCP in every quarter for 12 quarters before the switch through 12 quarters after the switch as describe in Table 1.5 Column (2).

Figure 1.2: Share of Primary Care Physician (PCP) Claims with Main PCP Around PCP Switch

(a) Consistent Matches, Balanced Panel



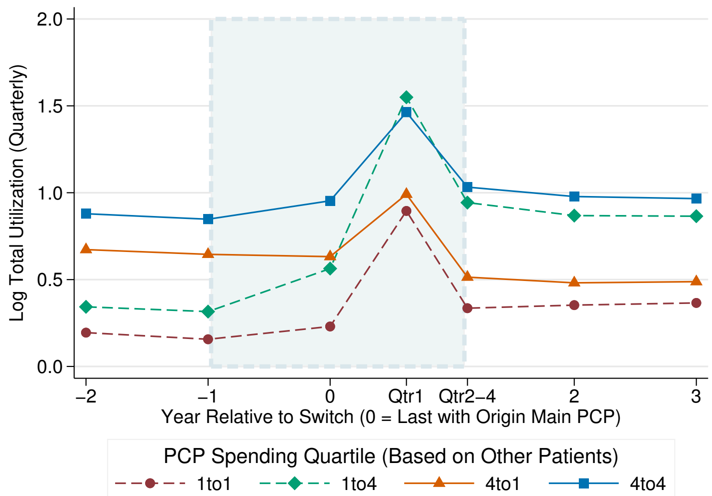
(b) All Matches, Balanced Panel



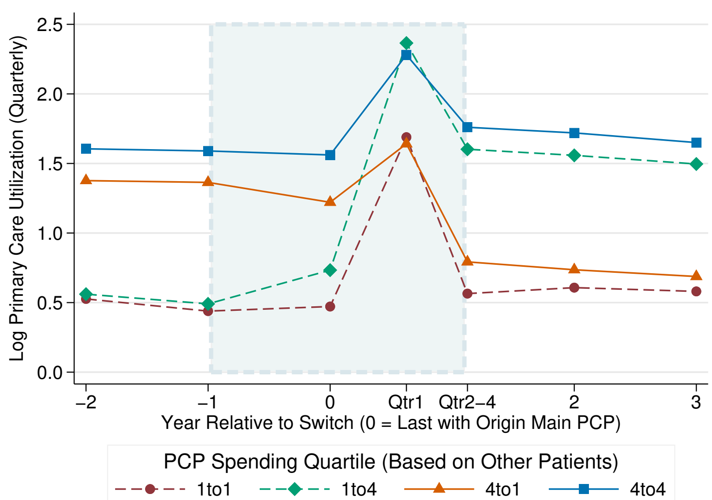
Notes: These figures present the patterns of the share of claims with the origin PCP, and the destination PCP (conditional on having any PCP claim) around the time of a PCP switch. The vertical axis plots whether a patient has a claim with a PCP in the quarter. The sample for Panel (a) includes only consistent patient-PCP matches, which I define as patients who consistently assigned the origin PCP for 12 quarters before the switch and consistently assigned the destination PCP for 12 quarters after the switch as described in Table 1.5 Column (3). The sample for Panel (b) is a balanced panel of all patient-PCP matches, i.e., patients who have *any* assigned main PCP in every quarter for 12 quarters before the switch through 12 quarters after the switch as describe in Table 1.5 Column (2).

Figure 1.3: Event Study Representation of Primary Care Physician (PCP) Switches

(a) Total Utilization



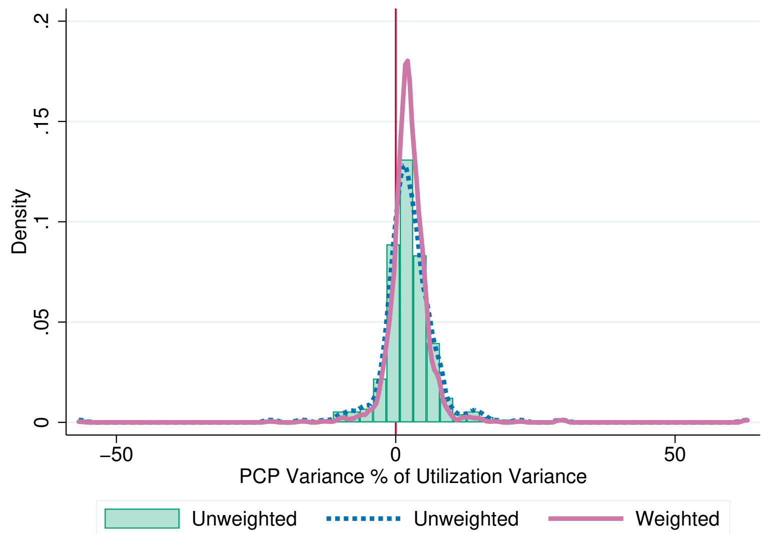
(b) Primary Care Utilization



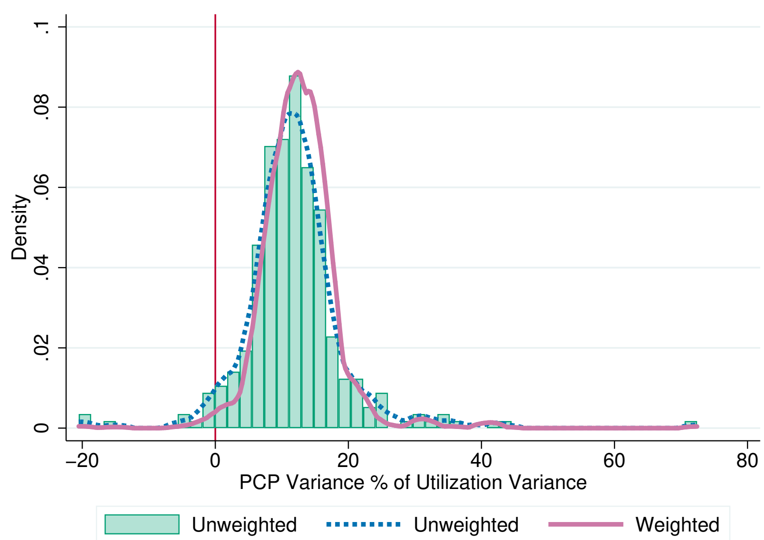
Notes: These figures present the mean demographics-adjusted log utilization for patients who switch PCPs as described in Section 1.3.1. The sample includes only consistent patient-PCP matches, who are assigned the origin PCP for 12 quarters before the switch and the destination PCP for 12 quarters after the switch as described in Column (3) of Table 1.6. Each of the patients who switch is classified into quartiles, defined within markets, by their origin PCP's other patients ("copatients") in a pre-switch period (year -1) and their destination PCP's copatients in a post-switch period (year 2). Quarters are binned into years, such that year 0 includes the last 4 quarters with a patient's origin PCP. The first quarter with the destination PCP is separated from the remainder of the year. Log utilization adjusted for utilization for patient age, gender, and cohort/date.

Figure 1.4: Primary Care Physician (PCP) Fixed Effects Variance Distribution

(a) Total Utilization



(b) Primary Care Utilization



Notes: Each of these figures presents the distribution of 306 within-market estimated variances of primary care physician (PCP) fixed effects as shares of the variance of total utilization. The variance estimates come from a two-way fixed effects model with patient fixed effects and PCP fixed effects. The estimation uses patient-quarter level observations in the leave-out patient-PCP match procedure described in Section 1.5.1. The outcome variable in the estimations is the *log of yearly utilization* in the past year. In Panel (a), the outcome variable is the *log of yearly total utilization* in and the estimates correspond with the results in Table 1.6. In Panel (b), the outcome variable is the *log of yearly primary care utilization* and the estimates correspond with the results in Table 1.7. The histogram is unweighted, and the kernel density plots are unweighted and weighted by the number of Original Medicare beneficiaries in each market.

Chapter 2

Effects of Switching Primary Care Physicians on Healthcare Utilization

2.1 Introduction

Patients switch healthcare providers for a number of reasons, and many patients are forced to switch healthcare providers due to physician retirements, physician relocations, and health plan provider network changes. Health insurance payers are offering a greater number of narrow network health plans, especially in health insurance marketplaces established by the Affordable Care Act.[1] Furthermore, an increasing number of older patients are joining private Medicare Advantage plans (rather than Original Medicare), which have health plan networks such that patients could lose access to their physicians when they switch health plans or their health plan networks change. In fact, about one-third of Medicare Advantage enrollees are in health plans with narrow physician networks (Jacobson, Rae, et al. 2017). Many patients who switch into these narrow network plans discover that their physicians become out-of-network, which means they have large financial incentives to leave their physicians and switch to in-network physicians. PCP switches could have substantial effects on medical care because PCPs hold information on patient medical history, informally coordinate care, and in some cases, formally manage access to specialists. The effects of PCP switches on patient healthcare utilization, in particular, has implications for the cost-effectiveness of policies that reallocate patients across PCPs (e.g., narrow health plan networks), reduce involuntary PCP switches, and facilitate PCP switches.

This chapter examines patient switches across PCPs to estimate switching costs, the potentially excess healthcare utilization that is incurred when patients switch PCPs.[2] My empirical strategy uses patients who involuntarily switch PCPs because their PCPs leave

[1] Source: McKinsey Center for U.S. Health System Reform "Hospital Networks: Evolution of the Configurations on the 2015 Exchanges" (https://healthcare.mckinsey.com/sites/default/files/2015HospitalNetworks.pdf).

[2] These switching "costs" could be positive (e.g., if patients receive redundant care) or negative (e.g., if patients experience delays in care). Studies have found that some changes are associated with a temporary increase in healthcare utilization. For example, Finkelstein, Gentzkow, and Williams (2016) show that, among patients who migrate across hospital referral regions (HRRs), "moving is correlated with an increase in utilization, including a spike in utilization in the year of move."

their states or leave Medicare (generally due to retirement), so the timing of the PCP departures is exogenous to the patients. I use an event study model with PCP fixed effects and patient fixed effects that is consistent with Chapter 1 such that I estimate the utilization of patients who switch relative to the baseline of the same patients if they do not switch and have the same PCPs.[3]

For patients who involuntarily switch PCPs, I find that switching costs are approximately \$726 among patients who switch to PCPs in different physician practice groups and \$499 among patients who switch to PCPs in the same physician practice groups. Of these switching costs, about 20-30% comes from short-run increases in primary care utilization, with smaller though substantial contributions from short-run increases in tests, imaging, and specialty care utilization. My estimation of switching costs focuses on healthcare utilization and does not include other welfare-relevant costs, such as patient hassle costs of finding new PCPs or medical record copy fees. Also, though switching PCPs generates immediate costs, switching PCPs could produce some benefits that I do not capture (e.g., catching up on delayed preventive care that leads to future, long-run savings).

Combining my findings with results from Chapter 1, I calculate counterfactuals that are relevant for policies that seek to alter PCP practice styles and reallocate patients across PCPs. The difference between PCPs at the 75th and 25th percentiles is \$617 per year for a representative patient. The difference between PCPs at the 60th and 40th percentiles is substantially smaller, at \$231 per year for a representative patient. The one-time cost of \$726 to reallocate patients across practice groups and the potential multi-year savings are similar in magnitude. Therefore, policies that induce patients to switch to lower-spending PCPs could potentially be counterproductive, especially since the one-time costs are paid upfront and patients incur search and transactions costs that I do not capture in my analysis. Policymakers and payers would need to consider both long-run savings and short-run switching costs.

This chapter contributes to the sparse literature on provider continuity and fragmentation by estimating costs of switching PCPs. Johnson, et al. (2016) find that physicians, specifically obstetricians, make different clinical decisions for existing patients than for new patients. Agha, Frandsen, and Rebitzer (2019) investigate the related concept of care fragmentation, in which a patient's care is split across multiple physicians, and make comparisons across healthcare markets. My study estimates the causal effects of switching PCPs – a form of primary care fragmentation across time – keeping the healthcare markets constant.

More closely related papers examine the effects of PCP departures from the Veteran's Health Administration and the effects of PCP retirements in Medicare. Reddy et al. (2015) study effects of provider turnover on patients whose primary care providers leave the Veterans Health Administration. They find that patients with primary care provider turnover had worse patient care experience but not significantly worse ambulatory care quality, except for being less likely to control blood pressure. Zhang (2018) studies effects of PCP retirements in Original Medicare. She finds that PCP retirements result in an increase in total spending, a decline in primary care spending, and increases in specialty care and emergency care

[3]Since the timing of PCP switches is defined based on utilization (specifically patient visits with PCPs), I aggregate the excess utilization over the quarters before and after the switches to measure the switching costs independent from the exact timing of how the PCP switch is defined.

spending. My study estimates effects of switching PCPs in a way that disentangles the short-run effects from the long-run effects of switching PCPs by accounting for PCP compositional changes that might be correlated with PCP retirements, relocations, or departures from healthcare systems.

This chapter proceeds with the following sections. Section 2.2 describes the context of my study, the data, and the sample. Section 2.3 presents my methodology for estimating the costs of switching physicians, and Section 2.4 presents the results. Section 2.5 combines the results from Chapter 1 with the switching costs results to construct counterfactuals. Section 2.6 provides an overview of potential mechanisms that could generate the healthcare utilization patterns. Section 2.7 concludes with a discussion of significance, limitations, and policy implications.

2.2 Context, Data, and Sample

In this chapter, I use the context, data, and sample from Chapter 1 as described in Section 1.2. Patients in Original Medicare do not require referrals to see specialists and have access to a relatively large network of physicians, so they may continue to visit their specialists or substitute toward other forms of care even when they lose access to their PCPs and are in the process of switching PCPs.

As discussed in Section 1.2.6, my outcome measures are payment-based utilization, which I define to be total payments in dollars from Medicare, the patient, and any primary payer (a payer who has primary responsibility for the payment, e.g., employer group health plan, Department of Veteran Affairs).[4,5] My two main outcome measures are (a) total utilization, which is important for cost savings and policy, and (b) primary care utilization, which is the category most likely to be affected by involuntary PCPs switches. I repeat my analyses with other categories of utilization – including tests, imaging, emergency department visits, inpatient hospitalizations, and specialty care – to examine the effects of PCP switches on other medical care and investigate potential mechanisms through which PCP switches affect total utilization.

2.3 Methodology: Physician Switching Costs

2.3.1 Event Study of Switches

I estimate the costs of switching PCPs in each of the 306 Hospital Referral Region (HRR) markets. My empirical strategy uses samples of patients who involuntarily switch PCPs. I classify a switch as involuntary if the patient's main PCP leaves the state or leaves Medicare (e.g., due to retirement) within one year before or after the main PCP switch.

[4] I include year-by-quarter fixed effects in my estimations, which accounts for inflation and other increases in the prices of healthcare.

[5] In some cases Medicare is the primary payer and there is a secondary payer (e.g., Medigap supplemental insurance), but I do not observe the payments made by the secondary payer versus the patient or the identity of the secondary payer.

I return to the model from Section 1.4.1, where my parameters of interest are now the event time coefficients $\theta^{g,k}$, which capture temporary utilization effects around the time of a PCP switch. In contrast to Equation 1.1, I define $\widetilde{\gamma}_{j(i,t)}$ as the PCP fixed effects that correspond to baseline main PCPs and allow them to be different from those that correspond to the main PCPs as defined in Section 1.4.1. The event study model with two-way fixed effects is

$$y_{it} = \alpha_i + \widetilde{\gamma}_{j(i,t)} + x_{it}\beta + \sum_g \sum_k \theta^{g,k} D_{it}^{g,k} + \varepsilon_{it}, \tag{2.1}$$

where α_i are patient fixed effects, $\widetilde{\gamma}_{j(i,t)}$ are baseline PCP fixed effects, x_{it} are controls as discussed in Section 1.4.1.

My goal is to estimate the excess utilization incurred due to involuntary PCP switches relative to the baseline of the same patients having the same main PCPs. One empirical challenge is to accurately define the baseline PCP. The main PCP assignment is retrospective, so I allow the baseline main PCP fixed effect to be a weighted average between the origin PCP and the destination PCP based on the timing within the switch period. Specifically, I define

$$\widetilde{\gamma}_{j(i,t)} = \begin{cases} \frac{1-k}{4}\gamma_{j(i,t),\text{origin}} + \frac{3+k}{4}\gamma_{j(i,t),\text{destination}} & \text{if } k \in [-2,0] \\ \gamma_{j(i,t)} & \text{otherwise.} \end{cases} \tag{2.2}$$

This specification assumes a simple linear decline in influence between the origin PCP and the destination PCP.[6,7]

As in Section 1.4.1, I include indicators $D_{it}^{g,k}$ for whether patient has a specific type of switch g that is $k \in [-8, 12]$ quarters relative to the event time $k = 0$, the last quarter a patient is assigned a main PCP. I define the leads to be whether the patient switches away from their current main PCP and the lags to be whether the patient switched to their current main PCP.[8]

In my specification, I include six types of switches g: (a1) *involuntary* switch between two main PCPs in the same physician practice group, (a2) *voluntary* switch between two main PCPs in the same physician practice group, (b1) *involuntary* switch between two main PCPs in different physician practice groups, (b2) *voluntary* switch between two main PCPs

[6] The linear decline roughly matches the patterns in Figures 1.1 and 1.2. In ongoing work, I am examining alternative main PCP weightings, including the simpler assignment rule in which the patient is assigned the main PCP (i.e., such that all of the weight would be with the origin PCP and no weight would be on the destination PCP in Equation 2.2), as well as the assignment rule in which the patient is assigned to the destination PCP as the other extreme for robustness. I am also estimating the switching costs in a specification that substitutes the long-run PCP fixed effects estimated using the specification from Section 1.5 and Equation 1.2 for $\widetilde{\gamma}_{j(i,t)}$, such that only the patient fixed effects and the coefficients on event time indicators and controls are estimated in Equation 2.1.

[7] In my estimation, I duplicate the observations with two different baseline main PCPs, assign each of the two observations to either the origin PCP or the destination PCP, and weight the observations according to Equation 2.2.

[8] In an alternative specification, I could include separate indicators for additional switches (e.g., leads for whether a patient switches away from their next main PCP, lags for whether a patient switched to their previous main PCP), but relatively few patients make these additional switches and any effects of these additional switches would be less precisely estimated.

in different physician practice groups, (c) from no main PCP to a main PCP, and (d) from a main PCP to no main PCP.

For types of switches between two main PCPs (i.e., types (a1), (a2), (b1), and (b2)), I further estimate a separate set of coefficients that correspond to patients who have a *balanced panel* of indicators over $k \in [-6, 8]$ – i.e., they are assigned to their origin PCPs for $k \in [-6, 0]$ *and* to their destination PCPs for $k \in [1, 8]$.[9] I use the estimated coefficients on the balanced panel indicators in my switching cost estimations.

In standard event study designs, the main identifying assumption would be that utilization does not change with other factors at the timing of the event (Jacobson, LaLonde, and Sullivan 1993; McCrary 2007). An empirical challenge in my setting is that PCP switch timing is defined based on patient PCP visits, so the coefficients $\theta^{g,k}$ are mechanically correlated with utilization and not directly interpretable. There are also potential pre-trends as patients prepare to switch PCPs or as PCPs prepare to retire or relocate. My empirical strategy relies on the fact that among the patients with involuntary switches, the timing of the PCP departures is exogenous, and involuntary switches occur for all of the departing PCPs' patients. Only the exact timing of how PCP switches are defined is mechanically correlated with non-switch related utilization patterns.

2.3.2 Switching Costs Estimation

To estimate the net switching costs, I take the sum over the utilization deviations from baseline in terms of dollar spending using the coefficients $\theta^{g,k}$ estimated on the balanced panels. My main identifying assumption is that the sum of patient utilization over a range of quarters around the PCP switch is not systematically different for patients who involuntarily switch PCPs for reasons other than the PCP switch events.

I define the switching costs $\hat{S}^g_{a,b}$ for the balanced panels of patients with switch type g as the sum of the corresponding coefficients scaled to levels of dollar spending over the quarters $k \in [a, b]$ for a representative patient with switch type g. Specifically, I define the switching costs as

$$\hat{S}^g_{a,b} = \sum_{k=a}^{b} \left[\exp\left(\hat{\theta}^{g,k} + \overline{y}^g_a\right) - \exp\left(\overline{y}^g_a\right) \right] \tag{2.3}$$

where $\overline{y}^g_a$ is the mean log utilization of the patient-quarters in pre-event time a with switch type g that scales the estimated coefficients $\hat{\theta}^{g,k}$ to dollar spending.[10]

[9] Specifically, I generate separate sets of indicators for the balanced panel. $D^{g,k}_{it}$ consists of 186 indicators. For the balanced panel, each of the four types of switches between PCPs has indicators for 15 event time quarters $k \in [-6, 8]$. For the patient-quarters not in the balanced panel, each of the four types of switches between PCPs has indicators for 21 event time quarters $k \in [-8, 12]$. Each of the two types of switches from a PCP to no PCP has indicators for 9 event time quarters $k \in [-8, 0]$. Each of the two types of switches from no PCP to a PCP has indicators for 12 event time quarters $k \in [1, 12]$.

[10] In an alternative specification, I could allow the pre-event time to differ from the first quarter in which switching costs are calculated, such that the switching costs would be $\hat{S}^g_{a,b,c} = \sum_{k=a}^{b} \left[\exp\left(\hat{\theta}^{g,k} + \overline{y}^g_c\right) - \exp\left(\overline{y}^g_c\right) \right]$, where $\overline{y}^g_c$ is the mean log utilization of the patient-quarters in pre-event time c with switch type g that scales the estimated coefficients $\hat{\theta}^{g,k}$ to dollar spending.

I estimate Equation 2.1 with $a = -6$ and $b = 8$ within each market with robust standard errors three-way clustered by patient, by main PCP, and by quarter. For each market, I then compute the switching costs $\hat{S}^g_{a,b}$ in Equation 2.3 and the standard errors using the delta method allowing for correlation across the estimated coefficients $\hat{\theta}^{g,k}$ (across both g and k) among the balanced panels within each market.[11] The estimated switching costs include effects on utilization from six quarters before to eight quarters after the switch and are scaled by the mean utilization for switch group g at six quarters before the switch.

2.3.3 Estimation Outcome Measures and Samples

My main outcome measures are contemporaneous quarterly log utilization.[12] I also use this outcome measure in my practice styles analysis in Chapter 1 and present the results in Appendix C.2.

For my estimation sample, I use the "connected set" sample of PCPs and patients that I define in Section 1.5.1. The PCP fixed effects and patient fixed effects are identified within this connected set. I do not omit the patient-quarter observations that correspond to the switch period. For the balanced panels, I allow for the pre-switch and post-switch main PCPs combined to meet the requirement that patients visit their main PCPs for at least 75% of their PCP visits over the past year.[13] Column (3) of Table 1.4 reports the summary statistics.[14]

2.4 Results: Physician Switching Costs

2.4.1 Switching Costs from Involuntary Switchers

Table 2.1 reports the main results on switching costs. Each column represents the results from 306 hospital referral region (HRR) market-level regressions weighted by their Original Medicare population.[15,16] The first four rows report the switching costs and standard errors

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[11] By estimating the event study regressions by market, I allow the event study coefficients to vary across markets as they do in the two-way fixed effects model estimation. In principle, I could estimate switching costs in one event study regression with the full, multi-market sample by including market fixed effects and interactions of market fixed effects and the controls. In practice, this approach is not yet computationally feasible due to the large number of observations, the large number of event time indicators, and the large number of fixed effects. In ongoing work, I am estimating the switching costs in one event study regression with the full, multi-market sample, but in a specification that substitutes the long-run PCP fixed effects estimated using the specification from Section 1.5 and Equation 1.2 for $\widetilde{\gamma}_{j(i,t)}$. With this approach, only the patient fixed effects and the coefficients on event time indicators and controls need to be estimated in the full, multi-market sample in Equation 2.1.

[12] I use quarterly utilization such that y_{it} is defined as the log of sum of the current quarter of utilization and one.

[13] I do not include the non-balanced sample because doing so would add noise to the estimates of my PCP fixed effects.

[14] In ongoing work, I am also using subsamples corresponding to patients and PCPs in Table 1.4 Column (4) for comparison, though they have fewer observations.

[15] I compute the weighted means of the point estimates, means, and counts. I compute the standard errors that correspond to the weighted point estimates.

[16] Results are similar with an unweighted average across HRRs.

for the balanced panels of involuntary switchers. The last four rows report the switching costs and standard errors for the balanced panels of voluntary switchers.

Column (1) of Table 2.1 reports the results for total utilization. The total utilization switching costs are \$499 for patients who involuntarily switch PCPs to destination PCPs within the same practice groups as the origin PCPs and \$726 for patients who involuntarily switch PCPs to destination PCPs in different practice groups from the origin PCPs, on average across markets. Column (2) of Table 2.1 reports the results for primary care utilization. The primary care utilization switching costs are \$144 for patients who involuntarily switch PCPs to destination PCPs within the same practice groups and \$160 for patients who involuntarily switch PCPs to destination PCPs in different practice groups on average across markets. These results suggest that approximately 20-30% of the total switching costs comes from temporary increases in primary care utilization.

Figures 2.1a and 2.1b plot the estimated event study coefficients with a balanced panel over $k \in [-6, 8]$ for involuntary switchers from 306 hospital referral region (HRR) market-level regressions weighted by their Original Medicare population.[17] As shown in Figure 1.1, patients are mechanically more likely to have utilization at event times $k = -3$ and $k = 1$ based on the definition of PCP switches. There are no pre-trends before event time $k = -4$, which supports my identifying assumption that patients who involuntarily switch PCPs do not have systematically different utilization for reasons other than the PCP switch events. Furthermore, the coefficients are approximately zero at $k = -6$ and $k = 8$, which means that accounting for switching costs from six quarters before to eight quarters after the switch accurately captures the majority of switching costs. I define my switching costs over this shorter range for a larger balanced panel of patients. Table A.11 reports the results with balanced panels over multiple event time ranges ($k \in [-4, 6]$, $k \in [-6, 8]$, and $k \in [-8, 12]$) and switching costs calculated over multiple event time ranges ($k \in [-4, 6]$, $k \in [-6, 8]$, and $k \in [-8, 12]$) for comparison, and Table A.4 reports the descriptive statistics for the balanced samples.

The difference in primary care switching costs for (a) patients who switch to destination PCPs in the same practice groups and (b) patients who switch to destination PCPs in different practice groups is similar in magnitude to the differences in prices between new patient office visits and established patient office visits as shown in Table 1.3.[18] I cannot interpret the differences between these two groups of switchers as causal though. The patients in these two groups might be different (e.g., patients whose origin PCPs are the only PCPs in their practice groups would need to switch to destination PCPs in different practice groups), and the choice to switch PCP practice groups might be voluntary.

To examine components of switching costs and consider potential mechanisms, I examine tests, imaging, emergency department visits, inpatient hospitalizations, and specialty care. In Table 2.1, Column (3) reports results for tests utilization, Column (4) reports the results for imaging utilization, Column (5) reports the results for emergency department utilization, Column (6) reports the results for hospital inpatient utilization, and Column (7) reports

[17] For these figures, I average the coefficients and calculate their standard errors across the 306 hospital referral region (HRR) market-level regressions separately for each point for illustrative purposes. I do not use these aggregated coefficients in the computation of switching costs.

[18] A patient who has visited the physician or the practice group within the past three years is classified as an established patient.

the results for specialty care utilization. These results suggest that temporary increases in tests utilization account for approximately 5-7%, temporary increases in imaging utilization account for about 3%, and temporary increases in specialty care utilization account for approximately 3-5% of total switching costs on average across markets. Temporary increases in emergency department and hospital inpatient utilization, though statistically significant, contribute to less than 1% of total switching costs.

2.4.2 Comparison of Voluntary and Involuntary Switches

My analysis thus far focuses on involuntary switches. Voluntary switches and involuntary switches may capture different costs of switching that affect the interpretation of the results.

The involuntary switchers sample consists of patients who are forced to switch PCPs, potentially with various degrees of warning or notification. Involuntary switchers may be more likely to experience delayed care. Patients who switch to PCPs within the same practice groups might switch to destination PCPs who suddenly have more patients because the origin PCPs left the practice groups. Patients who switch to PCPs in other practice groups may face search costs in finding new PCPs and need to wait for new patient appointments.

The voluntary switchers sample consists of patients who generally choose to switch PCPs. They may plan their switch and be less likely to experience delayed care. Some patients may choose to switch PCPs for second opinions on health conditions. Table 2.1 shows that voluntary switchers have higher switching costs than involuntary switchers, and their utilization patterns are similar to those of involuntary switchers.[19]

In evaluating potential policies to reallocate patients across PCPs, policymakers would need to consider whether the switching costs would be similar to those of involuntary switches or whether they would likely be larger, as in the case of voluntary switches.

2.5 Counterfactuals

With estimates of the long-run and short-run effects of switching PCPs, I now consider counterfactuals that alter PCP practice styles or reallocate patients across PCPs. I first calculate the differences in utilization between percentiles of PCP practice styles, as measured by spending. I then construct two sets of counterfactuals that roughly represent two extremes of reallocating patients across PCPs within their markets in a partial equilibrium context. In these counterfactuals, I provide results that correspond to representative patients in a representative market in the U.S.[20]

My goal is to estimate the difference between the observed utilization and counterfactual utilization when the PCP practice style, $\gamma_{j(i,t)}$, is changed for a subpopulation of PCPs.

[19] Figures B.5 and B.6 plot the involuntary switches on the same plots as the involuntary switches. Table A.12 reports the estimates and Figure B.9 plots the estimates in which the involuntary switchers and voluntary switchers are pooled and share sets of event study indicators.

[20] I construct counterfactuals at the U.S. national level because individual market-level estimates of the variance of PCP fixed effects and the covariance of PCP fixed effects and patient fixed effects are noisily estimated. The estimated PCP fixed effects $\hat{\gamma}_j$ in each market from Section 1.5.1, which are estimated from an ordinary least squares regression of Equation 1.2, have substantial sampling error. The variances of PCP fixed effects calculated from these estimates are positively biased.

I return to my utilization measure from Section 1.5.1 that partials out the effects of the controls x_{it} and the effects of the switching indicators $D_{it}^{g,k}$

$$\widetilde{y_{it}} = y_{it} - x_{it}\hat{\beta} - \sum_g \sum_k \hat{\theta}^{g,k} D_{it}^{g,k} \tag{2.4}$$

where y_{it} is the log utilization outcome and coefficients $\hat{\beta}$ and $\hat{\theta}^{g,k}$ are estimated from the first-stage ordinary least squares regression of Equation 1.2.

To construct counterfactual utilization patterns, I first find the expected utilization conditional on a given $\gamma_{j(i,t)}$, denoted as $\gamma_{j(i,t)^*}$, because I change different sets of $\gamma_{j(i,t)}$ in the various counterfactuals. I assume that α_i and $\gamma_{j(i,t)}$ have a bivariate normal distribution, both normalized to have mean zero.[21] With this assumption, the conditional expectation of the observed utilization is

$$\mathbb{E}\left[\widetilde{y_{it}} | \gamma_{j(i,t)^*}\right] = \frac{Cov\left(\alpha_i, \gamma_{j(i,t)}\right)}{Var\left(\gamma_{j(i,t)}\right)} \gamma_{j(i,t)^*} + \gamma_{j(i,t)^*} + \bar{y} \tag{2.5}$$

where the first term is the patient component, $\gamma^*_{j(i,t,)}$ is the PCP component, and $\bar{y}$ is the sample mean utilization. Similarly, the conditional expectation of the counterfactual utilization is

$$\mathbb{E}\left[\widetilde{y_{it}}^{CF} | \gamma_{j(i,t)^*}\right] = \frac{Cov\left(\alpha_i, \gamma_{j(i,t)}\right)}{Var\left(\gamma_{j(i,t)}\right)} \gamma_{j(i,t)^*} + \gamma^{CF} + \bar{y} \tag{2.6}$$

where the first term is again the patient component, γ^{CF} is the counterfactual PCP component, and $\bar{y}$ is again the sample mean utilization.

I convert the differences between the observed utilization and counterfactual utilization from the log of dollars spending to levels of dollars spending. I define $D_{it} = \exp\left(\widetilde{y_{it}}\right) - 1$ for observed levels of spending and $D_{it}^{CF} = \exp\left(\widetilde{y_{it}}^{CF}\right) - 1$ for counterfactual levels of spending. The expected difference in levels of dollars spending conditional on patients at a PCP with effect $\gamma_{j(i,t)^*}$ being reallocated to a PCP with counterfactual effect γ^{CF} is

$$\begin{aligned} \mathbb{E}\left[D_{it} - D_{it}^{CF} | \gamma_{j(i,t)^*}\right] &= \exp\left(\bar{y}\right) \times \exp\left(\frac{Cov\left(\alpha_i, \gamma_{j(i,t)}\right)}{Var\left(\gamma_{j(i,t)}\right)} \gamma_{j(i,t)^*}\right) \times \\ &\quad \left[\exp\left(\gamma_{j(i,t)^*}\right) - \exp\left(\gamma^{CF}\right)\right]. \end{aligned} \tag{2.7}$$

To calculate the expected difference for patients at a range of PCP fixed effects $\gamma_{j(i,t)^*} \in [\gamma_\ell, \gamma_u]$ that corresponds with patients reallocated to PCPs with counterfactual effect γ^{CF}, I take the integral over the corresponding range of PCP fixed effects $\gamma_{j(i,t)^*} \in [\gamma_\ell, \gamma_u]$. The expression is

[21] The distribution is at the patient-quarter observation level, consistent with the estimation in Section 1.5.

$$\mathbb{E}\left[D_{it}-D_{it}^{CF}\right] \quad = \quad \exp\left(\bar{y}\right)\times \tag{2.8}$$

$$\int_{\gamma_\ell}^{\gamma_u} \exp\left(\frac{Cov\left(\alpha_i,\gamma_{j(i,t)}\right)}{Var\left(\gamma_{j(i,t)}\right)}\gamma_{j(i,t)^*}\right)\left[\exp\left(\gamma_{j(i,t)^*}\right)-\exp\left(\gamma^{CF}\right)\right] f\left(\gamma_{j(i,t)^*}\right) d\gamma_{j(i,t)^*}$$

where $f\left(\gamma_{j(i,t)}\right)$ is the normal probability density function of the PCP fixed effects distributed $\gamma_{j(i,t)} \sim \mathcal{N}\left(0, Var\left(\gamma_{j(i,t)}\right)\right)$.

To compute my counterfactuals, I use the weighted means of the estimated $Var\left(\gamma_{j(i,t)}\right)$ and $Cov\left(\alpha_i,\gamma_{j(i,t)}\right)$ across markets from Section 1.5.[22] The share of patients reallocated approximately corresponds to the percentiles I consider in my counterfactuals (e.g., reallocating patients at the top 10% of PCP observations means reallocating 10% of patients).[23]

My first set of results calculates the utilization difference from reallocating patients from one PCP to another PCP as in Equation 2.7. I calculate the counterfactuals in which (a) patients at 75th percentile PCPs are reallocated to 25th percentile PCPs and (b) patients at 60th percentile PCPs are reallocated to 40th percentile PCPs within their markets. Column (1) in Panel A of Table 2.2 reports the results. The difference between PCPs at the 75th and 25th percentiles is \$617 per year for a representative patient. The difference between PCPs at the 60th and 40th percentiles is \$231 per year for a representative patient.

In my second set of results, I consider cases in which health insurance payers could identify and target the highest spending PCPs. Specifically, I consider the simple counterfactuals in which patients who visit high-spending PCPs are reallocated to median PCPs using Equation 2.8. This counterfactual would be around the upper bound of the potential cost savings because these types of switches could occur if patients do not sort to PCPs with the same practice styles (e.g., if patients at high-spending PCPs do not sort back to high-spending PCPs) or are incentivized to switch to PCPs with specific practice styles. For instance, a health insurance plan could induce patients to switch to PCPs in narrow networks or PCPs in Accountable Care Organizations (ACOs) in which those PCPs are roughly near the median of the PCP practice style distribution. Column (1) in Panel B of Table 2.2 reports the results. Policies that reallocate patients from the top 10% or top 30% of PCPs to a median PCP would yield mean savings of \$970 and \$611, respectively, per year for a representative patient.

I then consider a similar set of counterfactuals in which high-spending PCPs are excluded but patients are reallocated to the highest-spending remaining PCPs using Equation 2.8. This counterfactual would be around the lower bound of the potential cost savings and roughly maintains the sorting of patients across PCPs. Column (1) in Panel C of Table 2.2 reports the results. Policies that reallocate patients from the top 10% of PCPs to 90th percentile PCPs or from the top 30% of PCPs to 70th percentile PCPs would yield mean savings of only \$304 and \$359, respectively, per year for a representative patient.

These estimates of potential reallocation savings are similar in magnitude to the short-run switching costs of \$499-726 that I estimate in Section 2.3. Policies that induce patients

[22] The individual market-level estimates are substantially more noisily estimated.

[23] The percentage is not precise because the patients who would be reallocated based on all patient-quarter observations in the panel are not necessarily the same as the patients who would be reallocated based on a cross-section of patient-quarter observations in a specific quarter.

to switch to lower-spending PCPs would need to consider both long-run savings and short-run switching costs. Whether policies that reallocate patients away from high-spending PCPs could actually be cost effective depends on (a) whether health insurance payers could accurately identify and target high-spending PCPs, (b) whether patients are reallocated to median-spending PCPs or return to other relatively high-spending PCPs, and (c) how long patients would remain matched with their new PCPs.

Columns (2) and (3) of Table 2.2 report the "break-even" number of years, which is the minimum time period that patients would need to be matched with their counterfactual PCPs versus their observed PCPs for the reallocations to have net cost savings, without discounting. In the sample, patients are matched with PCPs for a median of 4 years, which is close to the break-even time period ranges.[24]

When policies take into account the discounting of future savings, the upfront switching costs in terms of utilization that patients would need to at least partially incur, and other switching costs not captured by the utilization estimates (e.g., search costs, medical record copy fees), the reallocation of patients could potentially be counterproductive.

2.6 Potential Mechanisms

I have abstracted away from the mechanisms that generate the short-run switching costs thus far. Multiple potential mechanisms likely generate these switching costs and the utilization patterns they reflect, and the mechanisms have different implications for patient welfare.

2.6.1 Primary Care Disruption

One effect of involuntary PCP switches is a disruption in primary care. Patients may lose access to primary care if their departing PCPs are sole practitioners (i.e., the only PCPs in their physician practice groups). Patients may experience delays in obtaining new PCPs and seeking primary care, which would generate negative switching costs for some patients in the short run.

These delays could be due to a few factors: (a) wait times for new patient appointments, (b) lack of information (e.g., before PCPs make planned departures), (c) inattention (e.g., to notification of PCPs departures before the patients seek primary care), and (d) procrastination (e.g., of beneficial primary care due to immediate search and transaction costs in obtaining new PCPs).

Patients could delay primary care due to wait times for new patient appointments with PCPs. Average surveyed wait times for family medicine physicians range from 20 to 29 days in major U.S. metropolitan areas, though the wait times vary greatly by the specific physician or the market.[25] Patients might not be informed of planned PCP retirements and

[24]In quarter 1 of 2007 (approximately the midpoint of the sample), the median spell length of a patient-PCP match in this cross section of patients is 16 quarters; the 25th percentile is 7 quarters, and the 75th percentile is 28 quarters.

[25]Source: Merritt Hawkins Survey of Physician Appointment Wait Times and Medicare and Medicaid Acceptance Rates 2017
(https://www.merritthawkins.com/uploadedFiles/MerrittHawkins/Content/Pdf/mha2017waittimesurveyPDF.pdf).

relocations because state laws vary in when physicians are required to notify their patients (e.g., at the time of departure, no later than 30 days prior to departure) (Wall 2005).

Behavioral factors – such as inattention and procrastination – contribute to healthcare delays and underuse in areas such as preventive care, chronic conditions management, and prescription drugs (Bai, Handel, Miguel, and Rao 2017; Baicker, Mullainathan, and Schwartzstein 2015). Inattention occurs because patients have limited time and cognitive resources to process information. In a given time period, with some positive probability, patients are not aware of information (e.g., a PCP's planned departure) or potential actions (e.g., finding a new PCP) (DellaVigna and Pollet 2009). Procrastination occurs because patients may be present-biased and naive about their present bias (DellaVigna and Malmendier 2006; O'Donoghue and Rabin 1999; O'Donoghue and Rabin 2001). With procrastination, patients delay actions they know are beneficial (e.g., finding new PCPs and seeking primary care) due to immediate costs (e.g., search and transaction costs).

In ongoing work, I am examining delays in primary care due to PCP retirements and relocations. My main outcome measures are "new patient" office visits, which are for patients who have not visited either the PCPs or the physician practice groups within the past three years, and "established patient" office visits. Preliminary results show that patients on average experience an immediate decline in primary care visits following their PCP retirements and relocations. This decline comes from a decline in established office visits and is partially offset by an increase in new office visits. The primary care visits decline is greater for patients whose PCPs are sole practitioners than for patients whose PCPs are part of multi-physician practice groups. Also, as observed in Section 2.4, even patients whose PCPs are part of multi-physician practice groups switch to PCPs in different practice groups, which could result in primary care delays.

2.6.2 Substitution Away from Primary Care

Patients who lose access to their PCPs and physician practice groups (in the case of PCPs who are sole practitioners) may substitute from primary care to other sources of care before they have appointments with new PCPs. These other sources of care include retail health clinics, urgent care facilities/centers, emergency departments, and specialist physicians. Patient substitution to emergency departments and some urgent care facilities/centers would increase healthcare spending due to their higher prices. For patient substitution to retail health clinics, healthcare spending might not necessarily increase and could provide valuable care to patients who do not have access to PCPs. For example, Mehrotra et al. (2008) find that retail clinics appear to serve patient populations that are underserved by PCPs. However, patient substitution to retail health clinics could result in inefficient care if the retail health clinics do not have access to patient medical records or delay the development of patient relationships with new PCPs.

In ongoing work, I am examining patient substitution to urgent care facilities/centers, emergency department, and specialist physicians.[26] Section 2.4 shows that patients who

[26]The CMS Place of Service code for "Walk-in Retail Health Clinic" has an effective date of May 1, 2010, so I am not able to measure visits to retail health clinics for most of my sample period. Source: https://www.cms.gov/Medicare/Coding/place-of-service-codes/Place_of_Service_Code_Set.html.

switch PCPs significantly increase emergency department utilization and specialty care utilization. Some of this increased emergency department utilization and specialty care utilization could potentially be driven by substitution. I can measure the excess patient visits to emergency departments and specialist physicians after the patients lose access to their PCPs and before the patients visit their new PCPs, which would capture substitution effects.

2.6.3 Comprehensive or Improved Primary Care Evaluation

Patients may receive some health benefits from switching PCPs in the form of more comprehensive or improved primary care evaluations. Patients who are new to PCPs and new to physician practice groups have "new patient" office visits that cover more components and are longer on average than "established patient" office visits. Even new PCPs whose patients switched from within the same practice groups may conduct more comprehensive evaluations of the new patients. These more comprehensive evaluations may help the patients catch up on delayed preventive care, encourage patients to seek delayed specialty care, and identify missed diagnoses. Furthermore, some PCPs are better (e.g., in terms of knowledge, skill, or expertise) for at least certain subsets of medical conditions. Therefore, switching PCPs either across or within practice groups could potentially lead to improved evaluations. More comprehensive or improved primary are evaluations could improve patient welfare and potentially lead to long-run savings.

In ongoing work, I am investigating whether patients catch up on delayed preventive care, visit specialist physicians, and receive new diagnoses upon visiting new PCPs. Not all visits to specialist physicians or new diagnoses are necessarily beneficial or cost-effective, so further research that examine associated patient health outcomes would be valuable.

2.6.4 Inefficient Primary Care or Care Coordination

Beyond the potential inefficiencies discussed in Sections 2.6.1 and 2.6.2, switching PCPs could generate some inefficiencies that lead to higher healthcare utilization, such as redundant care or lower PCP productivity. New PCPs may spend time documenting medical history and order redundant lab tests to establish new medical records. PCPs may be less productive with new patients, and for example, take two visits to diagnose and treat medical conditions rather than one visit for established patients. Furthermore, PCPs who are less familiar with patients could potentially provide lower quality medical care, leading to adverse health consequences and subsequent higher healthcare utilization.

In ongoing work, I am examining the effect of PCP switches on low-value care. I use the low-value care measures that Schwartz, et al. (2014) construct from Original Medicare administrative claims.[27] The six categories of low-value care are: low-value cancer screening,

[27] Schwartz, et al. (2014) include services that "have been characterized as low value by the American Board of Internal Medicine Foundation's Choosing Wisely initiative, the U.S. Preventive Services Task Force 'D' recommendations, the National Institute for Health and Care Excellence 'do not do' recommendations, the Canadian Agency for Drugs and Technologies in Health health technology assessments, or peer-reviewed medical literature" and that are "relevant to the Medicare population and could be detected using Medicare claims with reasonable specificity, meaning that major clinical factors distinguishing likely overuse from appropriate use could be identified or approximated with claims and enrollment data."

low-value diagnostic and preventive testing, low-value preoperative testing, low-value imaging, low-value cardiovascular testing and procedures, and other low-value surgical procedures. Section 2.4 shows that patients who switch PCPs significantly increase tests utilization and imaging utilization. Preliminary results show that at least some of the increases in tests utilization and imaging utilization could be classified as low-value care.

I am also examining the effect of PCP switches on the quality of primary care by measuring ambulatory care sensitive conditions (ACSCs) as defined for the Agency for Healthcare Research and Quality (AHRQ) Prevention Quality Indicators.[28] The AHRQ defines ACSCs as “conditions for which good outpatient care can potentially prevent the need for hospitalization or for which early intervention can prevent complications or more severe disease.”[29] The ACSCs relevant for the elderly Medicare population can be classified into three categories: acute admissions, diabetes admissions, and other chronic conditions admissions.

Finally, I am examining the effect of PCP switches on the intensity of medical treatments by measuring preference-sensitive care. The Dartmouth Atlas of Health Care defines preference-sensitive care as, “treatments for conditions where legitimate treatment options exist – options involving significant tradeoffs among different possible outcomes of each treatment.”[30,31]

2.6.5 Idiosyncrasies Across Primary Care Physicians

Finally, some components of the temporary increase in healthcare utilization could be due to idiosyncrasies across PCPs that are within the range of acceptable physician discretion and do not necessarily generate health benefits for patients or inefficiencies. Individual PCPs differ (e.g., in training, experience, expertise) such that switching to new PCPs could lead to new diagnoses, diagnostic tests, and specialist visits. For example, different PCPs may be more likely to refer patients to specialists for different conditions.

2.7 Discussion

2.7.1 Significance and Limitations

I estimate switching costs among patients who involuntarily switch PCPs because their physicians relocate or retire using an event study framework with both patient fixed effects and PCP fixed effects to control for any changes in PCP composition. I find that the

[28] See the AHRQ “Prevention Quality Indicators Overview” webpage (https://www.qualityindicators.ahrq.gov/modules/pqi_overview.aspx) for details.

[29] Source: Dartmouth Atlas of Health Care “Preference-Sensitive Care” webpage (http://archive.dartmouthatlas.org/keyissues/issue.aspx?con=2938).

[30] Source:

[31] The preference-sensitive care categories are: (a) mastectomy for early-stage breast cancer, (b) coronary artery bypass grafting (CABG) surgery for stable angina, (c) percutaneous coronary intervention (PCI) for stable angina, (d) back surgery for low back pain, (e) knee replacement for osteoarthritis of the knee joints, (f) hip replacement for osteoarthritis of hip joints, (g) carotid endarterectomy for carotid artery disease, (h) cholecystectomy for gallstones, (h) transurethral resection of the prostate (TURP) for benign prostatic hyperplasia (BPH), (i) prostate-specific antigen (PSA) test for early-stage prostate cancer, and (j) prostatectomy for early-stage prostate cancer.

cost of changing PCPs is approximately $499-726 per switch, and about 20-30% of these switching costs come from short-run increases in primary care utilization. These switching costs also come from other medical care, such as tests, imaging, and specialty care. In my counterfactuals, I find that the potential savings from reallocating patients to lower-spending PCPs are approximately the same magnitude as the switching costs.

My study has a few limitations. First, my research design does not comprehensively capture costs and benefits associated with PCP switches. My estimation of switching costs focuses on spending in Medicare claims and does not include other welfare-relevant costs, such as patient hassle costs of finding new PCPs and medical record copy fees. Also, my estimation focuses on short-run effects of switching PCPs within the first two to three years and does not capture long-run effects. Though switching PCPs generates immediate costs, switching PCPs could produce some benefits that I do not capture (e.g., catching up on delayed preventive care that leads to future, long-run savings).

Second, the counterfactuals can be interpreted only as partial equilibrium results in the context of Original Medicare. The data in this study are limited to 20% of Original Medicare patients, so I cannot observe capacity constraints and how likely they would bind even under more realistic counterfactuals. Also, a broader model of physician supply would be needed to make predictions on general equilibrium PCP supply-side responses to hypothetical policies. For example, if health plans incentivized patients to switch to lower-spending PCPs (e.g., through high deductibles, narrow health plan networks), higher-spending PCPs may respond by decreasing their patients' utilization on average.

Third, my main aggregate results likely mask heterogeneity both across PCPs and across patients. PCPs vary in the way they manage departures from practices and retirements; some PCPs refer patients to other PCPs, whereas others do not. Patients experience different long-run and short-run effects when they switch to different PCPs based on various factors, including patient demographic characteristics, patient chronic conditions, and healthcare market characteristics.

2.7.2 Policy Implications

My findings have implications for policies that reallocate patients across physicians, such as through health plan networks, and for patients who seek to switch health plans. Patients and payers (depending on cost-sharing) would bear the switching costs of $726 per switch on average across markets.[32] There are a couple of levers that health plans can use to change the distribution of PCPs that patients visit: (a) restricting PCPs from joining the network, and (b) excluding previously in-network PCPs from the network (e.g., not renewing contracts). With such high switching costs, a health plan may prefer to keep a high-spending PCP in their network rather than to exclude that PCP and force that PCP's patients to switch to other in-network PCPs. Similarly, a patient may actually spend less on medical care by keeping a slightly more expensive health plan than switching to a cheaper health plan in which their PCP is out-of-network. More broadly, my research relates to the literature on health plan networks and offers additional context for its findings. For example, Gruber

[32]In some cases, the payers would pass the costs back to other patients (e.g., through increased premiums, Medicare payroll taxes).

and McKnight (2016) find that savings from limited network plans are concentrated among patients whose PCPs are included in those limited network health plans. My results relate to this finding and suggest that temporarily higher utilization due to PCP switches could lead to reduced cost savings among patients who lose access to their PCPs when they switch to lower-cost health plans.

My finding of substantial switching costs has implications for the broad class of policies that aim to reduce involuntary physician switching, facilitate the transfer of medical records, and otherwise mitigate switching costs. To reduce involuntary PCP switches, governments may choose to enact policies to increase network transparency and restrict changes in provider networks during plan years. To help reduce redundant information acquisition, policies could incentivize improvements in the portability of electronic health records, and states could place stricter limits on medical record copy fees. In the literature, Baker, Bundorf, and Kessler (2015) find that patients from states that adopted limits on medical record copy fees are significantly more likely to switch physicians. This finding suggests that reducing switching costs in utilization could also potentially lead to more efficient levels of PCP switching (e.g., a patient who relocates locally may prefer to switch to another PCP who is closer to their new residence).

2.7.3 Conclusion

The significant switching costs I find suggest that policies that induce patients to switch to lower-spending PCPs could potentially be counterproductive and would need to consider both long-run savings and short-run switching costs. Future research could investigate the effectiveness of cost-saving strategies that incentivize patients to switch PCPs, such as narrow network health plans, and the incidence of these switching costs between patients and payers. Future research could also study the effects of policies that promote positive effects of switching PCPs (either with or without actual PCP switching) or that help mitigate negative effects of switching PCPs. Regarding positive effects of switching PCPs, if more comprehensive primary care evaluations are valuable, then policies could incentivize PCPs to provide occasional comprehensive evaluations (e.g., with greater reimbursement for longer appointment times). Regarding negative effects of switching PCPs, policies could require that health plan networks include adequate numbers of PCPs to reduce primary care delays, and payers could incentivize the adoption of technology to facilitate medical records transfers. Health insurance plans could help match patients to new PCPs to reduce primary care delays and incentivize these new PCPs to reduce redundant medical care.

More generally, additional research is needed to quantify broader efficiency and welfare implications associated with my findings on physician practice styles and switching costs. Studies in healthcare face challenges in estimating welfare from effects on health outcomes, particularly in primary care settings where effects on objective measures of health status available in administrative claims data (e.g., mortality, readmissions) are likely to be small. Richer electronic medical records would enable researchers to use a broader range of health outcomes (e.g., blood pressure and cholesterol level measurements) to understand the influence of PCPs on efficiency and welfare.

Table 2.1: Switching Costs Results by Utilization Category

Switch Type		Switching Costs by Category ($, multi-market mean, SE in parentheses)							# Switches	Within-Mkt
	Switch	Total	Prim. Care.	Tests	Imaging	Emerg.	Hosp.	Spec. Care.	(mean/mkt)	Regressions
Voluntary	Practice Grp.	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
No	No	499.36	143.80	33.16	16.09	1.39	0.82	21.66	531	306
		(29.45)	(4.64)	(2.14)	(2.54)	(0.52)	(0.15)	(8.14)		
No	Yes	725.73	160.17	33.70	20.95	3.14	1.64	23.65	678	306
		(40.07)	(4.22)	(1.78)	(3.36)	(0.59)	(0.64)	(1.62)		
Yes	No	691.62	162.03	39.63	17.00	1.52	1.32	21.58	808	306
		(26.52)	(4.04)	(1.84)	(1.12)	(0.17)	(0.17)	(2.62)		
Yes	Yes	1066.42	197.91	46.52	23.57	3.37	2.37	34.41	1806	306
		(19.74)	(2.74)	(1.11)	(0.63)	(0.11)	(0.11)	(1.55)		
# patient-quarter obs. including switchers and non-switchers (mean/market):										493,547

Notes: This table reports the switching costs estimates from 306 within-market event study regressions weighted by the number of Original Medicare beneficiaries in each market as described in Section 2.3.1. Columns (1)-(7) report results with different utilization outcome measures: total, primary care, tests, imaging, emergency department, hospital inpatient, and specialty care. Each market-level event study regression includes a primary care physician (PCP) fixed effect, a patient fixed effect, sets of event time indicators corresponding to types of switches, and controls for age, gender, and date/cohort. Each market-level event study regression includes a set of event time indicators for each of the four switch types in the table assigned to a balanced panel of patients who are consistently matched with the origin PCP for 6 quarters before the switch and the destination PCP for 8 quarters after a switch, where event time 0 is the last quarter that a patient is matched with the origin PCP. The estimated event time coefficients are then used to calculate the total switching costs over the 15 quarters in levels of dollar utilization. The event study regressions have robust standard errors (SEs) three-way clustered by patient, by main PCP, and by quarter. The standard errors for each set of within-market switching cost estimates are calculated using the delta method, allowing for correlation among the four sets of event time coefficients corresponding to the four types of switches. When the within-market estimates are aggregated by weight, the standard errors are calculated accordingly. The sample is the connected set for quarterly utilization that does not omit the switch period in Column (3) of Table 1.4.

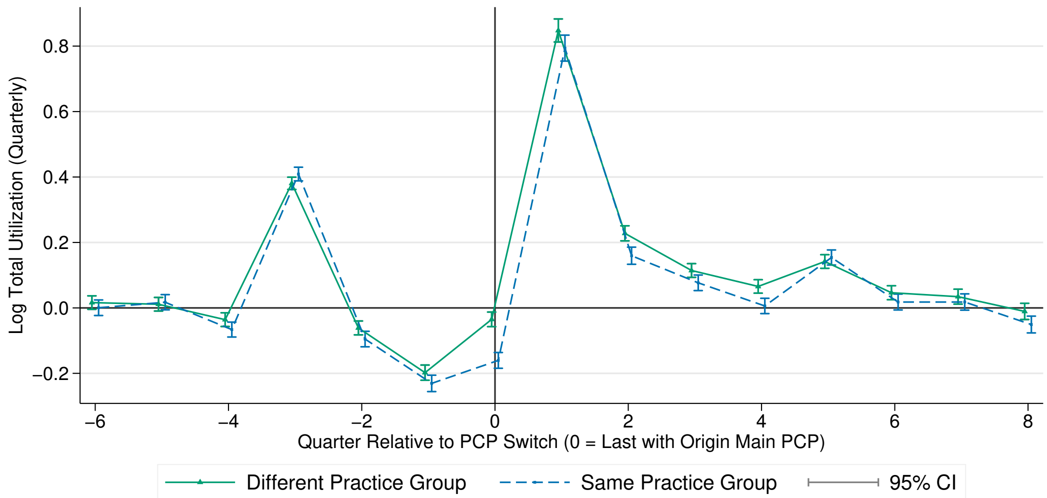
Table 2.2: Counterfactuals: Yearly Total Utilization

	Mean Savings per Switch per Year ($)	Years to Break Even by Any Practice Group Switch: Same Group	Different Group
	(1)	(2)	(3)
A. Reallocation Between Two Specific Percentiles			
Between 25-75th percentiles	617	0.81	1.18
Between 40-60th percentiles	231	2.16	3.14
B. Reallocation of Top Deciles to Median			
Top 10% to median	970	0.51	0.75
Top 20% to median	751	0.67	0.97
Top 30% to median	611	0.82	1.19
Top 40% to median	504	0.99	1.44
Top 50% to median	415	1.20	1.75
C. Reallocation of Top Deciles to Other High-Spending Percentiles			
Top 10% to 90th percentile	304	1.64	2.39
Top 20% to 80th percentile	332	1.50	2.18
Top 30% to 70th percentile	359	1.39	2.02
Top 40% to 60th percentile	385	1.30	1.88

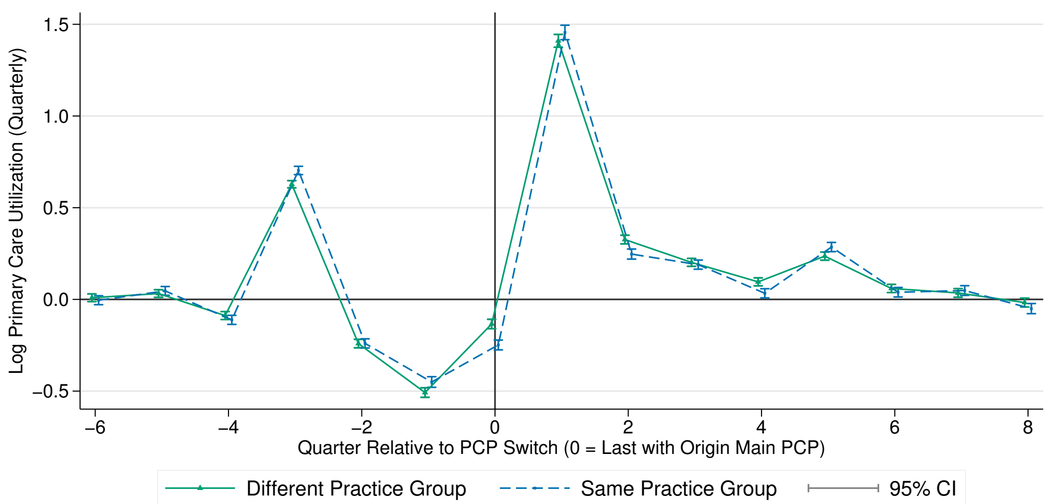
Notes: This table reports the results for counterfactuals for total utilization as described in Section 2.5. Panel A reports the hypothetical scenario in which patients are reallocated (a) from a 75th percentile PCP to a 25th percentile PCP or (b) from a 60th percentile PCP to a 40th percentile PCP in terms of total utilization. Panel B reports the counterfactuals in which patients who have PCPs estimated to be in the top deciles of utilization are reallocated to a median PCP. Panel C reports the counterfactuals in which patients who have PCPs estimated to be in the top deciles of utilization are reallocated to PCPs at the highest non-excluded percentile. Column (1) reports the mean savings per switch per year. Columns (2) and (3) report the time to "break even" given the switching costs estimated in Section 2.3 of $499 for PCP switches within the same practice groups and $726 for PCP switches to different practice groups.

Figure 2.1: Switching Costs Results: Total and Primary Care Utilization

(a) Total Utilization



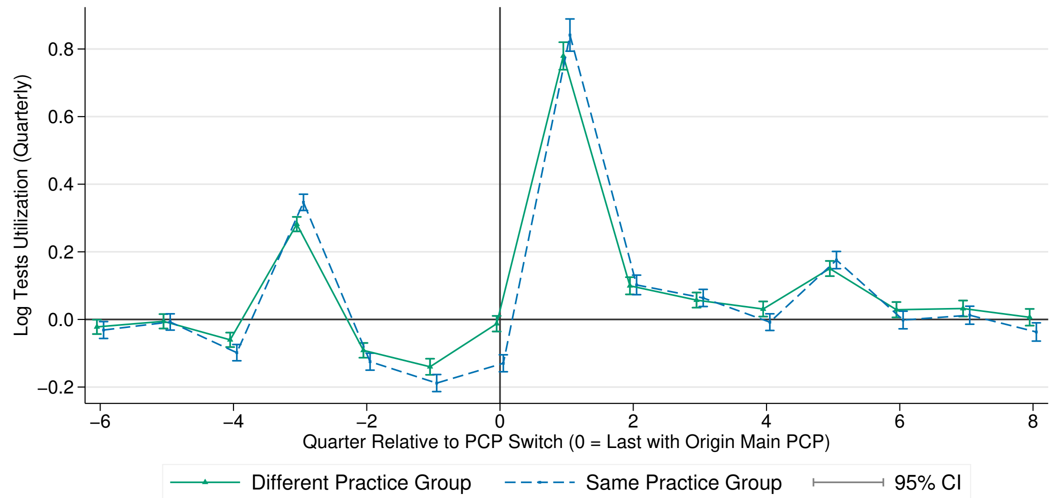
(b) Primary Care Utilization



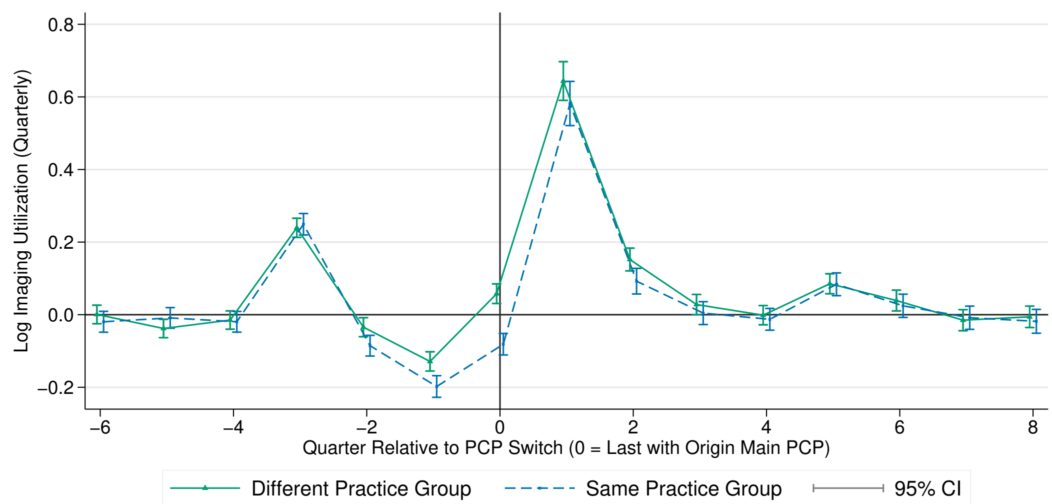
Notes: Each of these figures plots the event study estimates from 306 within-market event study regressions weighted by the number of Original Medicare beneficiaries in each market as described in Section 2.3.1. The outcome variable in the regressions is the *log of quarterly utilization*. In Panel (a), the outcome variable is the *log of quarterly total utilization*. In Panel (b), the outcome variable is the *log of quarterly primary care utilization*. Each event study regression includes a primary care physician (PCP) fixed effect, a patient fixed effect, sets of event time indicators corresponding to types of switches, and controls for age, gender, and date/cohort. For each of the switch type, the event study regression includes a set of event time indicators for a balanced panel of patients who are always assigned the origin PCP for 6 quarters before the switch and the destination PCP for 8 quarters after a switch. The sample is the connected set for quarterly utilization that does not omit the switch period in Column (3) of Table 1.4.

Figure 2.2: Switching Costs Results: Tests and Imaging Utilization

(a) Tests Utilization



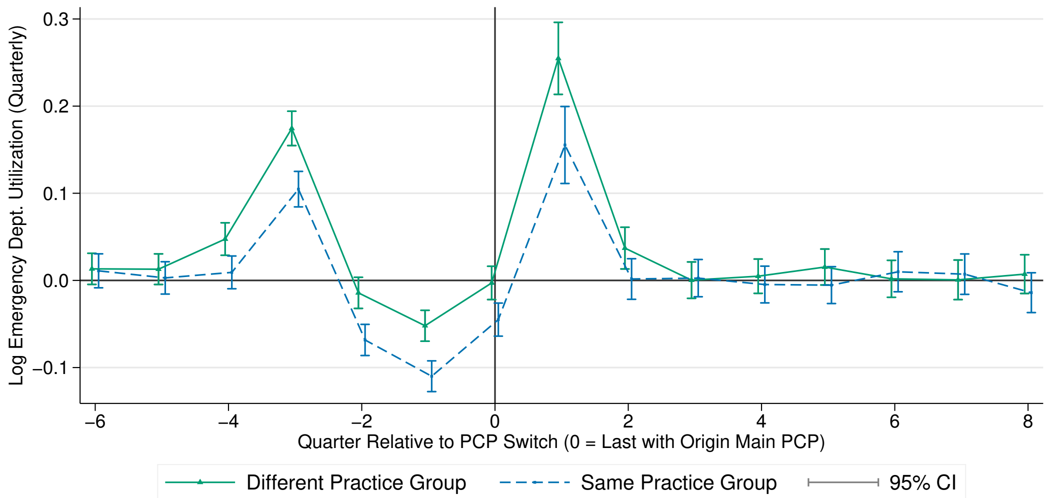
(b) Imaging Utilization



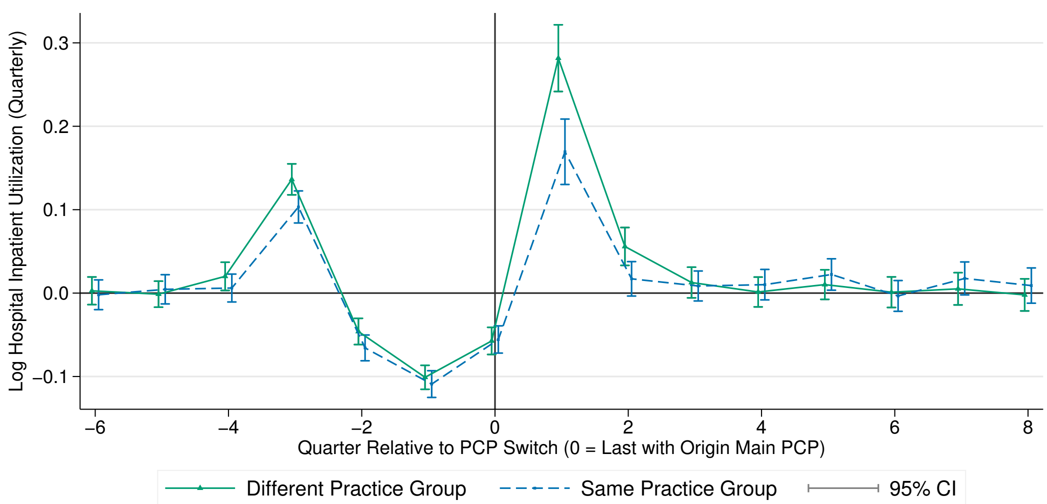
Notes: Each of these figures plots the event study estimates from 306 within-market event study regressions weighted by the number of Original Medicare beneficiaries in each market as described in Section 2.3.1. The outcome variable in the regressions is the *log of quarterly utilization*. In Panel (a), the outcome variable is the *log of quarterly tests utilization*. In Panel (b), the outcome variable is the *log of quarterly imaging utilization*. Each event study regression includes a primary care physician (PCP) fixed effect, a patient fixed effect, sets of event time indicators corresponding to types of switches, and controls for age, gender, and date/cohort. For each of the switch type, the event study regression includes a set of event time indicators for a balanced panel of patients who are always assigned the origin PCP for 6 quarters before the switch and the destination PCP for 8 quarters after a switch. The sample is the connected set for quarterly utilization that does not omit the switch period in Column (3) of Table 1.4.

Figure 2.3: Switching Costs Results: Emergency Department and Hospital Inpatient Utilization

(a) Emergency Department Utilization



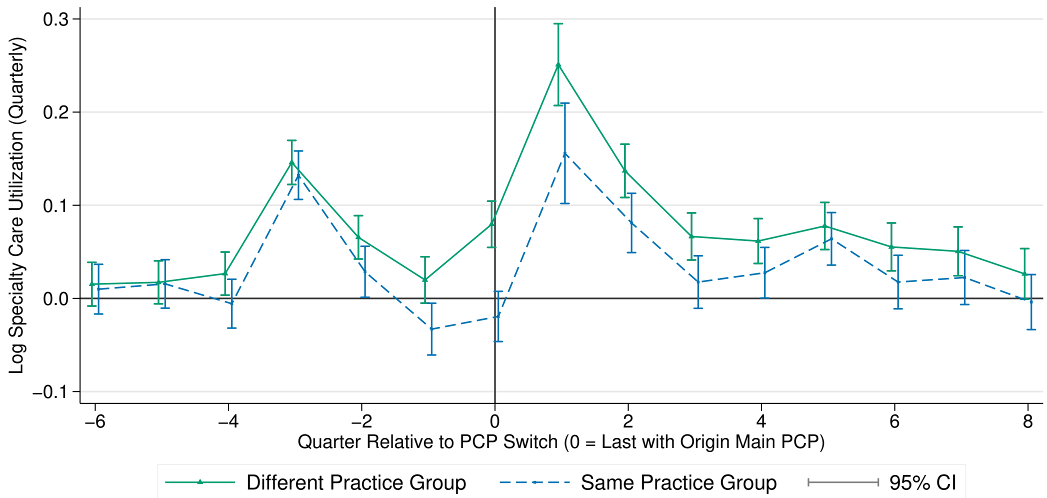
(b) Hospital Inpatient Utilization



Notes: Each of these figures plots the event study estimates from 306 within-market event study regressions weighted by the number of Original Medicare beneficiaries in each market as described in Section 2.3.1. The outcome variable in the regressions is the *log of quarterly utilization*. In Panel (a), the outcome variable is the *log of quarterly emergency department utilization*. In Panel (b), the outcome variable is the *log of quarterly inpatient hospitalization utilization*. Each event study regression includes a primary care physician (PCP) fixed effect, a patient fixed effect, sets of event time indicators corresponding to types of switches, and controls for age, gender, and date/cohort. For each of the switch type, the event study regression includes a set of event time indicators for a balanced panel of patients who are always assigned the origin PCP for 6 quarters before the switch and the destination PCP for 8 quarters after a switch. The sample is the connected set for quarterly utilization that does not omit the switch period in Column (3) of Table 1.4.

Figure 2.4: Switching Costs Results: Specialty Care Utilization

(a) Specialty Care Utilization



Notes: This figure plots the event study estimates from 306 within-market event study regressions weighted by the number of Original Medicare beneficiaries in each market as described in Section 2.3.1. The outcome variable in the regressions is the *log of quarterly utilization*. In Panel (a), the outcome variable is the *log of quarterly specialty care utilization*. Each event study regression includes a primary care physician (PCP) fixed effect, a patient fixed effect, sets of event time indicators corresponding to types of switches, and controls for age, gender, and date/cohort. For each of the switch type, the event study regression includes a set of event time indicators for a balanced panel of patients who are always assigned the origin PCP for 6 quarters before the switch and the destination PCP for 8 quarters after a switch. The sample is the connected set for quarterly utilization that does not omit the switch period in Column (3) of Table 1.4.

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Appendix A

Additional Tables

Table A.1: Descriptive Statistics for Practice Styles Estimation Samples: Patients in Connected Sets and Leave-Out Connected Sets

		Yearly Outcome w/o Switch		
	Main	Connected Sets	Leave-Out Connected Sets	
	Analysis Sample	All Patients	All Patients	Switchers Only
	(1)	(2)	(3)	(4)
A. Patients (thousands)	7,512	4,464	4,323	647
Female (%)	58.5	60.4	60.3	65.3
White (%)	87.4	89.4	89.7	90.3
# main PCPs ever (mean)	2.51	2.53	2.52	3.55
# quarters in sample (mean)	33.9	40.0	40.1	49.0
B. Patient-Qtrs. (thousands)	133,522	61,628	59,988	9,837
Age (years, mean)	76.9	77.1	77.1	78.2
Quarterly Utilization				
Total util. mean ($)	2,247	1,292	1,290	1,259
Total util. std. dev. ($)	7,032	3,999	3,996	3,568
Any total util. (%)	90.6	90.6	90.7	91.6
Primary care util. mean ($)	136	97	97	99
Prim. care util. std. dev. ($)	281	144	144	144
Any primary care util. (%)	69.9	70.7	70.8	71.6
Past Year Utilization				
Total util. mean ($)	8,151	5,032	5,026	4,945
Total util. std. dev. ($)	16,122	9,649	9,598	8,686
Primary care util. mean ($)	500	378	377	389
Prim. care util. std. dev. ($)	666	392	390	399

Notes: This table reports the descriptive statistics for my connected set samples, which I use for analysis in Section 1.5. Column (1) includes the *main analysis sample* from Column (5) of Table 1.1. Columns (2) and (3) include the samples that I use for analysis in Section 1.5. Column (2) includes the patient-quarter connected sets sample that omits the quarters during PCP switches from Column (4) of Table 1.4. Column (3) includes the patient-quarter leave-out connected sets sample that omits the quarters during PCP switches. Column (4) includes the patient-quarter leave-out connected sets sample that omits the quarters during PCP switches and restricts patients to switchers. The leave-out connected sets samples are composed of the largest connected set in each market that remains when each patient-PCP pair is separately omitted from the sample and is identified in the estimation procedure. The patients and PCPs in Column (4) are a subset of those in Column (3), which are a subset of those in Column (2).

Table A.2: Descriptive Statistics for Practice Styles Estimation Samples: Patients in Leave-Out Connected Sets and during Switch Quarters

	Yearly Outcome w/o Switch				
	Connected Sets	Leave-Out Connected Sets			
	All Qtrs.	All Qtrs.	Switch Quarters Only		
			All Switches	Involuntary Switches	Voluntary Switches
	(1)	(2)	(3)	(4)	(5)
A. Patients (thousands)	4,464	4,323	352.9	48.2	310.8
Female (%)	60.4	60.3	60.3	60.1	60.3
White (%)	89.4	89.7	91.8	93.5	91.6
# main PCPs ever (mean)	2.53	2.52	3.66	3.66	3.66
# quarters in sample (mean)	40.0	40.1	46.0	45.5	46.2
B. Patient-Qtrs. (thousands)	61,628	59,988	386.1	48.8	337.3
Age (years, mean)	77.1	77.1	77.1	76.7	77.2
Quarterly Utilization					
Total util. mean ($)	1,292	1,290	1,368	1,122	1,404
Total util. std. dev. ($)	3,999	3,996	4,256	3,823	4,314
Any total util. (%)	90.6	90.7	86.3	85.1	86.5
Primary care util. mean ($)	97	97	59	50	61
Prim. care util. std. dev. ($)	144	144	93	86	94
Any primary care util. (%)	70.7	70.8	52.2	49.9	52.3
Past Year Utilization					
Total util. mean ($)	5,032	5,026	4,844	4,023	4,963
Total util. std. dev. ($)	9,649	9,598	9,320	8,099	9,478
Primary care util. mean ($)	378	377	236	202	241
Prim. care util. std. dev. ($)	392	390	230	207	233

Notes: This table reports the descriptive statistics for my connected set samples, which I use for analysis in Section 1.5. Columns (1) and (2) include the samples that I use for analysis in Section 1.5. Column (2) includes the patient-quarter connected sets sample from Column (2) of Table A.1. Column (3) includes the patient-quarter leave-out connected sets sample from Column (3) of Table A.1. Columns (3)-(5) are restricted to patient-quarter observations that correspond to a switch, defined as the last quarter a PCP is assigned to a patient. The patient-quarters observations in Column (3) are split into Columns (4) and (5), and there is some overlap between patients in Column (4) and Column (5).

Table A.3: Descriptive Statistics for Switching Costs Estimation Samples: Patients in Balanced Panels around PCP Switch

	Connected Sets Sample w/ Switch	Balanced Panel, Switch Quarters Only: Involuntary Switch, Same Group	Balanced Panel, Switch Quarters Only: Involuntary Switch, Different Group	Balanced Panel, Switch Quarters Only: Voluntary Switch, Same Group	Balanced Panel, Switch Quarters Only: Voluntary Switch, Different Group
	(1)	(2)	(3)	(4)	(5)
A. Patients (thousands)	5,184	49.1	57.6	74.2	142.1
Female (%)	59.9	62.2	63.9	65.3	67.5
White (%)	88.9	90.9	89.2	91.2	88.6
# main PCPs ever (mean)	2.56	3.11	3.00	3.24	3.20
# quarters in sample (mean)	38.4	47.5	47.6	47.5	47.2
B. Patient-Qtrs. (thousands)	81,287	49.6	58.0	75.6	145.7
Age (years, mean)	76.7	77.3	77.4	77.5	77.8
Quarterly Utilization					
Total util. mean ($)	1,313	1,048	1,209	1,281	1,680
Total util. std. dev. ($)	4,091	3,138	3,305	3,699	4,630
Any total util. (%)	90.0	89.7	90.6	90.2	92.0
Primary care util. mean ($)	95	77	104	94	134
Prim. care util. std. dev. ($)	147	100	127	131	176
Any primary care util. (%)	69.1	65.1	67.4	66.9	71.0
Past Year Utilization					
Total util. mean ($)	5,133	4,427	4,985	5,147	6,539
Total util. std. dev. ($)	9,939	8,339	8,452	8,724	10,791
Primary care util. mean ($)	375	338	411	389	499
Prim. care util. std. dev. ($)	398	287	355	369	485

Notes: This table reports the descriptive statistics for my connected set samples, which I use for analysis in Section 2.3. Column (1) includes the patient-quarter connected sets sample that includes the quarters during PCP switches from Column (3) of Table 1.4. Columns (2)-(5) are restricted to patient-quarter observations that correspond to a switch, defined as the last quarter a PCP is assigned to a patient, and split by the type of switch. Columns (2)-(3) correspond to involuntary switches, and Columns (4)-(5) correspond to voluntary switches. Columns (2) and (4) correspond to switches between PCPs within the same physician practice groups. Columns (3) and (5) correspond to switches between PCPs in different physician practice groups.

Table A.4: Descriptive Statistics for Switching Costs Estimation Samples: Patients in Balanced Panels of Different Lengths around PCP Switch

	Involuntary Switches						Voluntary Switches					
	Same Practice Group			Different Practice Group			Same Practice Group			Different Practice Group		
Pre-Switch/Post-Switch Qtrs.:	4 / 6	6 / 8	8 / 12	4 / 6	6 / 8	8 / 12	4 / 6	6 / 8	8 / 12	4 / 6	6 / 8	8 / 12
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
A. Patients (thousands)	74.9	49.1	22.6	88.6	57.6	27.5	109.8	74.2	35.7	210.5	142.1	69.2
Female (%)	62.4	62.2	62.2	64.2	63.9	63.6	65.2	65.3	65.5	67.2	67.5	68.4
White (%)	90.9	90.9	91.1	89.4	89.2	89.0	91.0	91.2	92.0	88.3	88.6	88.9
# main PCPs ever (mean)	3.25	3.11	2.83	3.14	3.00	2.74	3.39	3.24	2.94	3.34	3.20	2.92
# quarters in sample (mean)	46.4	47.5	49.8	46.3	47.6	49.8	46.3	47.5	49.7	46.0	47.2	49.4
B. Patient-Qtrs. (thousands)	76.1	49.6	22.7	89.6	58.0	27.5	113.1	75.6	35.9	219.0	145.7	69.8
Age (years, mean)	77.3	77.3	77.3	77.5	77.4	77.4	77.6	77.5	77.5	77.9	77.8	77.7
Quarterly Utilization												
Total util. mean ($)	1,061	1,048	1,028	1,251	1,209	1,167	1,300	1,281	1,268	1,713	1,680	1,639
Total util. std. dev. ($)	3,220	3,138	3,042	3,432	3,305	3,171	3,793	3,699	3,698	4,655	4,630	4,770
Any total util. (%)	89.0	89.7	90.7	90.1	90.6	91.0	89.6	90.2	90.9	91.6	92.0	92.5
Primary care util. mean ($)	78	77	79	105	104	103	95	94	93	134	134	133
Prim. care util. std. dev. ($)	103	100	96	132	127	122	138	131	122	180	176	167
Any primary care util. (%)	64.5	65.1	67.3	67.0	67.4	68.2	66.3	66.9	68.5	70.2	71.0	72.3
Past Year Utilization												
Total util. mean ($)	4,483	4,427	4,368	5,099	4,985	4,804	5,237	5,147	5,079	6,675	6,539	6,351
Total util. std. dev. ($)	8,517	8,339	7,545	8,729	8,452	8,022	9,063	8,724	8,576	11,177	10,791	10,520
Primary care util. mean ($)	339	338	340	412	411	404	393	389	385	502	499	491
Prim. care util. std. dev. ($)	307	287	272	373	355	332	383	369	351	503	485	462

Notes: This table reports the descriptive statistics for my connected sets sample, which I use for analysis in Section 2.3 and report in Columns (2)-(5) of Table A.3, in Columns (2), (5), (8), and (11). This connected sets sample consists of a balanced panel of patients who are always assigned the origin PCP for 6 quarters before the switch and the destination PCP for 8 quarters after a switch. The table compares these columns to those of alternative samples, with different numbers of quarters in the pre/post-switch requirements. All columns are restricted to patient-quarter observations that correspond to a switch, defined as the last quarter a PCP is assigned to a patient, and split by the type of switch. Columns (1)-(6) correspond to involuntary switches, and Columns (7)-(12) correspond to voluntary switches. Columns (1)-(3) and (7)-(9) correspond to switches between PCPs within the same physician practice groups. Columns (4)-(6) and (10)-(12) correspond to switches between PCPs in different physician practice groups.

Table A.5: Practice Styles Results: Variance in Yearly Total Utilization, Estimation Comparison

Sample:	Connected Set	Leave-Out Connected Set	
Estimation Method:	OLS	OLS	Leave-Out
	(1)	(2)	(3)
# of within-market estimations	306	306	306
A. Variance and Covariance Estimates (multi-market mean as % share of total variance)			
Variance of PCP FEs (%)	19.839	16.968	**2.449**
Covariance of patient & PCP FEs (%)	-16.826	-14.062	0.011
Variance of patient FEs (%)	68.433	65.596	
B. Other Statistics and Results (multi-market mean)			
# of PCP fixed effects	846	726	726
# of patient-qtr. obs.	370,822	361,421	361,421
Mean of log util.	7.733	7.735	7.735
Std. dev. of log util.	1.271	1.270	1.270
Var. of log util.	1.618	1.616	1.616
Var. of PCP FEs	0.321	0.274	0.040
Std. dev. of PCP FEs	0.552	0.514	0.180
R-squared	0.509	0.507	–
C. Match Model Results (multi-market mean)			
R-squared	0.521	–	–

Notes: This table reports the results of the 306 within-market estimations of (a) the variance of primary care physician (PCP) fixed effects (FEs), (b) the covariance of the PCP fixed effects and the patient fixed effects, and (c) the variance of patient fixed effects in a two-way fixed effects model with different estimation methods. Column (1) reports the ordinary least squares regression results, where the sample is the connected set for yearly utilization that omits the switch period in Column (4) of Table 1.4. Column (2) reports the ordinary least squares regression results, where the sample is the connected set for yearly utilization that omits the switch period in Column (4) of Table 1.4 that remains connected when each patient-PCP pair is left out. Column (3) results from the leave-out patient-PCP match procedure described in Section 1.5.1, where the sample is the connected set for yearly utilization that omits the switch period in Column (4) of Table 1.4 that remains connected when each patient-PCP pair is left out. The outcome variable is the *log of yearly total utilization* in the past year. The PCP fixed effects share, the covariance of PCP fixed effects and patient fixed effects share, and the patient fixed effects share are means weighted by the number of Original Medicare beneficiaries in each market, and the standard errors are computed accordingly. The standard deviation of the PCP fixed effects is imputed to be zero in markets where the point estimate of the variance of PCP fixed effects is negative. Markets are hospital referral regions (HRRs).

Table A.6: Practice Styles Results: Variance in Yearly Total and Primary Care Utilization, Weighted versus Unweighted

	Total		Primary Care	
	Weighted	Unweighted	Weighted	Unweighted
	(1)	(2)	(3)	(4)
# of within-market estimations	306	306	306	306
A. Variance and Covariance Estimates (multi-market mean, SE in parentheses)				
Variance of PCP FEs	**2.449**	**2.345**	**12.626**	**11.862**
as % share of total variance	(0.136)	(0.217)	(0.131)	(0.211)
Cov. of patient & PCP FEs	0.011	-0.054	0.173	-0.100
as % share of total variance	(0.134)	(0.214)	(0.124)	(0.202)
B. Other Statistics and Results (multi-market mean)				
# of PCP fixed effects	726	380	726	380
# of patient-qtr. obs.	361,421	196,243	361,421	196,243
Mean of log util.	7.735	7.695	5.599	5.558
Std. dev. of log util.	1.270	1.284	0.791	0.793
Var. of log util.	1.616	1.651	0.628	0.630
Var. of PCP FEs	0.040	0.039	0.080	0.075
Std. dev. of PCP FEs	0.180	0.180	0.275	0.261

Notes: This table reports the results of the 306 within-market estimations of (a) the variance of primary care physician (PCP) fixed effects (FEs) and (b) the covariance of the PCP fixed effects and the patient fixed effects in a two-way fixed effects model. The estimation uses patient-quarter level observations in the leave-out patient-PCP match procedure described in Section 1.5.1. In Columns (1) and (2), the outcome variable is the *log of yearly total utilization* in the past year. In Columns (3) and (4), the outcome variable is the *log of yearly primary care utilization* in the past year. Columns (1) and (3) report the unweighted results, and Columns (2) and (4) report the weighted results. All four columns report the estimates for all 306 markets weighted by the number of Original Medicare beneficiaries in each market. The PCP fixed effects share and the covariance of PCP fixed effects and patient fixed effects share are the weighted means of the corresponding estimates, and the standard errors are computed accordingly. The standard deviation of the PCP fixed effects is imputed to be zero in markets where the point estimate of the variance of PCP fixed effects is negative. The sample is the connected set for yearly utilization that omits the switch period in Column (4) of Table 1.4 that remains connected when each patient-PCP pair is excluded. Markets are hospital referral regions (HRRs).

Table A.7: Practice Styles Results: Variance in Yearly Total Utilization, Switchers

	Example Markets			Markets by Spending	
	Miami	Minne-apolis	All Markets	Above Median	Below Median
	(1)	(2)	(3)	(4)	(5)
# of within-market estimations	1	1	306	153	153
A. Variance and Covariance Estimates (market/multi-market mean, SE in parentheses)					
Variance of PCP FEs	3.105	3.428	**2.622**	2.491	2.808
as % share of total variance	(1.487)	(2.072)	(0.136)	(0.123)	(0.277)
Cov. of patient & PCP FEs	1.391	-0.813	0.469	0.874	-0.103
as % share of total variance	(1.939)	(2.142)	(0.140)	(0.134)	(0.280)
Variance of patient FEs	34.853	19.676	28.385	28.965	27.567
as % share of total variance	(4.324)	(3.582)	(0.276)	(0.336)	(0.468)
B. Other Statistics and Results (market or multi-market mean)					
# of PCP fixed effects	1,011	1,261	726	867	526
# of patient-qtr. obs.	40,823	52,529	60,283	72,731	42,716
Mean of log util.	8.274	7.441	7.763	7.817	7.687
Std. dev. of log util.	1.215	1.217	1.216	1.172	1.275
Var. of log util.	1.374	1.626	1.482	1.480	1.484
Var. of PCP FEs	0.036	0.042	0.039	0.043	0.056
Std. dev. of PCP FEs	0.207	0.236	0.190	0.198	0.180
Explained variance	0.407	0.215	0.312	0.332	0.302

This table reports the results of the 306 within-market estimations of (a) the variance of primary care physician (PCP) fixed effects (FEs) and (b) the covariance of the PCP fixed effects and the patient fixed effects in a two-way fixed effects model *with only patients who switch PCPs at least once*. The estimation uses patient-quarter level observations in the leave-out patient-PCP match procedure described in Section 1.5.1. The outcome variable is the *log of yearly total utilization* in the past year. Column (1) reports the results for Miami (a high-spending market), and Column (2) reports the results for Minneapolis (a low-spending market). Column (3) reports the estimates for all 306 markets weighted by the number of Original Medicare beneficiaries in each market. Columns (4)-(5) report the weighted estimates of the above median and below median markets by spending. Columns (1) and (2) of Panel A report estimates of the shares of utilization that are the variance of PCP fixed effects and the covariance of PCP fixed effects and patient fixed effects along with their corresponding standard errors. In Columns (3)-(5) of Panel A, the PCP fixed effects share and the covariance of PCP fixed effects and patient fixed effects share are the weighted means of the corresponding estimates, and the standard errors are computed accordingly. The standard deviation of the PCP fixed effects is imputed to be zero in markets where the point estimate of the variance of PCP fixed effects is negative. The sample is the connected set for yearly utilization that omits the switch period in Column (4) of Table 1.4 that remains connected when each patient-PCP pair is excluded. Markets are hospital referral regions (HRRs).

Table A.8: Practice Styles Results: Variance in Yearly Primary Care Utilization, Switchers

	Example Markets			Markets by Spending	
	Miami	Minne-apolis	All Markets	Above Median	Below Median
	(1)	(2)	(3)	(4)	(5)
# of within-market estimations	1	1	306	153	153
A. Variance and Covariance Estimates (market/multi-market mean, SE in parentheses)					
Variance of PCP FEs	19.816	5.924	**14.821**	15.100	14.427
as % share of total variance	(1.266)	(2.055)	(0.125)	(0.126)	(0.244)
Cov. of patient & PCP FEs	-3.674	-1.428	-1.036	-0.277	-2.107
as % share of total variance	(1.511)	(2.088)	(0.129)	(0.127)	(0.256)
Variance of patient FEs	12.154	12.736	11.062	11.590	10.316
as % share of total variance	(3.616)	(3.603)	(0.287)	(0.340)	(0.499)
B. Other Statistics and Results (market or multi-market mean)					
# of PCP fixed effects	1,011	1,261	726	867	526
# of patient-qtr. obs.	40,823	52,529	60,283	72,731	42,716
Mean of log util.	6.010	5.313	5.623	5.665	5.564
Std. dev. of log util.	0.784	0.764	0.775	0.871	0.819
Var. of log util.	0.758	0.671	0.603	0.616	0.585
Var. of PCP FEs	0.094	0.085	0.090	0.150	0.040
Std. dev. of PCP FEs	0.388	0.199	0.290	0.302	0.274
Explained variance	0.246	0.158	0.193	0.261	0.205

This table reports the results of the 306 within-market estimations of (a) the variance of primary care physician (PCP) fixed effects (FEs) and (b) the covariance of the PCP fixed effects and the patient fixed effects in a two-way fixed effects model *with only patients who switch PCPs at least once*. The estimation uses patient-quarter level observations in the leave-out patient-PCP match procedure described in Section 1.5.1. The outcome variable is the *log of yearly primary care utilization* in the past year. Column (1) reports the results for Miami (a high-spending market), and Column (2) reports the results for Minneapolis (a low-spending market). Column (3) reports the estimates for all 306 markets weighted by the number of Original Medicare beneficiaries in each market. Columns (4)-(5) report the weighted estimates of the above median and below median markets by spending. Columns (1) and (2) of Panel A report estimates of the shares of utilization that are the variance of PCP fixed effects and the covariance of PCP fixed effects and patient fixed effects along with their corresponding standard errors. In Columns (3)-(5) of Panel A, the PCP fixed effects share and the covariance of PCP fixed effects and patient fixed effects share are the weighted means of the corresponding estimates, and the standard errors are computed accordingly. The standard deviation of the PCP fixed effects is imputed to be zero in markets where the point estimate of the variance of PCP fixed effects is negative. The sample is the connected set for yearly utilization that omits the switch period in Column (4) of Table 1.4 that remains connected when each patient-PCP pair is excluded. Markets are hospital referral regions (HRRs).

Table A.9: Practice Styles Results: Variance in Quarterly Total and Primary Care Utilization

	Total			Primary Care		
		Markets by Spend.			Markets by Spend.	
	All Markets	Above Median	Below Median	All Markets	Above Median	Below Median
	(1)	(2)	(3)	(4)	(5)	(6)
# of within-market estimations	306	153	153	306	153	153
A. Variance and Covariance Estimates (multi-market mean, SE in parentheses)						
Variance of PCP FEs	**1.201**	1.124	1.309	**6.209**	6.526	5.763
as % share of total variance	(0.071)	(0.071)	(1.141)	(0.069)	(0.070)	(0.134)
Cov. of patient & PCP FEs	0.228	0.449	-0.083	-0.654	-0.491	-0.883
as % share of total variance	(0.068)	(0.062)	(0.140)	(0.064)	(0.062)	(0.127)
B. Other Statistics and Results (multi-market mean)						
# of PCP fixed effects	893	1,071	642	893	1,071	642
# of patient-qtr. obs.	438,247	525,690	314,847	438,247	525,690	314,847
Mean of log util.	5.567	5.646	5.456	3.113	3.168	3.035
Std. dev. of log util.	2.245	2.230	2.266	2.201	2.196	2.208
Var. of log util.	5.053	4.983	5.152	4.847	4.825	4.879
Var. of PCP FEs	0.060	0.054	0.068	0.300	0.314	0.279
Std. dev. of PCP FEs	0.246	0.250	0.242	0.539	0.554	0.518

This table reports the results of the 306 within-market estimations of (a) the variance of primary care physician (PCP) fixed effects (FEs) and (b) the covariance of the PCP fixed effects and the patient fixed effects in a two-way fixed effects model. The estimation uses patient-quarter level observations in the leave-out patient-PCP match procedure described in Section 1.5.1. The outcome variable is the *log of quarterly utilization*. Columns (1)-(3) report results for *log of quarterly total utilization*, and Columns (4)-(5) present results for *log of quarterly primary care utilization*. Columns (1) and (4) present the estimates for all 306 markets weighted by the number of Original Medicare beneficiaries in each market. Columns (2)-(3) and (5)-(6) report the estimates of the above median and below median HRRs by market-level spending, weighted by the number of Original Medicare beneficiaries in the market. Panel A reports estimates of the shares of utilization that are the variance of PCP fixed effects and the covariance of PCP fixed effects and patient fixed effects as the weighted means of the corresponding estimates across the within-market estimations, and the standard errors are computed accordingly. The standard deviation of the PCP fixed effects is imputed to be zero in markets where the point estimate of the variance of PCP fixed effects is negative. The sample is the connected set for quarterly utilization that omits the switch period in Column (2) of Table 1.4 that remains connected when each patient-PCP pair is excluded. Markets are hospital referral regions (HRRs).

Table A.10: Practice Styles Results: Variance in Quarterly Tests and Imaging Utilization

	Tests			Imaging		
		Markets by Spend.			Markets by Spend.	
	All Markets	Above Median	Below Median	All Markets	Above Median	Below Median
	(1)	(2)	(3)	(4)	(5)	(6)
# of within-market estimations	306	153	153	306	153	153
A. Variance and Covariance Estimates (multi-market mean, SE in parentheses)						
Variance of PCP FEs	**2.701**	2.871	2.462	**1.117**	1.189	1.015
as % share of total variance	(0.067)	(0.062)	(0.105)	0.057	0.053	0.117
Cov. of patient & PCP FEs	0.351	0.403	0.278	0.102	0.186	-0.016
as % share of total variance	(0.053)	(0.056)	(0.100)	(0.056)	(0.050)	(0.115)
B. Other Statistics and Results (multi-market mean)						
# of PCP fixed effects	893	1,071	642	893	1,071	642
# of patient-qtr. obs.	438,247	525,690	314,847	438,247	525,690	314,847
Mean of log util.	2.814	2.890	2.706	1.945	2.008	1.856
Std. dev. of log util.	2.191	2.200	2.180	2.528	2.560	2.483
Var. of log util.	4.805	4.842	4.753	6.401	6.565	6.169
Var. of PCP FEs	0.130	0.139	0.117	0.072	0.079	0.062
Std. dev. of PCP FEs	0.352	0.367	0.331	0.252	0.268	0.229

Notes: This table reports the results of the 306 within-market estimations of (a) the variance of primary care physician (PCP) fixed effects (FEs) and (b) the covariance of the PCP fixed effects and the patient fixed effects in a two-way fixed effects model. The estimation uses patient-quarter level observations in the leave-out patient-PCP match procedure described in Section 1.5.1. The outcome variable is the *log of quarterly utilization*. Columns (1)-(3) report results for *log of quarterly tests utilization*, and Columns (4)-(5) present results for *log of quarterly imaging utilization*. Columns (1) and (4) present the estimates for all 306 markets weighted by the number of Original Medicare beneficiaries in each market. Columns (2)-(3) and (5)-(6) report the estimates of the above median and below median HRRs by market-level spending, weighted by the number of Original Medicare beneficiaries in the market. Panel A reports estimates of the shares of utilization that are the variance of PCP fixed effects and the covariance of PCP fixed effects and patient fixed effects as the weighted means of the corresponding estimates across the within-market estimations, and the standard errors are computed accordingly. The standard deviation of the PCP fixed effects is imputed to be zero in markets where the point estimate of the variance of PCP fixed effects is negative. The sample is the connected set for quarterly utilization that omits the switch period in Column (2) of Table 1.4 that remains connected when each patient-PCP pair is excluded. Markets are hospital referral regions (HRRs).

Table A.11: Switching Costs Results: Sample Comparison

Switch Type		Total Switching Costs by Sample and Cost Interval ($, multi-market mean, SE in parentheses)								
Pre/Post Qtrs. for Bal. Panel:		4 Pre / 6 Post		6 Pre / 8 Post			8 Pre / 12 Post			
Pre/Post Qtrs. for Cost Calc.:		4 / 6	Switches	4 / 6	6 / 8	Switches	4 / 6	6 / 8	8 / 12	Switches
Vol.	Switch Prac. Grp.	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
No	No	544.58	817	476.90	499.36	531	1139.10	1485.50	1676.84	246
		(40.28)		(24.42)	(29.45)		(199.71)	(281.68)	(306.38)	
No	Yes	633.94	1055	653.64	725.73	678	716.22	844.99	1187.14	328
		(18.98)		(28.96)	(40.07)		(91.42)	(104.25)	(164.95)	
Yes	No	646.21	1216	659.72	691.62	808	594.71	641.01	717.41	381
		(18.39)		(22.64)	(26.52)		(31.15)	(36.02)	(43.90)	
Yes	Yes	1014.69	2726	1007.77	1066.42	1806	982.09	1050.81	1154.00	867
		(14.13)		(17.25)	(19.74)		(26.66)	(29.65)	(34.20)	
# patient-qtrs. (mean/mkt):			495,034			493,547				492,097

Notes: This table reports the switching costs estimates from 306 within-market event study regressions weighted by the number of Original Medicare beneficiaries in each market as described in Section 2.3.1. Columns (1), (3)-(4), and (6)-(8) report results for total utilization. Columns (6)-(8) include only 305 within-market event study regressions due to a switch type sample limitation. Each market-level event study regression includes a primary care physician (PCP) fixed effect, a patient fixed effect, sets of event time indicators corresponding to types of switches, and controls for age, gender, and date/cohort. Each market-level event study regression includes a set of event time indicators for each of the four switch types in the table that are assigned to a balanced panel of patients who are consistently matched with the origin PCP for the specified number of pre-switch quarters before the switch and the destination PCP for the specified number of post-switch quarters after a switch. The estimated event time coefficients are then used to calculate the total switching costs over the specified pre-switch quarters, quarter of the switch, and post-switch quarters in levels of dollar utilization. The event study regressions have robust standard errors three-way clustered by patient, by main PCP, and by quarter. The standard errors for each set of within-market switching cost estimates are calculated using the delta method, allowing for correlation among the four sets of event time coefficients corresponding to the four types of switches. When the within-market estimates are aggregated by weight, the standard errors are calculated accordingly. The sample is the connected set for quarterly utilization that does not omit the switch period in Column (3) of Table 1.4.

Table A.12: Switching Costs Results by Utilization Category, Involuntary and Voluntary Pooled

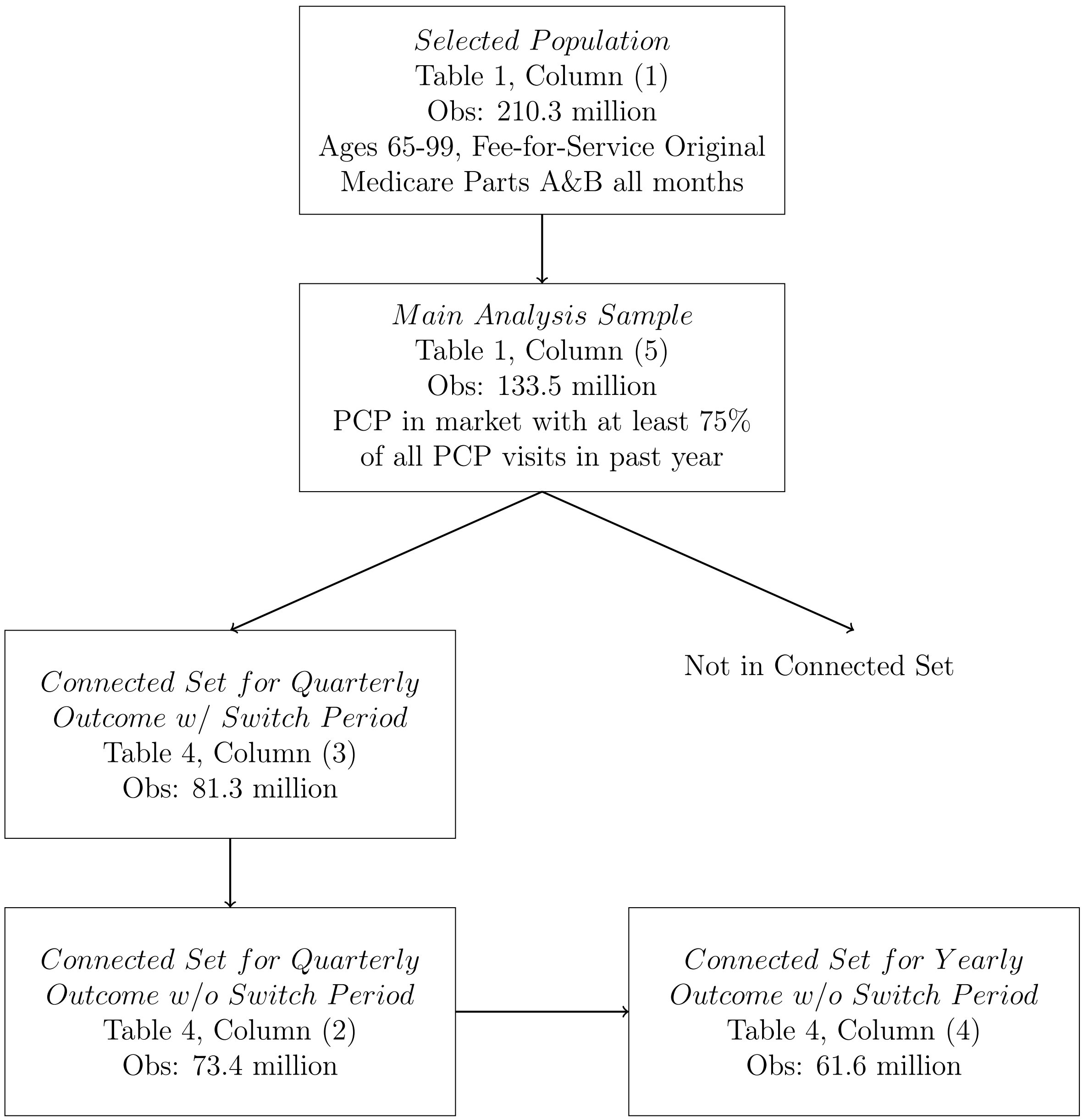
	Switching Costs by Category ($, multi-market mean, SE in parentheses)							# Switches	Within-Mkt
Switch	Total	Prim. Care.	Tests	Imaging	Emerg.	Hosp.	Spec. Care.	(mean/mkt)	Regressions
Practice Grp.	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
No	550.38	144.25	32.47	10.94	0.90	0.72	14.85	1,339	306
	(18.27)	(2.76)	(1.28)	(0.61)	(0.10)	(0.08)	(1.27)		
Yes	891.05	179.40	38.53	18.81	3.50	1.80	25.57	2,485	306
	(14.86)	(2.15)	(0.82)	(0.46)	(0.33)	(0.07)	(0.86)		
# patient-quarter obs. including switchers and non-switchers (mean/market):									493,547

Notes: This table reports the switching costs estimates from 306 within-market event study regressions weighted by the number of Original Medicare beneficiaries in each market as described in Section 2.3.1. Columns (1)-(7) report results with different utilization outcome measures: total, primary care, tests, imaging, emergency department, hospital inpatient, and specialty care. Each market-level event study regression includes a primary care physician (PCP) fixed effect, a patient fixed effect, sets of event time indicators corresponding to types of switches, and controls for age, gender, and date/cohort. Each market-level event study regression includes a set of event time indicators for each of the two switch types in the table assigned to a balanced panel of patients who are consistently matched with the origin PCP for 6 quarters before the switch and the destination PCP for 8 quarters after a switch, where event time 0 is the last quarter that a patient is matched with the origin PCP. The estimated event time coefficients are then used to calculate the total switching costs over the 15 quarters in levels of dollar utilization. The event study regressions have robust standard errors three-way clustered by patient, by main PCP, and by quarter. The standard errors for each set of within-market switching cost estimates are calculated using the delta method, allowing for correlation among the two sets of event time coefficients corresponding to the two types of switches. When the within-market estimates are aggregated by weight, the standard errors are calculated accordingly. The sample is the connected set for quarterly utilization that does not omit the switch period in Column (3) of Table 1.4.

Appendix B

Additional Figures

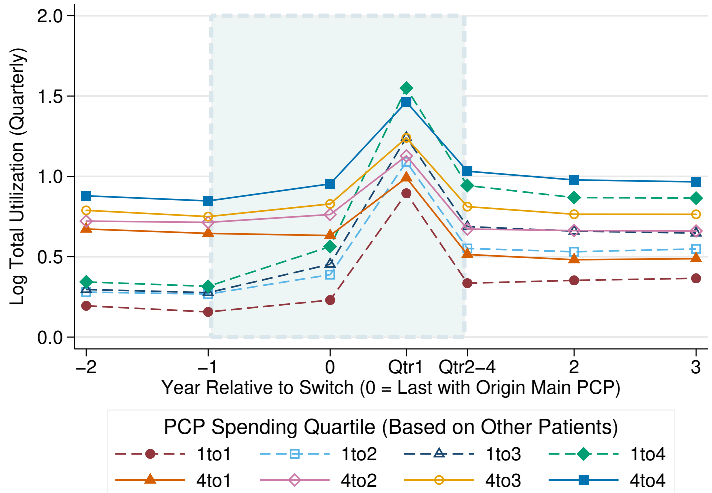
Figure B.1: Relationships among Samples



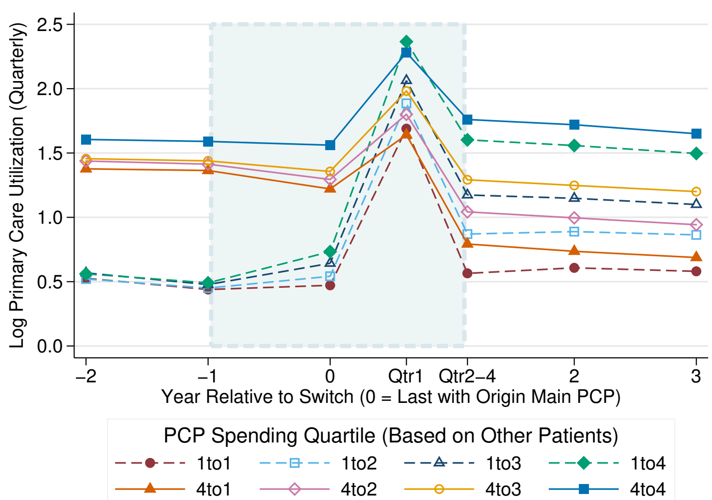
Notes: This figure illustrates the relationships among samples, where the arrows indicate subsets of samples. The *selected population* is restricted to (a) years 2002-2011 and (b) patient-quarters during which patients are 65-99 years old and are enrolled in traditional fee-for-service (Original) Medicare Parts A and B coverage in all three months as described in Section 1.2.5. The *main analysis sample* is restricted to patient-quarters during which the patient is assigned a main PCP in the same HRR who they visit for at least 75% of PCP visits over the past year as described in Section 1.2.5. The connected set samples are those described and used in Sections 1.5 and 2.3.

Figure B.2: Event Study Representation of Primary Care Physician (PCP) Switches

(a) Total Utilization



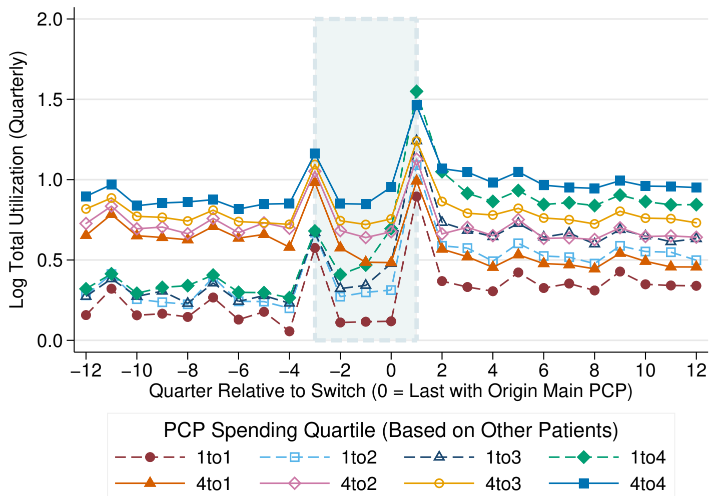
(b) Primary Care Utilization



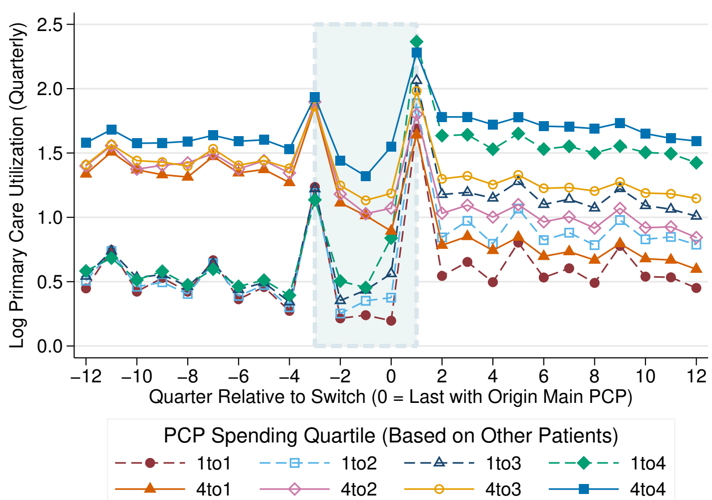
Notes: These figures present the mean demographics-adjusted log utilization for patients who switch PCPs as described in Section 1.3.1. The sample includes only consistent patient-PCP matches, who are assigned the origin PCP for 12 quarters before the switch and the destination PCP for 12 quarters after the switch as described in Column (3) of Table 1.6. Each of the patients who switch is classified into quartiles, defined within markets, by their origin PCP's other patients ("copatients") in a pre-switch period (year -1) and their destination PCP's copatients in a post-switch period (year 2). Quarters are binned into years, such that year 0 includes the last 4 quarters with a patient's origin PCP. The first quarter with the destination PCP is separated from the remainder of the year. Log utilization is adjusted for utilization for patient age, gender, and cohort/date.

Figure B.3: Event Study Representation of PCP Switches (Quarterly Level)

(a) Total Utilization



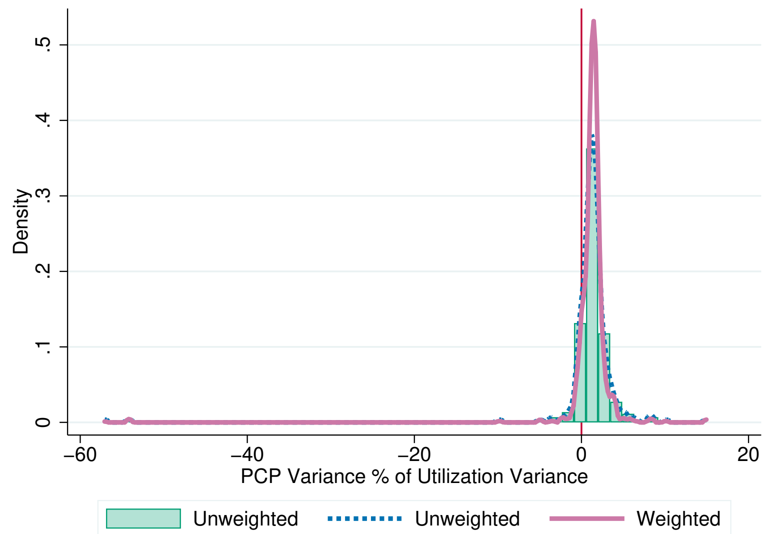
(b) Primary Care Utilization



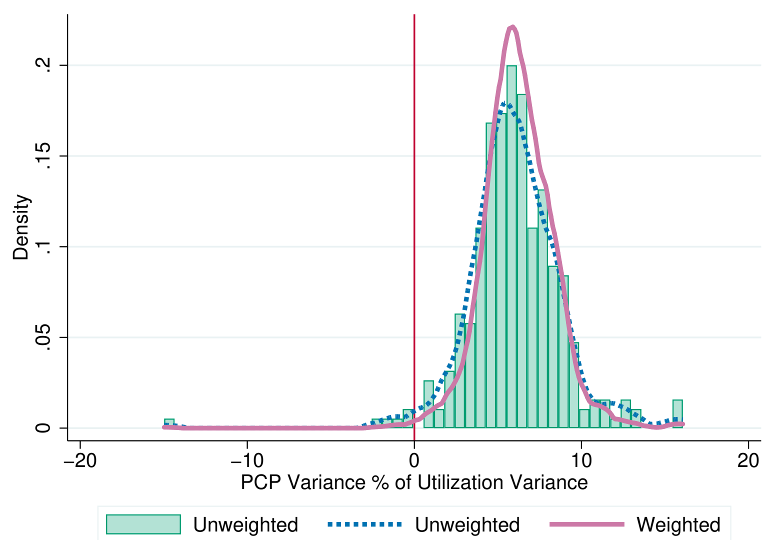
Notes: These figures present the mean demographics-adjusted log utilization for patients who switch PCPs. The sample includes only consistent patient-PCP matches, who are assigned the origin PCP for 12 quarters before the switch and the destination PCP for 12 quarters after the switch as described in Column (3) of Table 1.6. Each of the patients who switch is classified into quartiles, defined within markets, by their origin PCP's other patients ("copatients") in a pre-switch period (year -1) and their destination PCP's copatients in a post-switch period (year 2). For clarity, I include only switchers from quartile 1 and quartile 4. Log utilization is adjusted for utilization for patient age, gender, and cohort/date.

Figure B.4: Variance Distribution: Quarterly Utilization Estimates

(a) Total Utilization



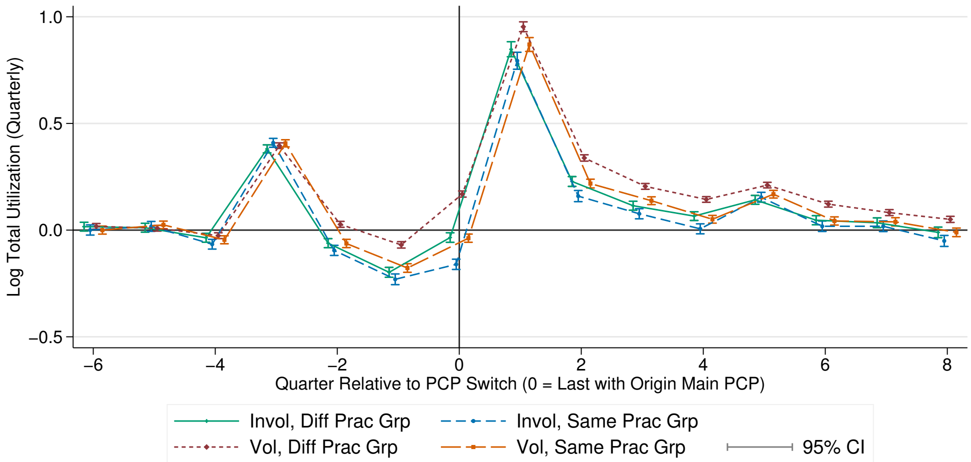
(b) Primary Care Utilization



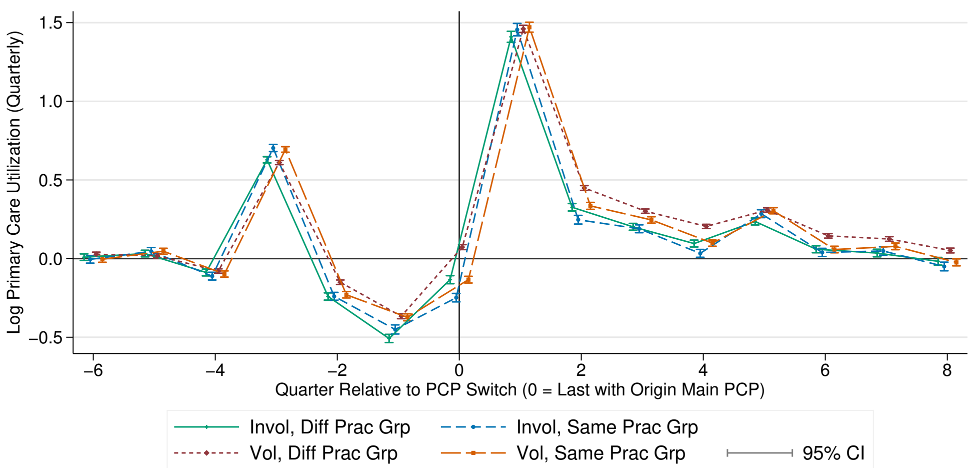
Notes: Each of these figures presents the distribution of 306 within-market estimated variances of primary care physician (PCP) fixed effects as shares of the total variance of utilization. The variance estimates come from a two-way fixed effects model with patient fixed effects and PCP fixed effects. The estimation uses patient-quarter level observations in the leave-out patient-PCP match procedure described in Section 1.5.1. The outcome variable in the estimations is the *log of quarterly utilization*. In Panel (a), the outcome variable is the *log of quarterly total utilization* and the estimates correspond with the results in Columns (1)-(3) of Table A.9. In Panel (b), the outcome variable is the *log of quarterly primary care utilization* and the estimates correspond with the results in Columns (4)-(6) of Table A.9. The histogram is unweighted, and the kernel density plots are unweighted and weighted by the number of Original Medicare beneficiaries in each market.

Figure B.5: Switching Costs: Total and Primary Care Utilization

(a) Total Utilization



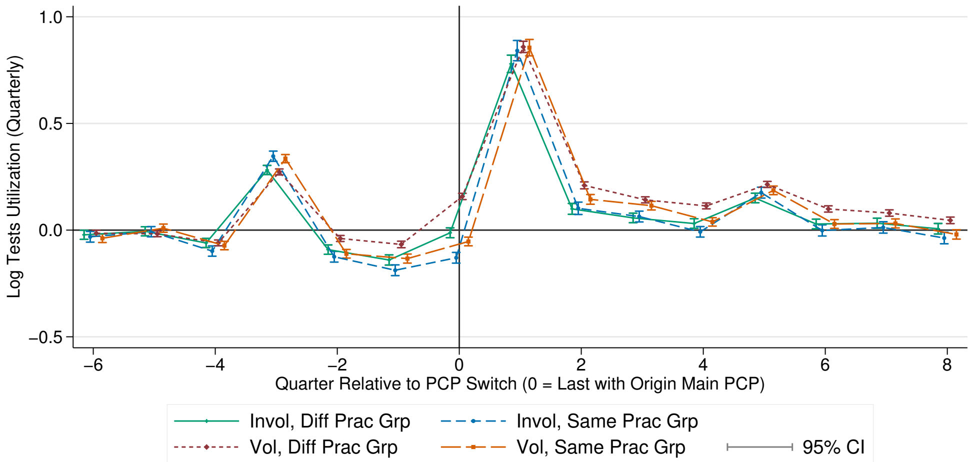
(b) Primary Care Utilization



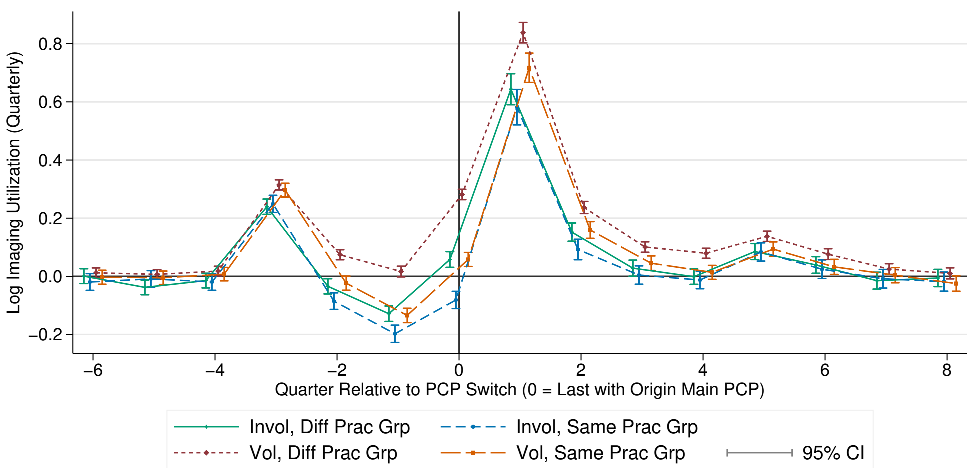
Notes: Each of these figures plots the event study estimates from 306 within-market event study regressions weighted by the number of Original Medicare beneficiaries in each market as described in Section 2.3.1. The outcome variable in the regressions is the *log of quarterly utilization*. In Panel (a), the outcome variable is the *log of quarterly total utilization*. In Panel (b), the outcome variable is the *log of quarterly primary care utilization*. Each event study regression includes a primary care physician (PCP) fixed effect, a patient fixed effect, sets of event time indicators corresponding to types of switches, and controls for age, gender, and date/cohort. For each of the switch type, the event study regression includes a set of event time indicators for a balanced panel of patients who are always assigned the origin PCP for 6 quarters before the switch and the destination PCP for 8 quarters after a switch. The sample is the connected set for quarterly utilization that does not omit the switch period in Column (3) of Table 1.4.

Figure B.6: Switching Costs: Tests and Imaging Utilization

(a) Tests Utilization



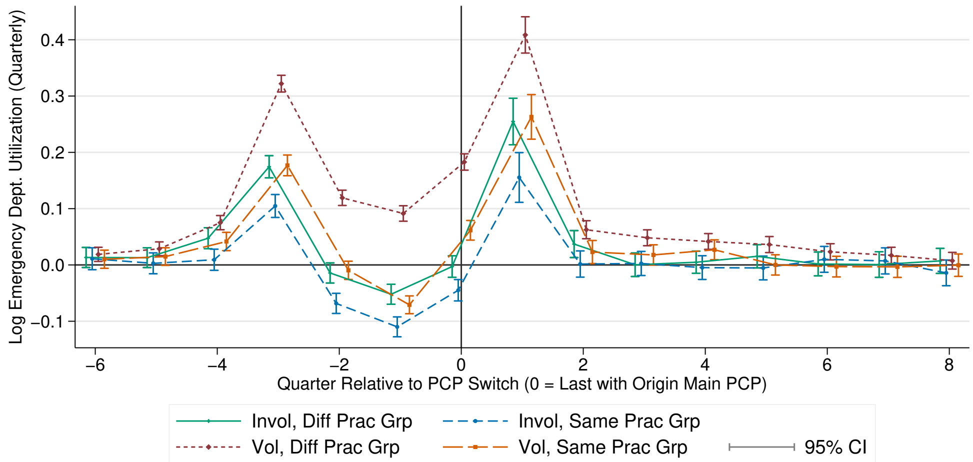
(b) Imaging Utilization



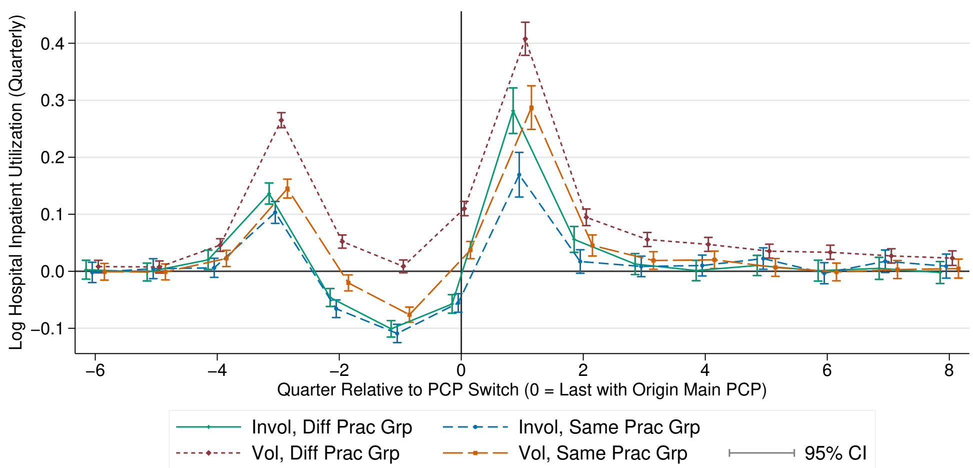
Notes: Each of these figures plots the event study estimates from 306 within-market event study regressions weighted by the number of Original Medicare beneficiaries in each market as described in Section 2.3.1. The outcome variable in the regressions is the *log of quarterly utilization*. In Panel (a), the outcome variable is the *log of quarterly tests utilization*. In Panel (b), the outcome variable is the *log of quarterly imaging utilization*. Each event study regression includes a primary care physician (PCP) fixed effect, a patient fixed effect, sets of event time indicators corresponding to types of switches, and controls for age, gender, and date/cohort. For each of the switch type, the event study regression includes a set of event time indicators for a balanced panel of patients who are always assigned the origin PCP for 6 quarters before the switch and the destination PCP for 8 quarters after a switch. The sample is the connected set for quarterly utilization that does not omit the switch period in Column (3) of Table 1.4.

Figure B.7: Switching Costs: Emergency Department and Hospital Inpatient Utilization

(a) Emergency Department Utilization



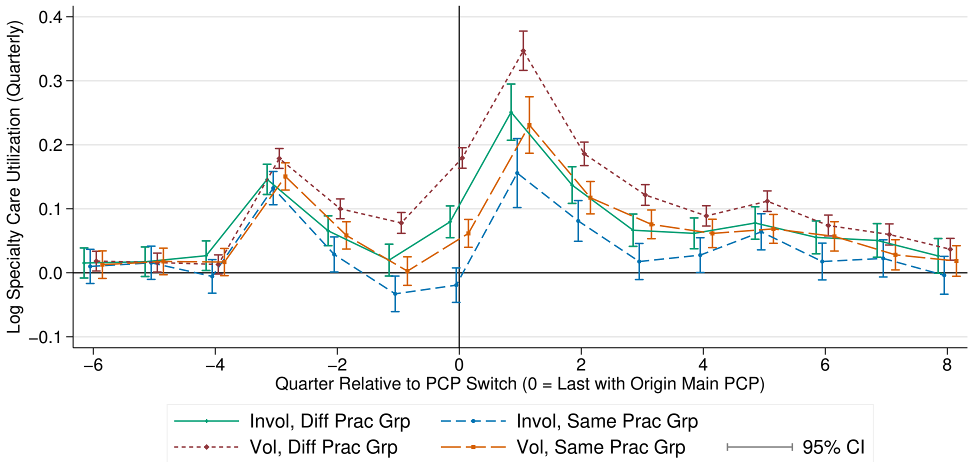
(b) Hospital Inpatient Utilization



Notes: Each of these figures plots the event study estimates from 306 within-market event study regressions weighted by the number of Original Medicare beneficiaries in each market as described in Section 2.3.1. The outcome variable in the regressions is the *log of quarterly utilization*. In Panel (a), the outcome variable is the *log of quarterly emergency department utilization*. In Panel (b), the outcome variable is the *log of quarterly hospital inpatient utilization*. Each event study regression includes a primary care physician (PCP) fixed effect, a patient fixed effect, sets of event time indicators corresponding to types of switches, and controls for age, gender, and date/cohort. For each of the switch type, the event study regression includes a set of event time indicators for a balanced panel of patients who are always assigned the origin PCP for 6 quarters before the switch and the destination PCP for 8 quarters after a switch. The sample is the connected set for quarterly utilization that does not omit the switch period in Column (3) of Table 1.4.

Figure B.8: Switching Costs: Specialty Care Utilization

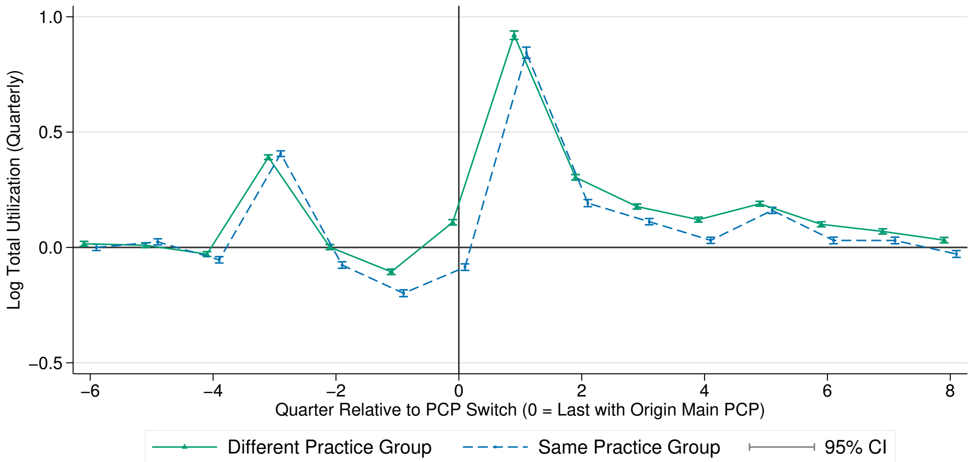
(a) Specialty Care Utilization



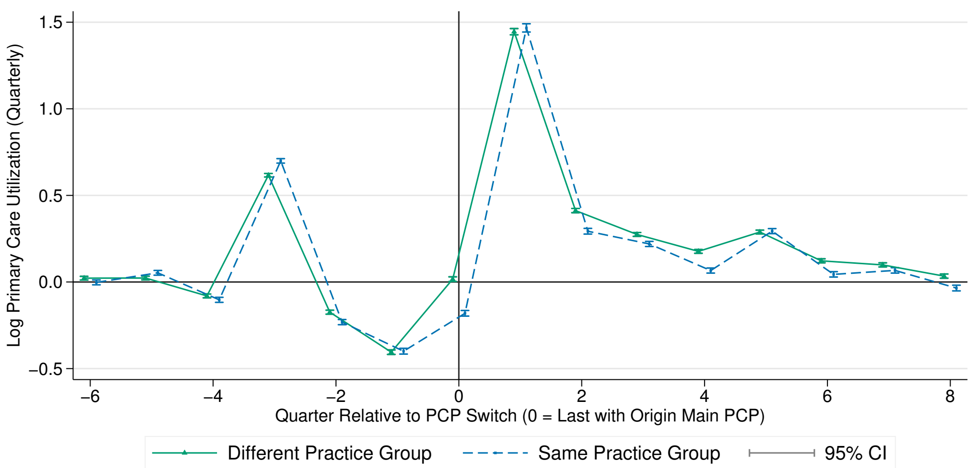
Notes: This figures plots the event study estimates from 306 within-market event study regressions weighted by the number of Original Medicare beneficiaries in each market as described in Section 2.3.1. The outcome variable in the regressions is the *log of quarterly utilization*. In Panel (a), the outcome variable is the *log of quarterly specialty care utilization*. Each event study regression includes a primary care physician (PCP) fixed effect, a patient fixed effect, sets of event time indicators corresponding to types of switches, and controls for age, gender, and date/cohort. For each of the switch type, the event study regression includes a set of event time indicators for a balanced panel of patients who are always assigned the origin PCP for 6 quarters before the switch and the destination PCP for 8 quarters after a switch. The sample is the connected set for quarterly utilization that does not omit the switch period in Column (3) of Table 1.4.

Figure B.9: Switching Costs: Combined Involuntary and Voluntary Switchers

(a) Total Utilization



(b) Primary Care Utilization



Notes: Each of these figures plots the event study estimates from 306 within-market event study regressions weighted by the number of Original Medicare beneficiaries in each market as described in Section 2.3.1 in which the involuntary and voluntary switchers share a set of event time indicators. The outcome variable in the regressions is the *log of quarterly utilization*. In Panel (a), the outcome variable is the *log of quarterly total utilization*. In Panel (b), the outcome variable is the *log of quarterly primary care utilization*. Each event study regression includes a primary care physician (PCP) fixed effect, a patient fixed effect, sets of event time indicators corresponding to types of switches, and controls for age, gender, and date/cohort. For each of the switch type, the event study regression includes a set of event time indicators for a balanced panel of patients who are always assigned the origin PCP for 6 quarters before the switch and the destination PCP for 8 quarters after a switch. The sample is the connected set for quarterly utilization that does not omit the switch period in Column (3) of Table 1.4.

Appendix C

Additional Information

C.1 Model of Healthcare Demand and Supply

I extend healthcare demand and supply model from Finkelstein, Gentzkow, and Williams (2016) – henceforth FGW – to explicitly capture dynamics of patients switching physicians. I present one modification to introduce a parameter that captures switching costs, though there are other modifications that could yield the same econometric model defined in Section 1.4.1.

On the demand side, patient i in time t utilizes health care $y_{it} \in \mathbb{R}^{+}$. Patients differ along several dimensions: health status h_{it}, physician switching status s_{it}, preferences η_i, and physician $j(i,t)$. I introduce physician switching status s_{it} to capture differences in information acquisition, productivity, etc. associated with new physician-patient relationship.

Consistent with FGW, I assume patients' expected continuation utility $u()$ is

$$u(y_{it}|h_{it}, s_{it}, \eta_i) = -\frac{1}{2}(y_{it} - (h_{it} + s_{it}))^2 + \eta_i y_{it}$$

such that $u()$ is maximized at $y^*_{it} = h_{it} + s_{it} + \eta_i$, level of care patient would choose if fully informed and faced a zero out-of-pocket price for care.

On the supply side, physician $j(i,t)$ in time t chooses health care $y_{it} \in \mathbb{R}^{+}$ with

$$y_{it} = \arg\max_y \tilde{u}_{j(i,t)}(y_{it}|h_{it}, s_{it}, \eta_i) - PC_{j(i,t),t}(y_{it})$$

As in FGW, $\tilde{u}_{j(i,t)}(y_{it})$ is the perceived utility of patients, and $PC_{j(i,t),t}(y_{it})$ is the normal (net, private) costs of care provision. Maximization of the physician's decision problem yields:

$$y_{it} = h_{it} + s_{it} + \eta_i + \lambda_{j(i,t)} - PC'_{j(i,t),t}()$$

The model can be written as the following two-way fixed-effect model, with two key assumptions, such that $p_{it}\delta$ capture the costs of switching physicians

$$y_{it} = \alpha_i + \gamma_j + \tau_t + x_{it}\beta + p_{it}\delta + \epsilon_{it}$$

Following FGW, I assume that the expectation of $y^*_{it} = h_{it} + s_{it} + \eta_i$ depends only on a patient fixed effect α_i, time-varying observables x_{it}, and indicators for periods pre/post-switch p_{it},

such that $E\left[y_{it}^{*} \middle| \{i, t, x_{it}, p_{it}\}\right] = \alpha_i + x_{it}\beta + p_{it}\delta$. As in FGW, I also assume $PC_{jt}()$ is linear in y and additively separable in j and t, with $\gamma_j + \tau_t = \lambda_j - PC'_{jt}()$.
In my setting, the $p_{it}\delta$ are the event study indicators defined in Sections 1.4.1 and 2.3.1.

C.2 Practice Style Variation in Quarterly Utilization Sample and Results

This section discusses the sample and results for the quarterly utilization outcome measure. As for the yearly utilization outcome measure, I omit any observation that would include part of a switch period in its outcome measure, which means that I omit five periods of outcomes (i.e., event times -3 to +1, where 0 is defined as the last quarter a patient is assigned their origin PCP).[1] Column (2) of Table 1.4 reports the descriptive statistics for this sample, which are similar to those for yearly utilization outcomes in Column (4) of Table 1.4. Figure B.1 illustrates the relationship of this sample to others used in this dissertation.

Table A.9 reports the results for quarterly total utilization and quarterly primary care utilization. Figure B.4 reports the distribution of the estimated variances across markets. Differences in PCP practice styles explain 1.2% of variance in total quarterly utilization and 6.2% of the variance in primary care quarterly utilization on average across markets, which are approximately half of the corresponding percentages estimated for yearly utilization. This difference primarily comes from the greater variability in quarterly utilization data.[2]

I compare the total utilization and primary care utilization results to other categories of healthcare utilization, specifically tests and imaging, which PCPs often use for diagnosis and preventive care. Table A.10 reports the results for tests utilization and imaging utilization. Differences in PCP practice styles explain substantially less of the variation in tests utilization than in primary care utilization, but more than in total utilization or in imaging. Differences in PCP practice styles explain about the same amount of the variation in imaging as they do in total utilization.

C.3 Data and Variable Details

C.3.1 Physician Data Sources

I use several additional physician datasets for physician characteristics and physician practice group characteristics.

- CMS Medicare Data on Provider Practice and Specialty (MD-PPAS). This dataset uses the physician national provider identifier (NPI) and the physician billing tax identification number (TIN), which I use to define physician practice groups. The file

[1] One advantage is that this contemporaneous quarterly estimation reduces the number of observations I exclude in order to fully omit the "switch period." The disadvantages are that there is more noise in quarterly utilization data and some observations have zero utilization.

[2] The results on yearly utilization data from Section 1.6 are more interpretable and relevant from a policy perspective.

assigns Medicare providers to medical practices based on tax identification numbers (TINs) and provides information provider specialty classification.

- CMS National Plan and Provider Enumeration System (NPPES). This dataset is publicly available and uses the physician national provider identifier (NPI). The dataset provides links to the CMS Unique Physician Identification Number (UPIN), physician names, and other physician identifiers.[3]
- Unique Physician Identification Number (UPIN) Directory. This dataset uses the physician Unique Physician Identification Number (UPIN). The dataset provides information on the physician full name, specialty, license state code, zip code, Medicare provider billing number, and state.[4]
- Unique Physician Identification Number (UPIN) Group File. This dataset uses the physician practice group Unique Physician Identification Number (UPIN). The dataset provides information on the physician practice group.[5]
- American Medical Association (AMA) Physician Masterfile.[6] The dataset provides information on the education, training and professional certification of Doctors of Medicine (MD) and Doctors of Osteopathic Medicine (DO).

C.3.2 Physician Definitions

C.3.2.1 Identification of Physicians

I identify unique physicians using the Carrier (Physician/Supplier Part B claims) data, which include information on the performing provider. The most direct way to identify the performing physician is to use the physician Unique Provider Identification Number (UPIN) until 2007 and the physician National Provider Identifier (NPI) starting in 2007.

The main challenge is that the performing UPIN or NPI may not be entered correctly or represent the performing provider. In some cases, primarily in earlier years, (a) physician group practices may have systematically entered the incorrect physician UPIN when it was not tied to reimbursement (e.g., selecting the physician at the top of an alphabetical list rather than the actual performing physician), and (b) nurse practitioners (NPs) and physician assistants (PAs) billed under a physician NPI rather than their own NPIs.

The National Bureau of Economic Research (NBER) offers a crosswalk between the UPIN and the NPI based on the CMS National Plan and Provider Enumeration System (NPPES).[7] I verify and improve upon the crosswalk by using additional information from various CMS datasets. I use physician names from the UPIN Member File, the Medicare Physician Identification and Eligibility Records (MPIER) file, and the Medicare Data on Provider Practice and Specialty (MD-PPAS).

[3]Source: https://www.cms.gov/Regulations-and-Guidance/Administrative-Simplification/NationalProvIdentStand/DataDissemination.html. Additional information on the file is available at: https://www.nber.org/data/npi.html.

[4]Source: https://healthdata.gov/dataset/unique-physician-identification-number-upin-directory.

[5]Source: https://healthdata.gov/dataset/upin-group-file.

[6]Source: https://www.ama-assn.org/life-career/ama-physician-masterfile.

[7]Source: http://www.nber.org/data/npi-upin-crosswalk.html.

C.3.2.2 Specialty Classification

I classify physicians based on the CMS (formerly Health Care Finance Administration (HCFA)) provider specialty codes in the Carrier data associated with line items of claims.[8] Primary care physicians are identified by general practice (01), family practice (08), internal medicine (11), or geriatric medicine (38).

C.3.3 Claims Data

My outcome measures include the following categories.

- Total utilization. Total utilization includes all physician claims, inpatient claims, and outpatient claims. Total utilization excludes skilled nursing facility, home health care, hospice, and durable medical equipment claims

- Primary care utilization. Primary care consists of Evaluation and Management (E&M) line items in claims associated with physician who have a primary care specialty: general practice (01), family practice (08), internal medicine (11), osteopathic manipulative therapy (12), pediatric medicine (37), geriatric medicine (38), public health or welfare agencies (federal, state, and local) (60), preventive medicine (84), nurse practitioner (50), and physician assistant (97). Primary care utilization includes but is not limited to services provided by main PCPs.

- Tests. Tests consists of Carrier claims with Berenson-Eggers Type of Service (BETOS) codes that begin with the letter "T" and outpatient claims with HCPCS codes that correspond to BETOS codes that begin with the letter "T."[9]

- Imaging. Imaging consists of Carrier claims with Berenson-Eggers Type of Service (BETOS) codes that begin with the letter "I" and outpatient claims with HCPCS codes that correspond to BETOS codes that begin with the letter "I."

- Emergency department visits. Emergency department claims include outpatient claims and inpatient claims.

- Inpatient hospitalization. Inpatient hospitalization claims include claims in the Inpatient file that are not classified as emergency department visits.

- Speciality care. Specialty care consists of Evaluation and Management (E&M) line items in claims associated with physician who have a medical specialty or a surgical specialty. Medical specialties include: allergy/immunology (03), cardiology (06), dermatology (07), gastroenterology (10), neurology (13), physical medicine and rehabilitation (25), psychiatry (26), pulmonary disease (29), nephrology (39), infectious disease (44), endocrinology (46), rheumatology (66), slide preparation facilities (75),

[8] Source: https://www.cms.gov/Medicare/Provider-Enrollment-and-Certification/MedicareProviderSupEnroll/Downloads/TaxonomyCrosswalk.pdf.

[9] BETOS codes are assigned for each Health Care Financing Administration Common Procedure Coding System (HCPCS) procedure code. Source: https://www.cms.gov/Research-Statistics-Data-and-Systems/Statistics-Trends-and-Reports/MedicareFeeforSvcPartsAB/downloads/betosdesccodes.pdf.

addiction medicine (79), critical care(81), hematology (82), hematology/oncology (83), neuropsychiatry (86), and medical oncology (90). Surgical specialties include: general surgery (02), otolaryngology (04), interventional pain management (09), neurosurgery (14), obstetrics/gynecology (16), ophthalmology (18), oral surgery (19), orthopedic surgery (20), plastic and reconstructive surgery (24), colorectal surgery (28), thoracic surgery (33), urology (34), hand surgery (40), ambulatory surgical center (49), peripheral vascular disease (76), vascular surgery (77), cardiac surgery (78), maxillofacial surgery (85), surgical oncology (91), and gynecologist/oncologist (98).