On Resource Allocation in Health Care:
The Case of Concierge Medicine

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Abstract

Resource allocation generally involves a tension between efficiency and equity, particularly in health care. The growth in exclusive physician arrangements using non-linear prices is leading to consumer segmentation with theoretically ambiguous welfare implications. We study *concierge medicine*, in which physicians only provide care to patients paying a retainer fee. We find limited evidence of selection based on health and stronger evidence of selection based on income. Using a matching strategy that leverages the staggered adoption of concierge medicine, we find large spending increases and no average mortality effects for patients impacted by the switch to concierge medicine.

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1. Introduction

Markets do not always allocate resources in ways that people judge to be fair, even if goods and services are distributed to members of society who would benefit from them the most (Kahneman, Knetsch, and Thaler 1986). In particular, many markets have evolved to produce a range of products that offer higher quality and amenities to those with sufficient willingness to pay (Schwartz 2020). Some pricing strategies to improve allocative efficiency and maximize profit are not very controversial: airline status for frequent flyers, loyalty and rewards programs for repeatedly engaging with a brand, or two-part tariffs in wholesale and online retail, for example. The efficiency and equity consequences of other pricing developments are less clear, particularly in areas more closely tied to goods such as education, criminal justice, and health.[1]

Motivated by these issues, we study a growing trend in the health care industry that provides greater access to care for those willing to pay an additional retainer fee. The contracts are often called "concierge medicine" and resemble a membership model: patients receive same-day appointments with the physician, longer visits, and other amenities in return for a membership fee. Physicians reduce the number of patients they routinely see to devote more attention to patients paying the fee.[2] While such pricing models are common in markets for many professional services (e.g., financial advisors, lawyers), they have historically been absent for physician services. Survey evidence estimates 7 percent of U.S. adults are enrolled in a concierge practice (Blendon 2020). Despite the growth of the model, research on concierge medicine is sparse, likely due to data limitations and its recent emergence.

In theory, concierge medicine can serve as a vehicle for improved efficiency. It provides a price mechanism to segment the population based on the value that different patients place on access, as reflected in willingness to pay.[3] This new model may improve health outcomes if willingness to pay reflects the sensitivity of the patient's health to improved access, and scarce provider time can be allocated to patients for whom increased attention is most beneficial. For

[1] In the United States, some parents had privately hired public school teachers to teach small groups of children during the pandemic for $125,000 per year. See, for example, David Zweig "$25,000 Pod Schools: How Well-to-Do Children Will Weather the Pandemic." *New York Times*. July 30, 2020.

[2] Most concierge physicians continue to bill insurance and use the membership fee to make up for lost revenue from reducing the number of patients they regularly see, from roughly 2,500 to less than 600. To some extent, concierge medicine has the features of a club good (Buchanan 1965) since the fee makes it excludable and the sufficiently small number of patients makes it non-rivalrous.

[3] See Tirole (1988), Varian (1989), Wilson (1993), and Stole (2007) for surveys on the theories studying the use of non-linear pricing schedules to discriminate based on consumer willingness to pay.

example, more time and access to the physician may reduce expensive costs like emergency room use and hospital admissions (van Loenen et al. 2014). On the other hand, health may not improve if willingness to pay instead reflects the value patients derive from other attributes of the model, such as convenience, service excellence, or amenities. In addition, patients who do not pay the membership fee (which we also refer to as the retainer fee) experience discontinuities in care that may be detrimental to health. Some people have raised equity concerns about sorting based on wealth.[4]

In this paper, we empirically analyze concierge medicine using Medicare insurance claims merged with novel data from a large concierge medicine company. We combine Medicare insurance claims with information on the exact timing of over 225 physicians switching to concierge medicine, provided by a large company that manages concierge practices. We use detailed claims information to first document the nature of patient selection into concierge medicine based on patient health status and income (at the zip-code level) prior to the switch. We employ machine learning methods to classify patients into groups of better or worse health according to their spending predicted by demographics and diagnoses of chronic conditions.

We then measure the change in spending and mortality through a series of event studies. Our identification strategy leverages the staggered timing of physicians switching from traditional models of primary care to concierge medicine. We compare patients of physicians who switch during our study period to observationally similar patients of physicians who switch to the same concierge company after our study period, using coarsened exact matching (Blackwell et al. 2009, Iacus, King, and Porro 2011). Our main analysis focuses on all patients of the physician's practice, regardless of whether they pay the fee to join or do not pay the fee and exit. We subsequently analyze the experiences of patients who elect to pay the membership fee and those who do not and leave the practice.

The health care industry adds important context to study these issues because it is the largest sector of the economy, and because it is one where many people question whether scarce resources should be allocated based on willingness to pay. Within the health care industry, primary care provides an important setting to study concierge medicine. Many patients place a high value on the relationship with their primary care physician (Sabety 2022) and issues of access and how to best allocate primary care providers are highly salient (Tai-Seale and McGuire 2012). Unlike

[4] See, for example, Nelson Schwartz "The Doctor Is In. Co-Pay? $40,000." *The New York Times*. June 3, 2017.

specialists, primary care physicians perform few procedures that are highly reimbursed, and instead generate revenues primarily on patient volume. Physicians in traditional practices often spend less than 15 minutes with each patient, in part because insurers do not generously reimburse longer visits (Yawn et al. 2003, Irving et al. 2017). Rushed appointments are a source of dissatisfaction by both patients and physicians and contribute to an increased prevalence of physician burnout, which exacerbates an existing shortage of primary care physicians (Bodenheimer 2010, Prasad et al. 2020).[5] Recent studies point to reductions in quality of care due to time pressures among primary care physicians (Neprash 2017, Freedman et al. 2021). Such time pressures are fundamentally linked to the high cost of care in the U.S., as shorter visits may mean insufficient time to listen, diagnose, and solve problems, which can result in excess testing, unnecessary prescriptions, and frequent referrals to specialists (Linzer et al. 2015).

Our paper has three main findings. First, there is limited patient selection into concierge medicine based on health status. We find evidence that income (at the level of patient zip code) has a stronger influence on the decision for patients to pay the retainer fee to join. Second, concierge medicine increases total health care spending. The increase is large starting in the year after the switch and grows to 30-50% higher compared to before the switch. Third, we find no evidence that concierge medicine leads to mortality changes, on average.

This paper is the first within the economics literature to study selection into concierge medicine and empirically measure its effects on health care spending and mortality. The subject has received policy discussion in the popular press and medical journals.[6] A handful of studies in medical journals, mostly performed in collaboration with the leadership of concierge medicine companies, have documented its members have significantly higher satisfaction rates from their encounters with their physician and reductions in hospitalization rates (Klemes et al. 2012, Klemes and Solomon 2015, Morefield et al. 2020). These studies' research designs do not account for selection and do not study patients who elect not to join concierge medicine, limiting what inferences can be drawn from the results. While other studies have examined different aspects of

[5] One national survey reported that four out of five physicians are overextended and often experience burnout (The Physicians Group 2018). In another survey focusing on key challenges in primary care, nearly one-half of U.S. physicians reported dissatisfaction with the amount of time spent with patients; a third claimed dissatisfaction with practicing medicine at large (Osborn et al. 2015).

[6] See, for example, Alexander et al. (2005), Majette (2009), French et al. (2010), Lucier et al. (2010), DuBois, Kraus, and Bakanas (2012), Simmons-Duffin (2020), among others.

allocative efficiency in health care, such as the ability of market forces to steer consumers to higher-quality hospitals (Chandra et al. 2016) or to match patients to surgeons who specialize in different treatments (Chandra and Staiger 2007), our focus on primary care—the most common point of contact for patients in the health care system—can inform broader discussions about current and future access to preventative care. Our paper also relates more broadly to the literature on non-linear pricing in markets for products and services.[7]

The paper proceeds as follows. Section 2 lays out a conceptual framework of patient selection into concierge medicine and the implications of selection for population health. Section 3 describes the specific concierge medicine company we study and provides an overview of the data and descriptive statistics. Section 4 analyzes selection into concierge medicine and Section 5 presents results for spending and mortality using the matched sample. Section 6 concludes with a brief discussion of our findings and presents directions for future research.

2. Conceptual Framework

We develop a stylized model in which patient selection into concierge medicine is based on their willingness to pay for more personalized and enhanced care. The two key determinants of patient willingness to pay for enhanced access are their levels of health and wealth. The purpose of the model is to illustrate how introducing a retainer fee can affect selection on these two dimensions. Whether selection occurs based on wealth, health, or both has implications for considering how concierge medicine affects equity in health care relative to other ways of allocating physician attention.

First consider selection by health. The value of accessing care is an important part of achieving better health outcomes and controlling long-term health care costs. In practice, access to care varies by geography, demographics, and insurance coverage. Access to care is more valuable the more likely a patient is to require a medical intervention, which is a function of their health condition. For this reason, we assume sicker people value timely access to high quality care more so than healthier individuals, consistent with the results of contingent valuation studies (Steigenberger et al. 2022). Sicker members are therefore more likely to choose concierge

[7] See Lambrecht et al. (2012) for a review of studies that have empirically examined such pricing and consumer demand in television, phones, utilities, entertainment, transportation, and other industries. In the context of health insurance, Lakdawalla and Sood (2013) theoretically discuss the premium-plus-copay structure of insurance as a two-part tariff.

medicine, holding wealth constant, as physician attention and accessibility are more valuable for people in worse health.

Now consider selection based on wealth. The value of time spent in both productive and leisure activities is increasing in income (Aguiar and Hurst 2007). Put differently, the opportunity cost of spending time at a doctor's office is higher for wealthier people than for people with less wealth. Wealthier people are therefore more likely to select concierge medicine, holding health constant, compared to people with less wealth.

We are interested in how the retainer fee changes the number and composition of patients that the physician serves based on their health and wealth. Our model summarizes the health and wealth dimensions into a single index, to allow for a comparison between an economy in which people self-select into concierge medicine and one in which a planner seeking to maximize population health selects members into a concierge arrangement based solely on their health level, matching sicker patients with higher-intensity primary care. We consider a planner that lexicographically values population health above willingness to pay as maximizing health equity. Appendix A provides details of the model and analyzes the sensitivity of health equity to the retainer fee. We find an increase in the out-of-pocket retainer fee reduces the proportion of members who derive health benefits from concierge medicine, as members sufficiently wealthy to enroll in concierge medicine join for reasons beyond health. Moreover, as the retainer fee increases, more individuals who are in poor health select out due to affordability.

In our empirical setting, physicians switch from traditional practice to concierge medicine, which can be interpreted as increasing the retainer fee from zero to some positive amount. The model predicts the introduction of the retainer fee would reduce the membership size, but also change the composition of patients served by the physician as some choose to pay the fee to retain the physician while others with lower willingness to pay choose to leave. Our framework suggests that these groups are selected on both health, which is partially observable in data, and wealth, which is rarely available in health care datasets but proxied for with variables like income.

3. Setting and Data

We study the transitions of over 800 physicians from traditional primary care practices to concierge medicine (CM). All physicians are affiliated with a single, large company that manages transitions to CM and performs administrative functions for physicians.[8] Under the CM model, each physician (or group of physicians) retains ownership of their practice. Their revenues rely on two sources: (1) billing of commercial and public insurers, and (2) a retainer fee, ranging between roughly $1,500 and $3,500 annually.[9] The average price nationwide among concierge practices ($2,400 per year) falls in the center of this range (Kostantinovsky 2021). Like other CM companies, the company we study receives a percentage of this fee in return for managing certain administrative operations for each physician.

In this company, physicians agree to limit their patient panel size to no more than 600 patients. With this smaller panel size, physicians offer 1-hour office visits, same-day appointments, and greater access to patients by phone and email. Physicians also commit to providing annual comprehensive health screenings, diagnostic tests not typically covered by insurance, and online access to their personal health records, including summaries of their visits, lab results, EKGs, and other medical information. This company does not offer a "hybrid option", in which patients who choose not to pay the retainer fee can still see the physician but not receive enhanced access. Patients who do not pay the fee must find another physician. The company provides operational support to physicians switching to CM to help patients transition to another physician if they choose not to pay the fee. The company includes physicians across the United States.[10]

The CM company that we study advertises that patients will get a personalized wellness plan, including screening and diagnostic tests, and the ability to see their CM physician the same or next day upon request. The company guarantees that CM physicians will be present for each appointment (which presumably means they will not be replaced by an advanced practice provider) and that CM physicians are available after hours. More utilization of preventative services and timelier appointments with CM physicians with a smaller patient panel may, in turn, increase access to specialists, although this is not explicitly advertised or guaranteed. One study of CM reports an increase in evaluation and management visits following a patient's enrollment but did not determine whether those visits were with specialists (Morefield et al. 2020).

[8] Several CM companies operate across the United States. We do not report the company's name or other identifying information to preserve its anonymity.
[9] A related but distinct model is "direct" primary care, in which physicians do not take insurance and instead receive payments directly from patients. It is not feasible for researchers to study total spending and utilization with direct primary care, since information on primary care utilization and spending is not recorded in insurance claims.
[10] In this company, patients are matched with a single CM physician. If either the patient or physician is traveling, the patient may be able to seek care from another CM physician depending on availability.

Many patients of these physicians are Medicare beneficiaries, and our empirical analysis focuses on this population. We use a 20 percent sample of Medicare fee-for-service beneficiaries that includes detailed line-item claims from 2007 through 2014. We match the company's physicians to the National Plan & Provider Enumeration System (NPPES) by names and addresses to obtain National Provider Identifiers (NPIs) and additional information. We then detect these physicians in the Medicare insurance claims, which records physician NPIs on each claim.

A second rationale for using Medicare insurance claims is their comprehensiveness in describing the patient's utilization and expenditures throughout the health care system, and the ability to follow patients who received regular care from the physician prior to switch but elected not to participate in the CM practice. Studying total health care spending will indicate where any savings or cost increases from CM occur. We measure spending (both Medicare and out-of-pocket) and utilization of physician services, inpatient, prescription drugs, testing and imaging, skilled nursing facility, and other services. [11] In addition to the raw claims, the data includes beneficiary-level summary files with information on dates of birth and death, sex, race, county, and the initial dates of diagnoses of 20 different chronic conditions (including any occurring prior to our sample period). We also merge in annual county-level information using the Area Health Resource Files (AHRF) and zip code median household income from the American Community Survey as constructed by the Michigan Population Studies Center, which are used for matching in Section 5.

The CM company provided us the official date that each of the 228 physicians that officially switched from traditional practice to CM between 2008 and 2013. We restrict attention to switches that occurred during this 6-year period so that we have at least one year of pre-switch data and one year of post-switch data for all patients. The switches occurred in an approximately uniform pattern throughout the sample period as shown in Appendix Figure B1. We then identify another 591 physicians who switched to CM between 2014 and 2021. As described in detail in Section 5, we match patients of the set of physicians who switch during our sample period to observationally similar patients of physicians who switch after our sample period to estimate the effects of CM.

[11] Claims are disaggregated into separate files for inpatient care, outpatient care, physician office visits, hospice, home health, durable medical equipment, skilled nursing facilities, and prescription drugs (Part D). See https://resdac.org for documentation and further details about the data.

Obtaining the official switch dates is crucial for our analysis; without this information, we would need to estimate the timing of the switch to CM based on changes in the number of unique beneficiaries recorded on claims. Such empirically-imputed measures, similar to testing for structural breaks (Perron 2006), would necessarily be imperfect and would require making additional assumptions. This procedure could introduce noise into the regression estimates given errors in measurement, or produce bias if the dates are systematically misjudged. We avoid these issues by observing the official switch date.

Figure 1 presents strong visual evidence that physicians reduce their panel size as they switch to CM. We graph the average Medicare panel size across our sample of physicians against days relative to the switch date.[12] Physicians begin to reduce their panel roughly 6 months prior to the official switch date, and ultimately reduce their Medicare patients by more than half.[13] The timing of the drop coincides with the official date provided by the company, validating our data and the measured timing of the switch to CM.

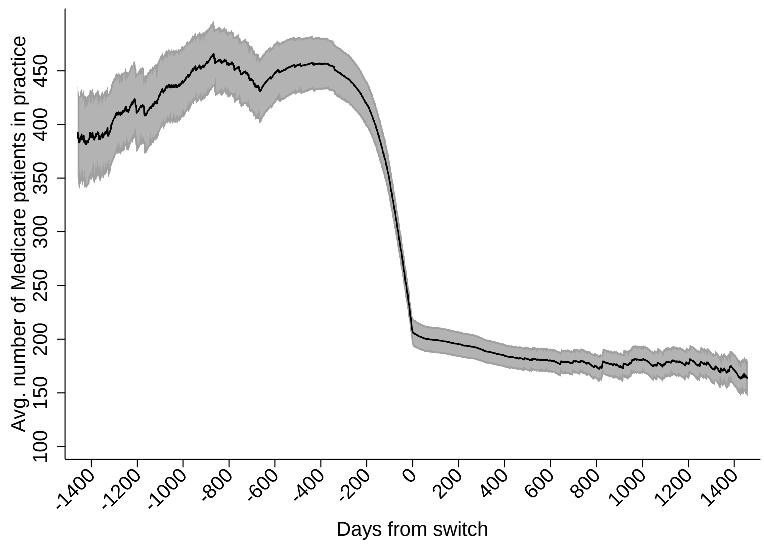
Our study sample includes over 28,000 Medicare beneficiaries attached to physicians who switched during our study period. We identify patient groups by tracking claims from before and after the switch: patients who saw the physician before and after the switch are referred to as "stayers", while patients who have a claim within one year before the switch, but not after, are called "leavers".[14] We observe approximately 123,000 Medicare beneficiaries with a claim with one of our physicians who do not switch to CM until after our study period.

[12] To calculate the size of the physician's panel, we first assign each patient to a single physician based on the plurality of their visits. We then record the first and last dates of services for each physician-patient pair and assume the patient is part of the physician's panel between these dates. If a patient has an equal number of visits with multiple physicians, we assign them to the physician with the longer time span between first and last dates of service. In the (extremely rare) case of further ties, we assign the patient to the physician with the plurality of spending as recorded in the claims. We count the total number of patients attached to our physicians as of each date in our data. Finally, we multiply panel sizes by 5 since we have a 20 percent sample of Medicare beneficiaries.

[13] This pattern indirectly suggests differential rates of take-up between FFS Medicare patients and privately insured patients. If the average panel were between 2,000 and 3,000 in traditional primary care and subsequently declined to at most 600, then non-FFS Medicare patients would necessarily select out of the CM at rates well above 50 percent. This may result in CM physicians becoming more specialized at treating older patients relative to younger patients.

[14] We note that we cannot determine which leavers would have left even if the physician had not switched to CM. However, the changes of the physician's panel size and volume relative to the switch date as shown in Figures 1 and 2 indirectly suggest that most leavers would not have left had the physician not switched.

Figure 1. Change in panel size from switch to concierge medicine



Notes. This figure plots the decline in panel size relative to the day of the switch to concierge medicine. Shaded area denotes 95 percent confidence intervals of panel sizes among the 228 physicians with verified switch dates. We multiply each physician's observed panel size by 5 because we use a 20 percent sample of all Medicare beneficiaries. The sharp decline begins roughly 6 months prior to the official switch date, and results in reducing the Medicare panel size by more than half.

We exclude patients who did not have a claim with the CM physician prior to the switch. Patients who are willing to switch to a CM physician experience both the treatment effect of CM and the effect of switching physicians. Including such patients who (endogenously) choose to switch to CM raises concerns about selection explaining differences in outcomes, rather than CM. It is therefore cleaner to only focus on the physician's existing patients prior to the switch to estimate the causal effect of CM.

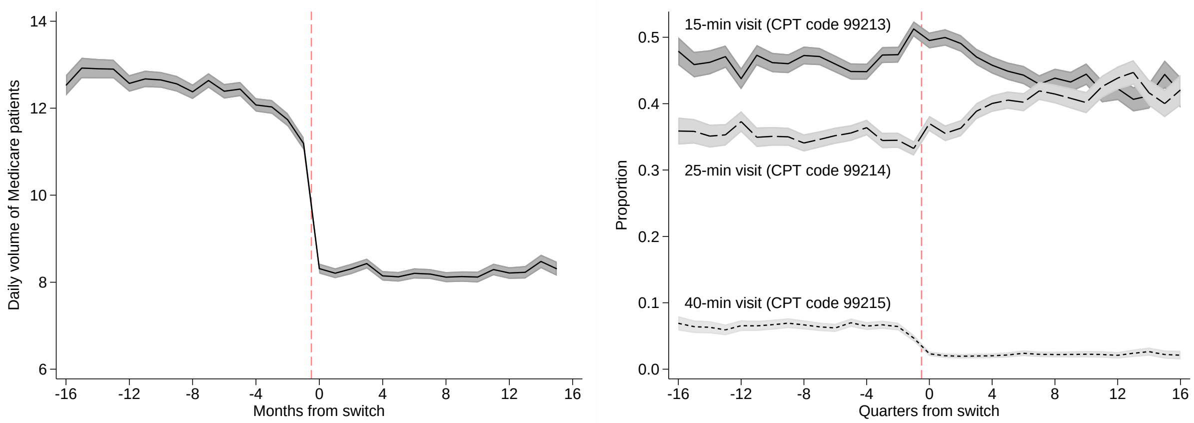
Figure 2 shows that physicians also reduce the volume of patients while increasing the average duration of each office visit. Figure 2a plots the change in the average number of Medicare patients per day. There is a sharp drop in volume coincident with the switch. We smooth the series by averaging daily volume within each month relative to the switch, rather than the day, for visual clarity. Figure 2b presents the proportion of 15-minute, 25-minute, and 40-minute visits for established patients, corresponding to CPT codes 99213, 99214, and 99215, respectively. Figure 2b is restricted to "stayers" to keep the composition of patients constant before and after the switch. After the switch, the proportion of 15-minute visits falls while that of 25-minute visits rises. By about 2 years after the switch to CM, 25-minute visits have become as common as 15-minute visits. Perhaps surprisingly, the proportion of 40-minute visits falls by a couple percentage points.

We exclude 5-minute and 10-minute visits for visual clarity since these are of similar magnitudes to the 40-minute visit. Appendix Figure B2 shows that the proportion of 5-minute visits is reasonably flat while that of 10-minute visits increases slightly. Collectively, these trends point to an increased amount of time spent with patients, on average, as would be expected under CM.

Figure 2. Change in volume and visit length

(a) Volume

(b) Distribution of Visit Length



Notes. Figure 2a plots the average daily Medicare volume among patients who stay with the concierge physician relative to the month of the switch. Shaded regions denote 95 percent confidence intervals. Figure 2b plots the average proportion of visits by length based on CPT codes among established patients. Figure 2b is restricted to patients who stay with the concierge physician to remove differences in the composition of patients before and after the switch. Proportions do not sum to 100 percent because 5-minute and 10-minute visit lengths are excluded.

In some analyses, we incorporate hand-collected information on the membership prices charged by CM physicians who switch during our sample period. We are able to record prices for just over two-thirds of these physicians (those who remain with the company as of 2021). The lowest price we observe is $1,580, the highest is $3,500, and the modal price is $1,800. Over 90 percent of physicians have prices that take four different values between $1,650 and $1,980. This information was collected in 2021, but we have reason to believe that prices were largely stable during our sample period. When physicians do raise their membership fee, they release a video explaining the rationale for the increase, and consistently note the infrequency of price adjustments according to a standard script. We have also verified the pricing information using historical snapshots collected from the Wayback Machine, an archive of internet sites.

4. Analysis of Selection into Concierge Medicine

Our empirical analysis first characterizes the nature of selection into CM. Summary statistics are shown in Table 1 for the first year we observe each observation (prior to anyone being treated). Perhaps not surprisingly, the spending, utilization, and demographics of patients whose physicians switch to concierge practices are very different prior to the switch than the demographics of patients in other practices. The first column presents means for patients whose physician switches to CM either during or after our sample period. The last column presents means for other Medicare beneficiaries. We require other beneficiaries to have at least 1 physician office visit and positive physician costs since we use physician office visits to identify patients of CM physicians. Total spending is similar, on average, for patients in CM practices compared to other Medicare beneficiaries.[15] Physician office visits and physician spending are, however, higher for patients whose physician switches to CM. The patients of physicians who switch to CM are slightly older, have slightly fewer chronic conditions diagnosed, and are more likely to be white. They also live in higher-income zip codes and are less likely to receive a low-income subsidy for Part D.

There are also differences in patient spending and demographics among physicians who switch earlier to CM, versus those who switch later. The second and third columns present means for patients whose physicians switch during our sample period. Patients who pay the membership fee ("stayers") are shown in column 2 and those who leave the practice ("leavers") are shown in column 3. These patients are restricted to those with a claim with the physician in the period spanning 18 months to 6 months before the physician's switch to CM.[16] The patients of physicians who switch prior to 2014 have lower spending and live in higher income zip codes than patients whose physicians switch between 2015 and 2021. This pattern may not be surprising if patients who are relatively healthy and live in high-income areas are likely to be the most profitable, and so would be targeted first by the CM company. Physicians who switch later still have patients who live in areas with above-average incomes.

Comparing the second and third columns, spending and utilization of patients who stay and those who leave are remarkably similar prior to the switch. Stayers are over 1 year older than

[15] Since other CM companies exist, a small fraction of the other Medicare beneficiaries group will be enrolled in a CM practice.

[16] This window is intended to capture leavers who might be omitted by classifying the sample based on the 12 months before the switch. For patients who choose to leave and only visit the physician once per year, notifying them their physician is switching in 6 months may lead them to find a new physician before the switch rather than seek a final visit.

leavers and have more chronic conditions, on average. Stayers also live in zip codes with higher median household income and are more likely to be white (93.9% vs. 90.4%). Appendix Table B1 presents *t*-tests of the variables in Table 1 between stayers and leavers. Some of the differences are statistically significant, though they are often small in magnitude. There are roughly twice as many leavers as stayers, and this rate varies little over time.

Table 1. Descriptive statistics prior to switch to concierge medicine

	Full CM Sample	CM: Switched Before 2014		Other Medicare Beneficiaries
		Stayers	Leavers	
	(1)	(2)	(3)	(4)
Total spending ($)	12,482	9,128	9,362	11,773
Physician office visits	7.67	8.29	7.55	6.71
Prescription fills	22.38	18.82	18.44	24.25
Hospital outpatient visits	5.66	4.12	4.13	6.46
ER visits	0.58	0.33	0.39	0.57
Acute inpatient stays	0.33	0.20	0.23	0.29
Physician visit costs ($)	610	642	592	530
Evaluation & Management costs ($)	595	410	425	492
Prescription drug costs ($)	1,488	1,270	1,202	1,577
Hospital outpatient costs ($)	1,554	1,119	1,171	1,740
Tests costs ($)	359	389	359	293
Imaging costs ($)	380	385	379	303
Inpatient costs ($)	3,378	2,200	2,330	3,071
Age	71.2	73.2	71.8	68.9
5+ chronic conditions (%)	56.1	59.6	55.8	48.0
10+ chronic conditions (%)	16.0	12.8	12.2	11.5
Female (%)	59.0	58.3	59.4	55.9
White (%)	88.4	93.9	90.4	83.1
Zip code median household income ($)	55,518	57,038	55,318	51,461
Low-income subsidy (%)	11.2	3.8	5.8	15.7
N	148,835	6,973	13,398	8,905,742

Notes: Table presents descriptive means of annual spending, utilization, and demographics for all patients who have a claim with a physician who switches to concierge medicine either before or after our sample period (column 1), patients whose physician switches during our sample period (columns 2 and 3), and all other Medicare beneficiaries with at least 1 physician office visit and positive physician visit costs (column 4). Patients with claims at the concierge physician after the switch are classified as stayers and those without claims after the switch are classified as leavers. Means are calculated in 2007 or the first year of data for each observation.

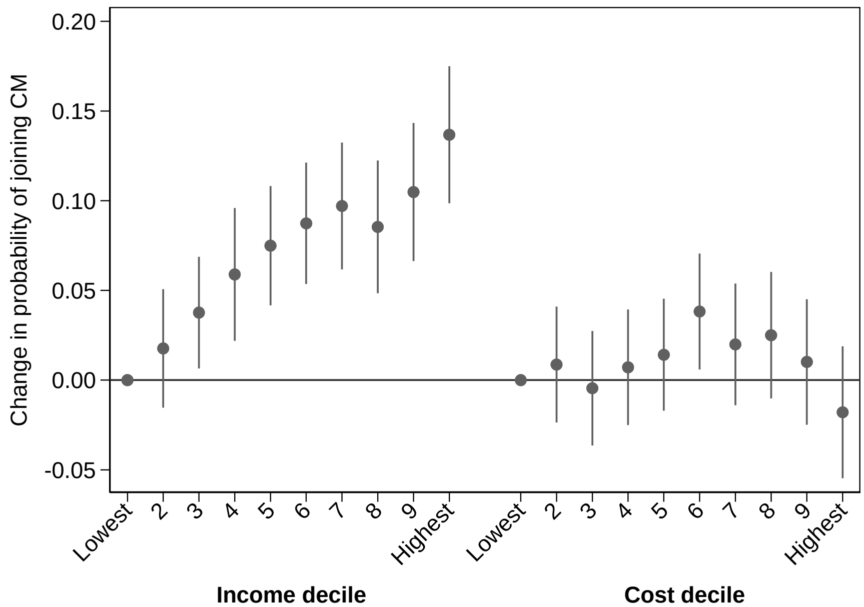
We now examine the conditional correlations between joining, health status, and income. We use information recorded on claims prior to the switch to construct a measure of "baseline health". We predict total health spending using LASSO regression estimated on the Medicare beneficiaries who are *not* attached to our CM company. We fit a LASSO that includes the following covariates: 1-year lags of total health spending, diagnoses for stroke, anemia, cancer, diabetes, hypertension, chronic obstructive pulmonary disease (COPD), acute myocardial infarction (AMI), ischemic heart disease, Alzheimer's disease, atrial fibrillation, hyperlipidemia, chronic kidney disease, congestive heart failure (CHF), rheumatoid arthritis, depression, glaucoma, hip fracture, osteoporosis, and cataracts, a quartic polynomial in age, indicators for gender, white, low-income subsidy for Part D, current and original reasons for Medicare coverage, and year effects. Using the model estimates, we predict health spending for patients whose physician switches to CM.[17]

Figure 3 plots the results of a linear probability model (LPM) of joining CM against deciles of expected health spending and deciles of zip code income in the year prior to the physician's switch. The regression also includes fixed effects for CM physician and fixed effects for year. Standard errors are clustered at the level of CM physician. We exclude controls like age, gender, and other demographics because they are used in predicting health spending. The lowest decile of income and the lowest decile of expected spending are omitted and serve as reference categories. Conditional on expected health spending, the relationship between income and joining is generally monotonic: patients living in the higher-income zip codes are more likely to join CM. The magnitudes are sizable. For example, patients in the 6th decile of zip code income are about 9 percentage points more likely to join CM than those in the lowest decile. Relative to the baseline mean of 28.8 percent of patients in the lowest decile, a 9 percentage point higher probability translates into an increase of over 30 percent. The probability of joining CM is over 13 percentage points higher for patients living in the highest decile of zip code income versus the lowest decile, which equates to an increase of close to 50 percent.

By contrast, the relationship is not monotonic in expected health spending, conditional on the income of the patient's zip code. Only those in the 6th decile of expected spending are significantly more likely to join CM than those in the lowest decile of expected cost. The magnitude is are much smaller than the estimates for income. The point estimate on the highest-cost decile is negative. These regressions are restricted to patients who are alive at the time of the physician's switch, so that death does not mechanically lower the probability of joining.

[17] For analyses that use LASSO-predicted spending, patients whose physicians switched in 2008 are dropped because we require data from 2006 to predict spending but the first year of our claims data is 2007.

Figure 3. Linear probability model: Patient selection into concierge medicine



Notes: Figure plots coefficient estimates from a linear probability model of joining concierge medicine against deciles of median household income of the patient's zip code, and deciles of expected health spending in the year prior to the switch. Expected health spending is calculated from a LASSO regression as described in the text. The regression also includes fixed effects for concierge medicine physician and year. Standard errors are clustered at the level of the concierge physician. Whiskers denote 95 percent confidence intervals.

5. Effects of Concierge Medicine on Mortality and Spending

Our second objective is to measure the effects of CM on mortality and spending. Our main strategy compares patients whose physician switches to CM during our sample period to patients whose physician switches after our sample period. This analysis pools stayers and leavers together among treated physicians. This perspective of studying all patients attached to the physician is similar to that of Sabety (2022) and Sabety, Jena, and Barnett (2021), who study the impact of physician retirements on patient health. We later split our results between stayers and leavers, but note the choice to pay the membership fee is an endogenous decision and so describe additional issues surrounding the interpretation of those regressions.

Physicians who switch to CM after our sample period serve as a useful control group. These later switches help to account for physician-level factors or practice styles that may affect patient health independently of CM. A group that does not receive treatment during the sample also has advantages when estimating difference-in-difference models with staggered treatment (Callaway and Sant'Anna 2021, Sun and Abraham 2021, Chaisemartin and D'Haultfoeuille 2020, Goodman-

Bacon 2021). As shown in Table 1, patient observables differ between physicians who switch earlier to CM versus those who switch later. We perform coarsened exact matching (Blackwell et al. 2009, Iacus, King, and Porro 2011) using a large set of demographics and chronic conditions prior to the switch to construct our matched sample. We match based on the following variables: age (measured in days based on date of birth), gender, year, white, low-income subsidy, median zip code household income, urban share, and indicators for Alzheimer's, acute myocardial infarction (AMI), anemia, atrial fibrillation, cancer, cataracts, congestive heart failure (CHF), chronic kidney disease, COPD, diabetes, hyperlipidemia, hypertension, ischemic heart disease, rheumatoid arthritis, and stroke.[18] We then apply a symmetric sample restriction to select the control group as the one used to select patients whose physician switches to CM prior to 2014. In particular, our main sample selected patients having a claim with their physician in the 12-month period spanning 18 months to 6 months prior to the physician's switch to CM. We require that controls matched to these patients have a claim during the same calendar period with their physician who (later) switches.

We match 13% of patients among physicians who switch during our sample period. In the case of multiple controls matched to a patient in the sample, we randomly choose one of the control patients as the match to the patient in the CM sample (1:1 matching).[19,20] Table 2 presents results of balance tests on our matched sample and demonstrates that observables are similar between patients in practices that switch prior to 2014 versus those that switch later. The bottom panel shows balance among chronic conditions that were not used in matching. Differences in total health spending are not statistically different. While differences in physician health spending are statistically significant, the magnitudes of the differences are not economically large.

[18] We do not match on lagged spending or other outcome variables to avoid the possibility of mean reversion (Daw and Hatfield 2018).

[19] We match each unique switch date one at a time and keep track of the controls that have already been matched, excluding these beneficiaries for selection as controls for other CM patients. We perform matching in this stepwise manner so that we can restrict selection of controls to beneficiaries who are alive as of the particular switch date. This restriction is important because stayers and leavers are classified based on surviving until the CM's switch date.

[20] Matching on chronic conditions and demographics yields a 35% match rate, which is then reduced when restricting to controls who have a claim with the future CM physician during the same calendar window pre-switch as their matched treated patient whose physician switches during the sample period.

Table 2. Matching analysis: covariate balance, 1-year pre-switch

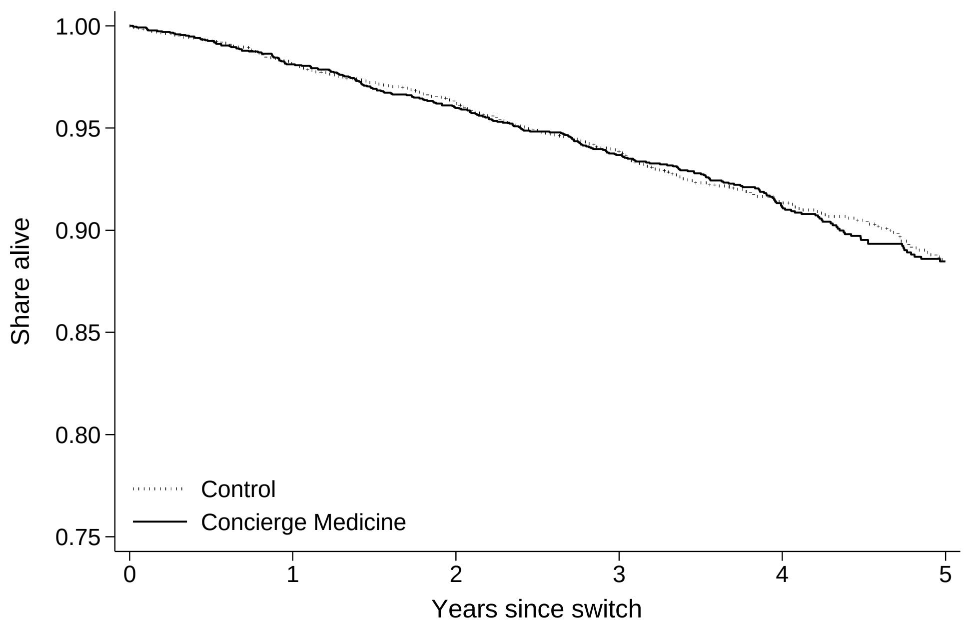
	CM mean	Matched control mean	*p*-value of difference	Diff % of control mean
Variables used in matching				
Age	74.01	73.96	0.793	0.1
Female	0.657	0.657	1.000	0.0
Year	2010	2010	1.000	0.0
White	0.978	0.978	1.000	0.0
Low Income Subsidy	0.011	0.011	1.000	0.0
Median zip code income	68,489	68,362	0.837	0.2
Urban share	0.926	0.927	0.899	0.0
AMI	0.004	0.004	1.000	0.0
Alzheimer's	0.020	0.020	1.000	0.0
Anemia	0.375	0.375	1.000	0.0
Atrial fibrillation	0.046	0.046	1.000	0.0
Cancer	0.073	0.073	1.000	0.0
Cataracts	0.689	0.684	0.682	0.8
CHF	0.066	0.066	1.000	0.0
Chronic Kidney Disease	0.055	0.055	1.000	0.0
COPD	0.074	0.074	1.000	0.0
Diabetes	0.212	0.212	1.000	0.0
Hyperlipidemia	0.840	0.840	1.000	0.0
Hypertension	0.765	0.765	1.000	0.0
Ischemic Heart Disease	0.321	0.321	1.000	0.0
Rheumatoid Arthritis	0.473	0.473	1.000	0.0
Stroke	0.035	0.035	1.000	0.0
Variables not used in matching				
Asthma	0.089	0.084	0.530	5.7
Depression	0.180	0.186	0.551	-3.4
Glaucoma	0.209	0.210	0.947	-0.4
Hip Fracture	0.018	0.016	0.597	11.6
Osteoporosis	0.235	0.233	0.848	0.9
Total health spending	8,869	9,136	0.496	-2.9
Physician health spending	753	719	0.033	4.8
Omnibus test: $F(29,\ 5{,}378)$	0.71 (p = 0.999)			

Notes: Table presents balance tests of covariates for the matched sample. We use coarsened exact matching to match patients whose physician switches to concierge medicine during our sample period to patients whose physician switches to the same concierge medicine company after our sample period. The final row performs an omnibus balance test, including the variables that are not used in matching.

5.1 Effects on Mortality

Figure 4 plots Kaplan-Meier survival curves over a five-year horizon. On average, there is no meaningful difference in survival for patients whose physician switches to CM. The curves are visually indistinguishable for much of the first five years. Integrating between the survival curves, there is an estimated decrease in survival of 0.005 years (less than 2 days) over a five-year horizon for patients whose physician switches to CM. The estimate is not statistically distinguishable from zero (SE = 0.025) based on the methods of Tian et al. (2014). The upper bound of the 95 percent confidence interval is 0.044 years, which equates to about 15 days over a 5-year period. Appendix Table B2 presents the estimates of linear probability models of dying within 2, 3, 4, or 5 years, which yield similar results.

Figure 4. Mortality results



Notes: This figure plots Kaplan-Meier survival curves for patients whose physician switches to concierge medicine (solid line) and their matched controls (dotted line). The curves denote the fraction of patients who are alive as a function of the number of years since the physician's switch to concierge medicine. Control patients are assigned the switch date corresponding to the concierge physician of their match. The area between the solid and dotted lines over the entire period represents the difference in number of year alive between groups.

We also use Cox proportional hazard models to test for changes in survival. We estimate models that take the following form:

$$\lambda_s = \alpha_s \exp(\beta_1 C + \beta_2 age + \beta_2 female + \beta_3 white + \beta_4 LIS + \beta_5 income + \beta_6 urban) \tag{1}$$

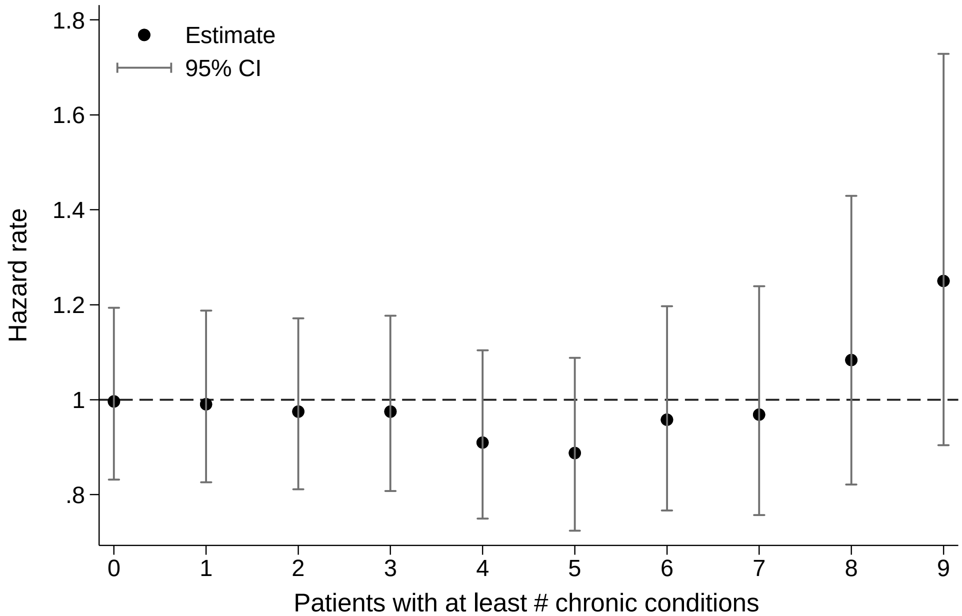
where λ_s *is* the hazard of death at time s relative to the switch, α_s represents an unspecified baseline hazard and C is an indicator for the patient's physician switching to CM. We also control for age (in days), female, white, low-income subsidy status, median income of the household zip code, and urban share to increase precision. The key coefficient is β_1, which measures the change in the hazard ratio from the switch. Hazards below 1 signify lower risks of death for treated units compared to their matched control, while ratios above 1 signify elevated risks. We censor survival at 5 years from the date of the switch.[21]

To explore heterogeneity by health status, we also run regressions that split the sample by the number of chronic conditions in the year prior to the switch. Figure 5 presents the estimates on β_1 from equation (1), where each point represents the estimated hazard ratio from a separate regression. Moving from left to right, the regressions are increasingly restricted to patients with more chronic conditions. The full sample is thus shown by the left-most estimates (patients with at least 0 chronic conditions at baseline), and the right-most denote the sickest patients (patients with at least 9 chronic conditions at baseline).[22]

Among the full sample, the Cox model regressions show CM is not estimated to change survival, consistent with the non-parametric survival curves in Figure 4. The hazard is close to 1 in magnitude and not statistically significant. The estimates increase as the sample is restricted to those with higher numbers of chronic conditions. The magnitudes are large for those with 9 or more chronic conditions – equal to approximately a 20 percent increase in the hazard – though the estimates are not statistically significant, possibly since this group comprises less than 10 percent of the sample.

[21] Patient-date observations are dropped after patients exit the sample. We do not use information from other sources to fill in dates of death after the sample period.
[22] For reference, approximately 3% have no chronic conditions, 90% have 2 or more, 65% have 4 or more, 34% have 6 or more, and 14% have 8 or more.

Figure 5. Cox model estimates



Notes: Figure plots results from estimating the Cox survival models in equation (1) on the matched sample. Each point is the estimate from a separate regression that compares treated units to their matched controls. Each regression is run on patients who have at least the number of chronic conditions listed on the x-axis. The largest sample therefore is patients with at least 0 chronic conditions and the smallest sample is patients with 9 or more chronic conditions. Control patients are assigned the switch date corresponding to the concierge physician of their match.

Appendix Figure B3 shows survival curves by those with different numbers of chronic conditions prior to the switch. Appendix Figure B4 presents survival curves split by above or below median expected health spending prior to the switch. These analyses provide little evidence that the effect of CM on mortality differs by health status. We return to analyzing how these changes in mortality differ by stayers versus leavers in Section 5.3.

5.2 Effects on Spending

To examine the effects on spending, we estimate staggered difference-in-difference models using the estimator of Chaisemartin and D'Haultfoeuille (2020). The estimator compares outcomes for patients whose physician switches into CM between time *t*–1 and time *t* to patients whose physician switches later. Following the notation of Chaisemartin and D'Haultfoeuille (2020), we denote $N_{1,0,t}$ as the number of patients whose physician switched to CM between time *t*–1 and time *t* and $N_{0,0,t}$ as the number of patients whose physician does not switch between time *t*–1 and time *t*. The estimator for the effect in time *t* is:

$$DID_t = \sum_{i:D_{i,t}=1,D_{i,t-1}=0} \frac{(Y_{i,t}-Y_{i,t-1})}{N_{1,0,t}} - \sum_{i:D_{i,t}=D_{i,t-1}=0} \frac{(Y_{i,t}-Y_{i,t-1})}{N_{0,0,t}} \qquad (2)$$

where $Y_{i,t}$ denotes spending for patient *i* in time *t* and the indicator $D_{i,t}$ equals 1 if patient *i*'s physician has switched to CM as of time *t*. During our study period, no physicians in the sample switched out of CM and back to traditional practice so $D_{i,t}$ equals 1 in all time periods after the switch. Since the physicians of the matched controls switch after our study period ends, these patients constitute a "never treated" group in the estimation. We aggregate spending data to the quarterly level to smooth noise. Our baseline specification clusters standard errors at the physician level since that is the level of treatment.

The identifying assumption is that outcomes in patients whose physician switched to CM would have evolved similarly to patients whose physicians had not yet switched (controls). We assess the plausibility of this assumption by examining the spending trends of switchers to controls before the switchers have switched. The estimator is robust to heterogeneity in treatment effects across patients or over time. Heterogeneity across patients seems more likely than assuming the effect of CM has the same effect on all patients. It is also conceivable that any effects of the switch may not be the same across time. For example, perhaps the effects of more enhanced access on spending show up earlier while care disruptions initially result in lower spending after the switch followed by higher spending as care is re-established. Allowing for heterogeneity in effects across patients and over time is therefore important.

Our main outcome variable of interest is total health spending. We exclude the membership fee for stayers in our main results to capture the effect of CM on health care utilization. In Appendix B, we present results that include the fee to capture the total change in money spent on health care. These supplementary results also disaggregate spending into different components (physician office visits, inpatient, outpatient, prescription drugs) to clarify the source of spending changes. Since spending is right-skewed with very high outliers, our main results apply an inverse hyperbolic sine transformation.[23] Figure 6 shows the regression estimates for total health spending. The estimates on DID_t for $t < 0$ are close to zero and generally not statistically significant, providing support to the identifying assumption of parallel trends. Spending rises sharply in the first year after the switch, and then grows more slowly over time. After a year from the switch,

[23] The transformation is $\ln(y + (y^2 + 1)^{\frac{1}{2}})$ for health spending y.

spending is over 25 percent higher among patients whose physician switches to CM relative to controls. Sample sizes by event time are shown in Appendix Table B6.

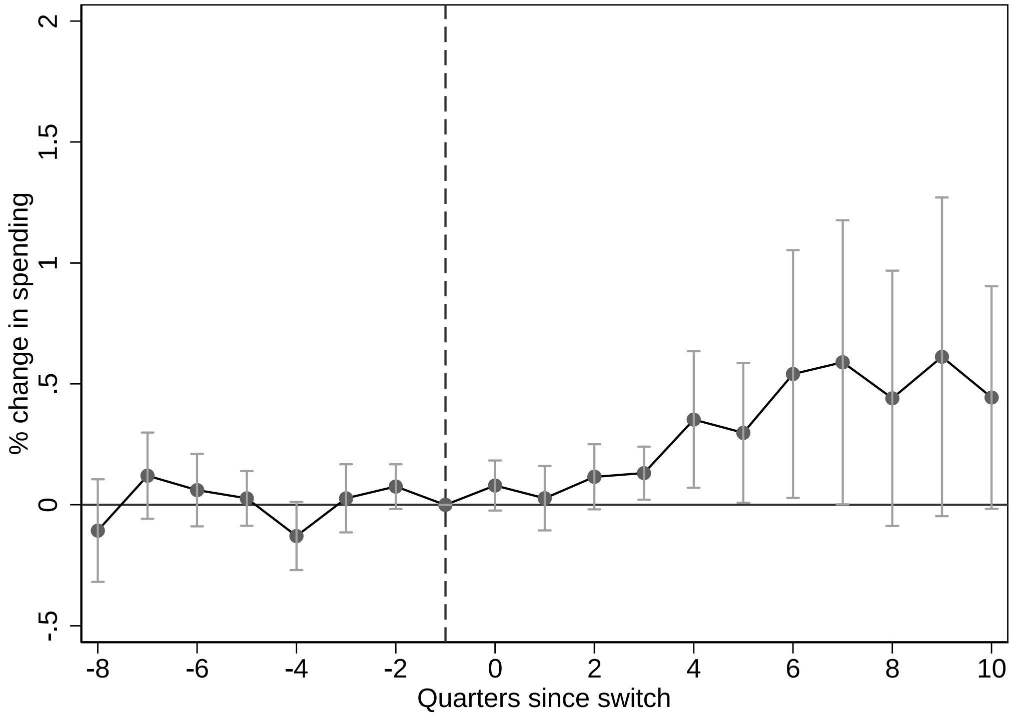
We obtain qualitatively similar results using alternative specifications for spending. Appendix Figure B5 shows the spending increase when measured in levels and winsorizing the top percentile within each calendar quarter for the matched sample. Appendix Figure B6 includes the membership fee for stayers in total health spending. The increases are larger, showing the membership fee is a major part of total resources devoted to health care.[24] We report regressions for the probability of any positive spending in Appendix Figure B7 and for log spending, conditional on positive spending, in Appendix Figure B8. The estimates are close to zero for having any spending and are not statistically significant. The bounds of the 95 percent confidence intervals are generally 3 percentage points or smaller, which is slightly over 3 percent of the baseline mean. We therefore interpret any change in extensive margin responses to likely be small and close to zero. Appendix Figure B8 shows estimated spending increases using log spending are of similar magnitudes, restricted to patients with positive spending.[25] Finally, Appendix Figure B9 reproduces Figure 6 when clustering by patient, instead of by physician.

Spending increases (excluding the membership fee) are driven by those in better health at baseline. Appendix Figures B10 and B11 present event study results that split the sample in terms of expected health spending or the number of chronic conditions in the year prior to the switch.

[24] Patients have the option of paying the membership fee quarterly, rather than all at once at the beginning of the year. We assume they pay it quarterly and add one-quarter of the fee to spending of stayers for as long as they remain with the physician. We use the modal membership fee if we do not observe the membership fee for a particular physician.

[25] The inverse hyperbolic sine transformations depend on the magnitude of spending levels (Aihounton and Henningsen 2021), but this does not make a meaningful difference in our regressions.

Figure 6. Event-study regressions: total health spending (%)



Notes: Figure plots results of estimating equation (2) in the text using the methods of de Chaisemartin and D'Haultfoeuille (2020) on the matched sample. The dependent variable is the inverse hyperbolic sine of total health spending at the quarterly level. Standard errors are calculated via bootstrapping 100 times. Control patients are assigned the switch date corresponding to the concierge medicine physician of their match.

5.3 Mortality and Spending Results for Stayers and Leavers

We now turn to discussing results when splitting the sample separately into stayers and leavers. Since the decision to join is endogenous, it is important to consider how to interpret these regressions. While we match on a large set of observables, there may be other factors that affect a patient's decision to join the concierge practice and are also correlated with spending and utilization. People may choose to join based on their anticipated response to receiving more time with the physician. If that anticipated response is not fully captured by the observables we match on, then a regression restricted to stayers and their matched pairs will not estimate the effect of introducing CM when people do not have a choice.[26] We therefore interpret results that split by the choice to join or leave as revealing information about spending responses in the presence of patient selection. Appendix Table B3 replicates Table 1 for the matched sample, split out by stayers

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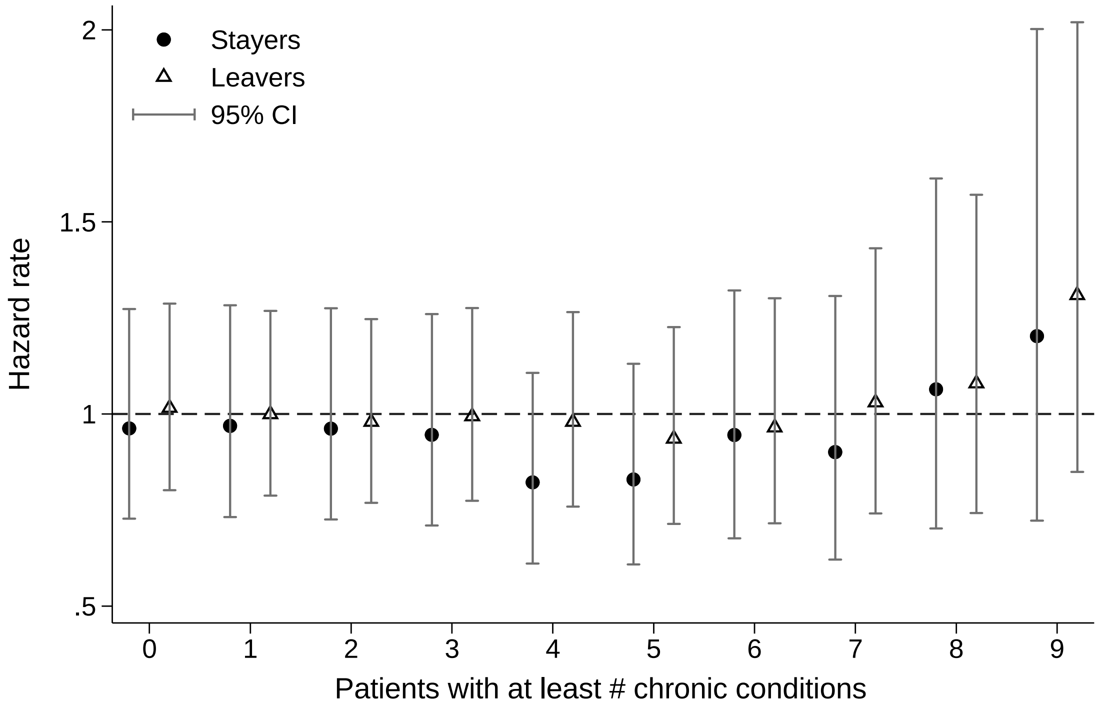
[26] This issue is analogous to the idea of "selection on moral hazard" in estimating how changing the generosity of health insurance would affect spending and utilization when using data from a setting where people have a choice of insurance plan (Einav et al. 2012).

and leavers, and Appendix Tables B4 and B5 replicate Table 2 for stayers and leavers, respectively. Our aim of splitting the results by stayers and leavers is to understand whether the results in Figures 5 and 6 are driven by those who stay, those who leave, or both. It is important to highlight that stayers experience the effect of CM, while leavers do not experience CM but do experience the effect of switching physicians. One should therefore not interpret the difference between stayers and leavers as the effect of CM.

Figure 7 replicates Figure 5 splitting the sample by stayers and leavers.[27] There is little evidence that the risk of dying varies by those who stay or leave. Among those with 9 or more chronic conditions, the estimated hazard of dying is substantially elevated compared to their matched controls but is imprecise. We observe qualitatively similar patterns if we use deciles of expected health spending rather than the number of chronic conditions (Appendix Figure B12). It is important to consider the interaction between wealth and health status when interpreting these graphs. People with many chronic conditions may have less wealth than people with fewer chronic conditions due to higher medical spending. If these constraints are binding, people with more chronic conditions may be unable to afford the retainer fee and so be classified as a leaver. That pattern would be consistent with the finding of Figure 3 that there is less selection on health than on zip code level income. The difference in wealth between stayers and leavers may then be larger for people with more chronic conditions versus those with fewer. While the regressions in Figures 5 and 7 control for zip code level income, one might expect higher hazards for those with more chronic conditions to the extent that differences in individual-level income remain unaccounted for.

[27] The series of stayers continues to include any patients who initially stay and subsequently leave the practice during the sample period to hold the composition of stayers and leavers fixed.

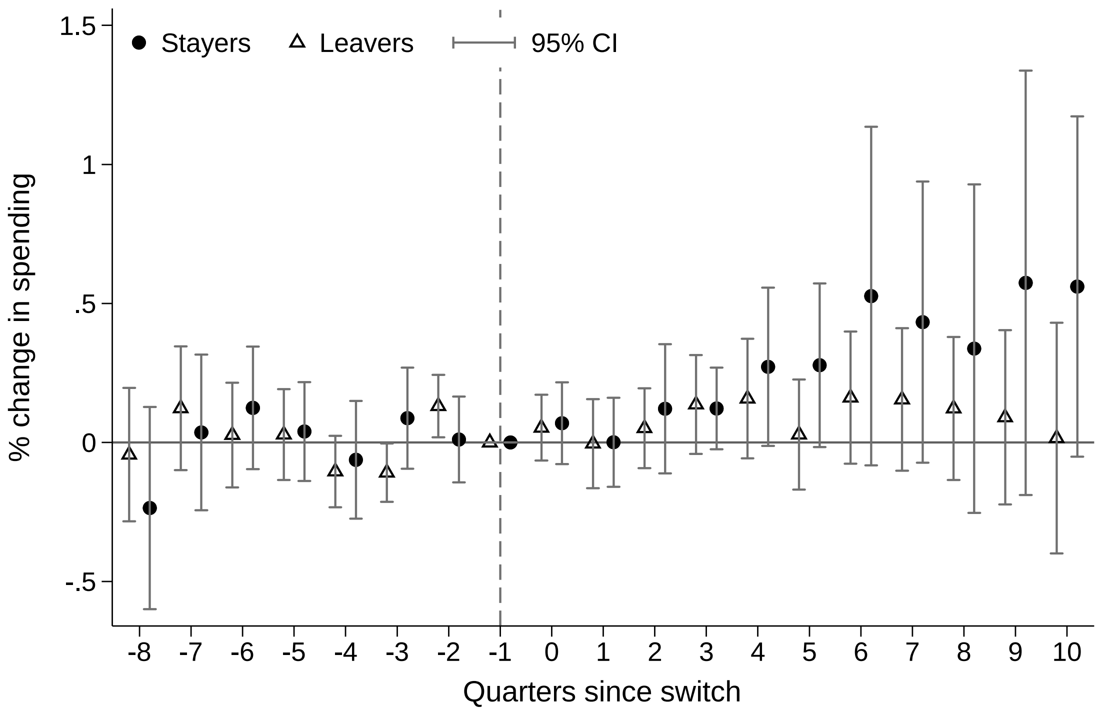
Figure 7. Cox model estimates stratified by stayers vs. leavers



Notes: Figure plots results from estimating the Cox survival models in equation (1) on the matched sample, separately for stayers and leavers. Each point is the estimate from a separate regression that compares treated units to their matched controls. Hazard estimates from the regressions of stayers are shown in circles and results for leavers are shown in triangles. Each regression is run on patients who have at least the number of chronic conditions listed on the x-axis. The largest sample therefore is patients with at least 0 chronic conditions and the smallest sample is patients with 10 or more chronic conditions. Control patients are assigned the switch date corresponding to the concierge physician of their match.

Figure 8 reproduces the spending event study in Figure 6, now separated for stayers and leavers. Both groups experience increases compared to their controls, though they are imprecisely estimated. The magnitudes of the spending increases are larger for stayers than for leavers, even without including the membership fee. Appendix Figure B13 shows that the total spending increases for stayers is much larger when including the fee and always statistically significant. The increase in spending for leavers is consistent in sign with the results of Sabety (2022) and Sabety, Jena, and Barnett (2021) who study responses to physician retirement. We should not expect the magnitudes to necessarily be the same as those studies, however, given the selection issues involved in conditioning on the choice to leave, as discussed above. Appendix Figure B14 further decomposes spending by type of service. There are increases in physician office spending for both groups. Prescription drug spending declines for stayers, which might be expected if physicians are spending more time with patients, and rises for leavers. Both outpatient and inpatient spending rise for stayers but not for leavers.

Figure 8. Event-study regressions: total health spending (%) by stayers vs. leavers



Notes: Figure plots results of estimating equation (2) in the text using the methods of de Chaisemartin and D'Haultfoeuille (2020) on the matched sample. Separate regressions are run for stayers (circles) and leavers (triangles). Dependent variable is the inverse hyperbolic sine of total health spending at the quarterly level. Standard errors are calculated via bootstrapping 100 times. The membership fee is added for stayers for the months between the switch and the month of their last observed claim with the concierge physician. Control patients are assigned the switch date corresponding to the concierge physician of their match.

6. Discussion

Concierge medicine is a growing trend in health care markets, particularly in primary care. In response to pressures for enhanced access, more physicians are offering contracts that offer longer visits and more physician attention in exchange for a fixed retainer fee. This paper empirically analyzes this growing phenomenon by combining detailed Medicare insurance claims with information on the precise timing of physician switches within a large concierge medicine company. We document limited patient selection based on health severity. Instead, selection appears to be predominately driven by income or demand for non-pecuniary aspects, such as a willingness-to-pay for increased attention and access.

We then use the staggered timing of physicians switching to concierge medicine to study the effect of this model on health care spending and mortality. Our research design is based on comparing observationally similar patients of physicians who switch during our study period to those of physicians who switch to the same concierge company after our study period. We do not find strong evidence of mortality effects, on average. Based on our 95 percent confidence intervals, any improvements in survival are likely to be modest in size. By contrast, there is robust evidence that concierge medicine increases total health spending, on average. These increases are largely driven by higher physician spending. We fail to detect reductions in downstream spending, such as inpatient care.

It is useful to interpret these results in terms of how they affect equity and efficiency in the allocation of health care. If society prefers to increase health care access to people in worse health and those living in lower-income areas, then concierge medicine harms equity objectives. People living in wealthier areas are more likely to benefit from increased access under concierge medicine, while those in less wealthy areas experience disruptions in care. Concierge medicine also does not appear to transfer more time and attention to patients in worse health.

In terms of efficiency, whether the increased spending is beneficial on net depends on what types of services are consumed and how they are valued. Among stayers, the increased spending might be beneficial if people underconsumed certain care prior to the switch, perhaps by not fully understanding the relative benefits and costs (Baicker, Mullainathan, and Schwartzstein 2015). On the other hand, if moral hazard led people to overconsume care before the switch, then enhanced access might drive an even larger wedge between the marginal benefits and costs of care. For leavers, it is difficult to expect improved efficiency from greater spending unless they were systematically mismatched with their initial physician. We have focused on mortality as an important and observable metric of health. The spending increases are large enough that it is reasonable to believe they might result in a mortality effect, should one exist, given evidence on the responsiveness of mortality to cost sharing in this population (Chandra, Flack, and Obermeyer 2021). There are, of course, other important health outcomes related to morbidity that we do not explore.

Our study has several limitations. First, the sample comprises Medicare FFS patients. These patients have the highest rates of chronic conditions and would presumably benefit the most from participating in this model of primary care, but the findings may not generalize to non-Medicare patients or patients enrolled in Medicare Advantage. Second, we do not observe individual-level income, but instead proxy for it using median income at the patient's zip code. Third, we are unable to assess the long-term effects of concierge medicine, which may not have an impact in the 3–5-year post-period we study. Fourth, our focus is on primary care, and the impact of concierge medicine may differ in specialty care. Recent trends suggest that concierge medicine may soon extend to specialties like pediatrics and endocrinology, for example (Bauer 2020). Finally, we study the experience of one large company. The company's model includes many of the representative features found in other companies, and its fees are close to the nationwide average. We view our findings as generalizable to other companies with similar (non-hybrid) structures and fees, but the results may not be externally valid when considering practices with fees that are either at the low end (e.g. $200 per year, such as One Medical) or the five-figure prices less frequently charged by some individual physicians.

We nonetheless view our results as providing important inputs to a comprehensive evaluation of concierge medicine. There are several important benefits and costs that we leave for future research. On the benefits side, there are likely non-pecuniary benefits such as convenience and greater access that patients are willing to pay for and that may be unrelated to mortality. The pattern that sorting is based on non-health factors is consistent with the importance of such amenities to patients. On the cost side, patients who are displaced by the switch to concierge medicine incur some hassle cost in finding a new physician. Some patients may have to travel further to access care. These types of costs may be unrelated to health care spending or mortality, and are also experienced by patients when their physician retires or relocates (Sabety 2022). Future work might also study heterogeneity in responses by the number of physicians in the concierge medicine physician's practice and whether some physicians in the practice continue with the traditional model or not. Our research has focused on differential effects by patient health status, but differences in the characteristics of provider organizations is also an important dimension of heterogeneity.

Another question for this calculation is whether concierge medicine affects physician labor supply. Being able to spend more time with patients without sacrificing income could encourage some physicians to delay retirement. It may also induce more physicians to enter primary care rather than other specialties, which may help ameliorate shortages in primary care. On the other hand, primary care shortages may be exacerbated since physicians see fewer patients under this model. One study of physicians who opt into concierge medicine finds that they are older on average (Nemzer and Neymotin 2020). That correlation may reflect the ability of concierge medicine to increase labor supply among older physicians, but it may also simply reflect selection: older physicians are more likely to have many loyal patients they have treated for decades and therefore are better candidates for sustaining a successful concierge practice. Understanding labor supply responses would be important for evaluating the general equilibrium effects of concierge medicine.

More broadly, our study points to potential tension between health-based allocation of enhanced primary care and outcomes from market dynamics—in particular, the tension between health equity and wealth-driven sorting. Concierge medicine and the use of retainer fees are growing in popularity, and our findings suggest that wealthier patients are opting into these pricing arrangements at higher rates than sicker patients are. Given that over 80 million Americans reside in health professional shortage areas (Bureau of Health Workforce 2021), understanding how the consequences of concierge medicine—and other consumer-oriented models of care delivery—confer benefits and costs to different patient populations warrants further study.

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Online Appendix A [Not for Publication]. Model of Selection into Concierge Medicine at the Population Level

We model utility from enrolling in a concierge medicine practice, which represents enhanced primary care, using a two-dimensional space of wealth and sickness, as shown by Figure A1.

The two dimensions account for the welfare mismatch between the population enrolled in concierge medicine (hereafter abbreviated as "CM") and the population standing to gain the most from an exclusive contract in terms of health. In the space, individuals are located throughout the unit square, with the point (1,1) representing the highest combination of wealth and sickness attainable, and hence the highest utility from joining CM. Our measure of utility is derived from an assessment of the balance between wealth and health. This combination reduces the wealth-health tradeoff to a single distance measure, so individuals with different positions in the space may have the same utility. For example, a wealthy but relatively healthy person who stands to benefit from CM (position B), could have a higher expected utility compared to a sicker person who is not as wealthy (position C). Position A represents a higher level of utility compared with positions B and C, as it is closer to (1,1).

The utility from joining CM for individual i is given by $u_i = \delta - r_i$, where δ is the value of CM at the optimal match and can be thought of as the highest attainable utility. r_i is individual i's Euclidean distance from the best possible combination. Specifically, a person i with wealth level w_i and sickness level s_i would have the following position $r_i = \sqrt{(1-w_i)^2 - (1-s_i)^2}$.

We consider two alternative thresholds for separating CM and non-CM patients. The first is arc-shaped, where each level of r produces an indifference curve in the wealth-sickness space separating members joining CM from those who do not. For each retainer fee R, there exist $r_i = \underline{r}$ such that u_i=0. Each $\underline{r}$ corresponds to a membership size $N^*(\underline{r})$. There are $N^*(\delta, R) = \frac{1}{4}\pi\underline{r}^2$ individuals with $r_i \leq \underline{r}$ who will join CM. The CM membership $N^*(\delta, R)$ is increasing in δ and decreasing in R. We assume health and wealth are uniformly distributed and independent to focus on the key intuition of the model. If health and wealth are positively correlated, there will be a greater mass of people in the green area and smaller mass of people in the yellow area. This will decrease the ratio of yellow to green and make the CM less appropriate from a public health perspective.

The second threshold ignores the wealth dimension and is concentrated on matching members to CM based solely on their health levels. Holding the CM membership fixed at N=N^* implies that there exists $s_i = \underline{s}$ such that $1 - \underline{s} = \frac{1}{4}\pi\underline{r}^2$. Under this arrangement, a public health maximizer would cover the retainer fee R for $N^*(\delta, R) = 1 - \underline{s}$ participating members.

Under the first threshold, individuals in the yellow and green areas in Figure A1 will join CM; under the second threshold, individuals in the yellow and blue areas will join CM. By construction (i.e. holding membership fixed), the blue and green area are identical. Under the first threshold, an individual in position B will be included in CM even though the health benefit from joining CM will be far lower than that of an individual in position C, who is excluded from the CM under this scenario. It is reasonable to assume that sorting based on willingness-to-pay (the first threshold) captures health and service aspects of CM. If the goal is for CM to maximize the health of the population (the second threshold), other pricing mechanisms should be considered.

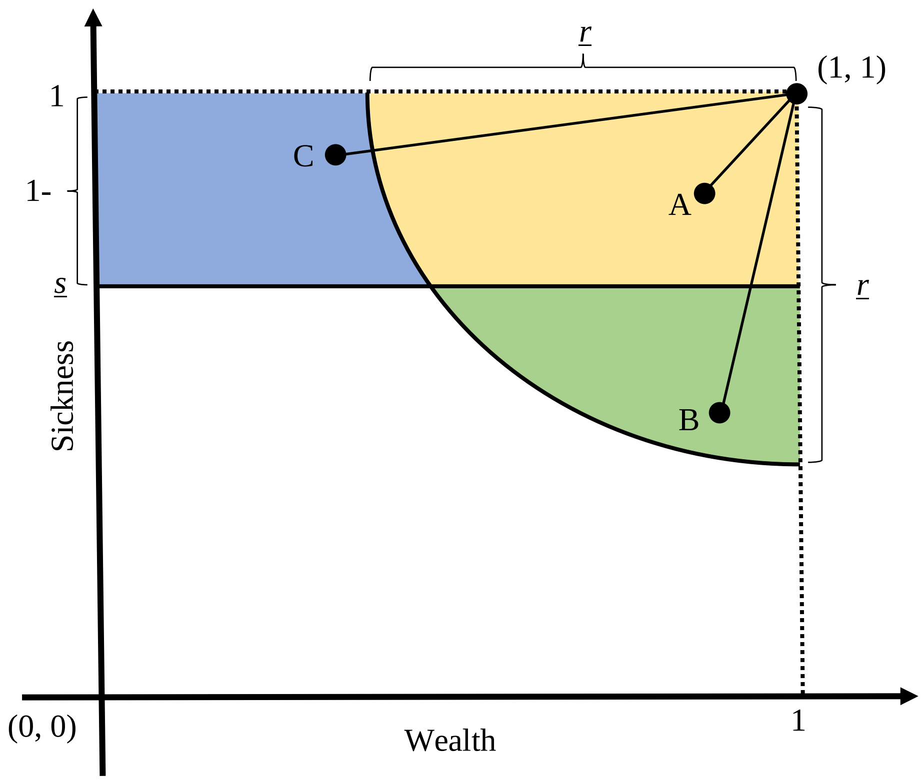
Members in the yellow area will choose to participate in CM under both thresholds. Therefore, the ratio of the yellow area to green area (which by definition equals to the ratio of the yellow to the blue area) is the odds ratio of CM appropriateness, i.e. the ratio of appropriate CM participation (yellow area) to inappropriate CM participation (green area), based on health threshold $\underline{s}$. We note this odds ratio as $A\left(\underline{s}(\underline{r}), \underline{r}\right)$. Setting aside insurance reimbursement for primary care visits and cost of care, the CM choice of retainer fee (and member panel size) is given by: $\max_R N(R)(R)$. We observe the following comparative statics

$$\frac{\partial(1 - \underline{r})}{\partial R} < 0\,, \frac{\partial N^*}{\partial R} < 0\,, \frac{\partial A}{\partial R} < 0$$

As the retainer fee increases, the threshold for joining CM, (1-$\underline{r}$), increases, the size of the membership decreases and the appropriateness ratio decreases. We provide technical notes below.

By separating patients who select out of CM from those who select in and classifying patients by their health status, we can empirically partition our sample into the four areas in Figure A1.

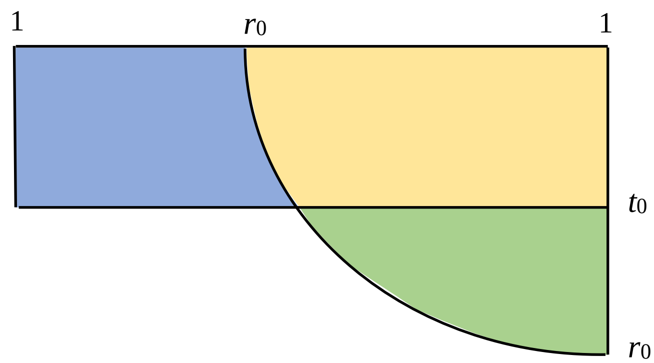
Figure A1. The Health-Wealth Space for Patients

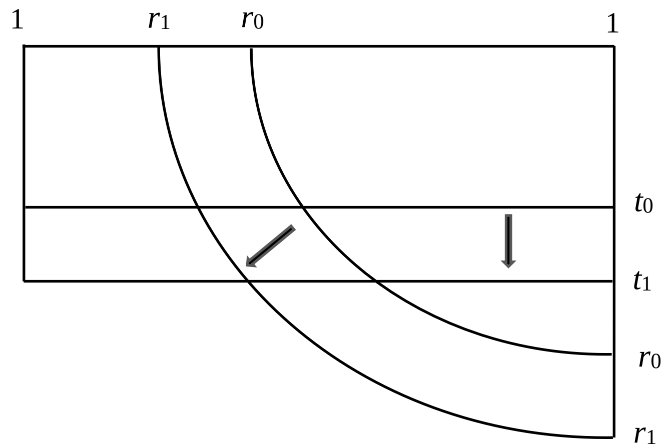


Notes: This graph sketches our conceptual framework for analyzing selection and welfare in concierge medicine (CM). The vertical axis denotes health, with higher levels of S corresponding to worse health. The horizontal axis denotes wealth. Efficient allocation of patients into CM is based on health alone, and represented by all patients with health worse that $\underline{s}$ selecting into CM. Patient selection above the blue curve, however, denotes selection on both health and wealth. The yellow area denotes patients who are inefficiently excluded from CM. The green area represents patients who are inefficiently included in CM.

Technical Notes of Model

Define the partition line between the yellow and green areas $t = 1 - \underline{s}$ and the radius $= \underline{r}$. Note that the areas $1 - \underline{s} = t = \frac{1}{4}\pi r^2$





The appropriateness ratio of the yellow area to green area (which by definition equals the ratio of the yellow to blue area) is given by:

$$A(t,r) = \frac{\int_0^t \sqrt{r^2 - x^2}dx}{\int_t^r \sqrt{r^2 - x^2}dx} = \frac{2\arcsin\left(\frac{t}{r}\right) + \sin\left(2\arcsin\left(\frac{t}{r}\right)\right)}{\pi - 2\arcsin\left(\frac{t}{r}\right) - \sin\left(2\arcsin\left(\frac{t}{r}\right)\right)}$$

Next substitute $t = \frac{1}{4}\pi r^2$ to obtain:

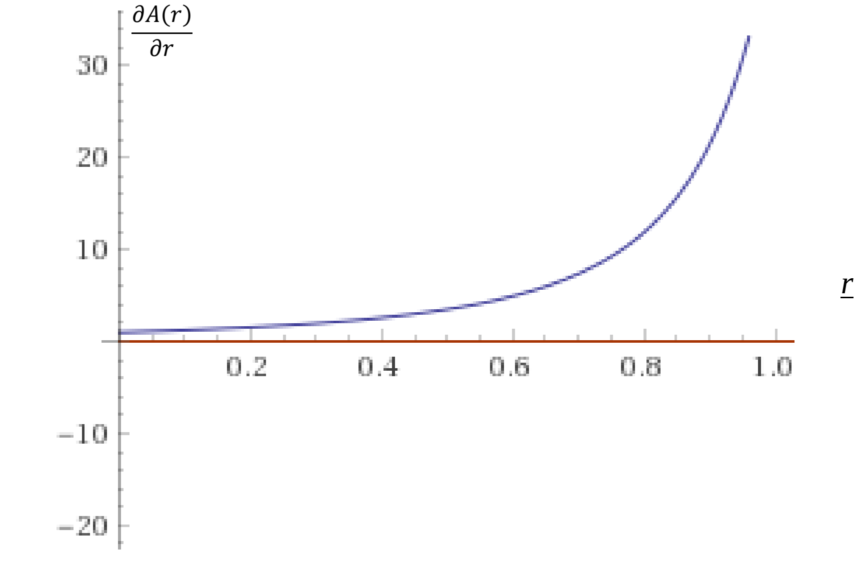
$$A(r) = \frac{2\arcsin\left(\frac{1}{4}\pi r\right) + \sin\left(2\arcsin\left(\frac{1}{4}\pi r\right)\right)}{\pi - 2\arcsin\left(\frac{1}{4}\pi r\right) - \sin\left(2\arcsin\left(\frac{1}{4}\pi r\right)\right)}$$

A reduction in retainer fees will increase the radius r. Therefore, a decrease in retainer fees will increase the radius and in turn, the appropriateness ratio (the yellow area divided by the green area) increases, making the CM model less public health distorting.

In particular:

$$\frac{\partial A(r)}{\partial r} = \frac{2\pi^2 + 2\pi^2\cos\left(2\arcsin\left(\frac{1}{4}\pi r\right)\right)}{\left(\pi - 2\arcsin\left(\frac{1}{4}\pi r\right) - \sin\left(2\arcsin\left(\frac{1}{4}\pi r\right)\right)\right)^2\sqrt{16 - \pi^2 r^2}} > 0$$

The figure below displays the comparative static as a function of radius $\underline{r}$:



Online Appendix B [Not for Publication]. Supplementary Analysis

Appendix Table B1. Selection regressions: stayers vs. leavers, 1-year pre-switch

	Mean difference (Stayers – Leavers)	S.E.	Mean of Leavers	Diff, % of control mean
Total costs ($)	-903.1	(395.2)	14,825	-6.1
Physician office visits	0.83	(0.13)	9.66	8.6
Prescription fills	0.01	(0.60)	27.28	0.1
Hospital outpatient visits	-0.24	(0.23)	6.04	-3.9
ER visits	-0.09	(0.02)	0.60	-15.8
Acute inpatient stays	-0.02	(0.01)	0.34	-4.8
Physician visit costs ($)	28.5	(10.8)	821	3.5
Evaluation & Management costs ($)	-19.8	(24.9)	698	-2.8
Prescription drug costs ($)	215.5	(88.8)	1,664	13.0
Hospital outpatient costs ($)	-34.7	(85.2)	1,779	-1.9
Tests costs ($)	26.2	(10.0)	455	5.8
Imaging costs ($)	26.8	(10.0)	406	6.6
Inpatient costs ($)	-255.7	(205.1)	3,759	-6.8
Age	1.37	(0.14)	75.24	1.8
5+ chronic conditions	0.02	(0.01)	0.773	2.7
10+ chronic conditions	0.01	(0.01)	0.259	4.6
Female	-0.01	(0.01)	0.595	-1.6
White	0.03	(0.00)	0.907	3.7
Median zip code income/capita ($)	5,024	(432)	65,387	7.7
Low income subsidy	-0.03	(0.00)	0.090	-36.4
Omnibus test: $F(20, 18{,}046)$	24.95 ($p < 0.001$)			

Note: Table shows results of linear probability models comparing outcomes for stayers and leavers in the year prior to the physician's switch to concierge medicine. Each row presents the results of a separate regression. The final row presents the result of the omnibus test.

Appendix Table B2. Linear probability models of mortality

	2-year mortality	3-year mortality	4-year mortality	5-year mortality
Concierge medicine	0.0026	0.0018	0.0011	0.0015
	(0.0052)	(0.0063)	(0.0072)	(0.0077)
Constant	0.0365	0.0571	0.0755	0.0862
	(0.0036)	(0.0045)	(0.0051)	(0.0054)
N	5,428	5,428	5,428	5,428
R^2	0.000	0.000	0.000	0.000

Notes: Table shows results of linear probability models of mortality within 2, 3, 4, or 5 year since the switch using the matched sample. The regression excludes controls and so the constant can be interpreted as the mean share of matched controls who die within that time horizon. Robust standard errors in parentheses.

Appendix Table B3. Descriptive statistics prior to switch for matched sample

	Stayers	Stayers - Controls	Leavers	Leavers - Controls
	(1)	(2)	(3)	(4)
Total spending ($)	8,955	9,264	8,818	9,059
Physician office visits	9.6	8.5	8.9	8.5
Prescription fills	22.6	22.6	21.8	20.8
Hospital outpatient visits	4.2	4.3	3.9	4.0
ER visits	0.3	0.3	0.3	0.3
Acute inpatient stays	0.2	0.2	0.2	0.2
Physician visit costs ($)	761	727	748	714
Evaluation & Management costs ($)	436	430	449	454
Prescription drug costs ($)	1,356	1,196	1,183	1,133
Hospital outpatient costs ($)	1,217	1,585	1,142	1,269
Tests costs ($)	447	413	404	411
Imaging costs ($)	399	383	354	354
Inpatient costs ($)	1,832	2,066	2,395	2,361
Age	74.82	74.72	73.52	73.50
5+ chronic conditions (%)	67.8	69.2	63.1	62.3
10+ chronic conditions (%)	10.1	10.9	10.3	10.5
Female (%)	66.3	66.3	65.4	65.4
White (%)	98.1	98.1	97.5	97.5
Zip code median household income ($)	56,617	57,528	54,725	56,369
Low-income subsidy (%)	0.3	0.4	0.4	0.2
N	1,017	1,017	1,697	1,697

Notes: Table presents means of annual spending, utilization, and demographics for different groups of the matched sample: stayers (column 1), matched controls for stayers (column 2), leavers (column 3), matched controls for leavers (column 4).

Table B4. Covariate balance for stayers in matched sample, 1-year pre-switch

	Stayer mean	Matched control mean	*p*-value of difference	Diff % of control mean
Variables used in matching				
Age	74.82	74.72	0.736	0.1
Female	0.663	0.663	1.000	0.0
Year	2010	2010	1.000	0.0
White	0.981	0.981	1.000	0.0
Median zip code income	71,153	70,978	0.874	0.2
Urban share	0.928	0.929	0.845	-0.1
Alzheimer's	0.015	0.015	1.000	0.0
Anemia	0.402	0.402	1.000	0.0
Atrial fibrillation	0.052	0.052	1.000	0.0
Cancer	0.093	0.093	1.000	0.0
Cataracts	0.732	0.729	0.881	0.4
CHF	0.066	0.066	1.000	0.0
Chronic Kidney Disease	0.057	0.057	1.000	0.0
COPD	0.070	0.070	1.000	0.0
Diabetes	0.209	0.209	1.000	0.0
Hyperlipidemia	0.854	0.854	1.000	0.0
Hypertension	0.787	0.787	1.000	0.0
Ischemic Heart Disease	0.330	0.330	1.000	0.0
Rheumatoid Arthritis	0.513	0.513	1.000	0.0
Stroke	0.030	0.030	1.000	0.0
Variables not used in matching				
Asthma	0.110	0.084	0.043	31.8
Depression	0.191	0.189	0.910	1.0
Glaucoma	0.232	0.226	0.752	2.6
Hip Fracture	0.020	0.019	0.872	5.3
Osteoporosis	0.246	0.244	0.918	0.8
Total health spending	8,955	9,264	0.610	-3.3
Physician health spending	761	727	0.184	4.8
Omnibus test: $F(29, 1996)$	0.28 (p = 0.999)			
N	1,017	1,017		

Notes: Table presents balance tests of covariates for the matched sample. We use coarsened exact matching to match patients whose physician switches to concierge medicine (CM) during our sample period to patients whose physicians switches to the same concierge medicine company after our sample period. The final row performs an omnibus balance test, including the variables that are not used in matching.

Appendix Table B5. Covariate balance for leavers in matched sample, 1-year pre-switch

	Leaver mean	Matched control mean	*p*-value of difference	Diff % of control mean
Variables used in matching				
Age	73.52	73.50	0.942	0.0
Female	0.654	0.654	1.000	0.0
Year	2010	2010	1.000	0.0
White	0.975	0.975	1.000	0.0
Low Income Subsidy	0.014	0.014	1.000	0.0
Median zip code income	66,893	66,795	0.893	0.1
Urban share	0.926	0.926	0.997	0.0
Alzheimer's	0.024	0.024	1.000	0.0
Anemia	0.359	0.359	1.000	0.0
Atrial fibrilation	0.042	0.042	1.000	0.0
Cancer	0.060	0.060	1.000	0.0
Cataracts	0.664	0.657	0.690	1.0
CHF	0.067	0.067	1.000	0.0
Chronic Kidney Disease	0.054	0.054	1.000	0.0
COPD	0.077	0.077	1.000	0.0
Diabetes	0.214	0.214	1.000	0.0
Hyperlipidemia	0.831	0.831	1.000	0.0
Hypertension	0.753	0.753	1.000	0.0
Ischemic Heart Disease	0.316	0.316	1.000	0.0
Rheumatoid Arthritis	0.450	0.450	1.000	0.0
Stroke	0.037	0.037	1.000	0.0
Variables not used in matching				
Asthma	0.076	0.084	0.376	-9.8
Depression	0.173	0.184	0.395	-6.1
Glaucoma	0.196	0.200	0.730	-2.4
Hip Fracture	0.016	0.014	0.576	16.7
Osteoporosis	0.229	0.227	0.870	1.0
Total health spending	8,818	9,059	0.636	-2.7
Physician health spending	748	714	0.096	4.9
Omnibus test: $F(29, 3352)$		0.31 (p = 0.999)		
N	1,697	1,697		

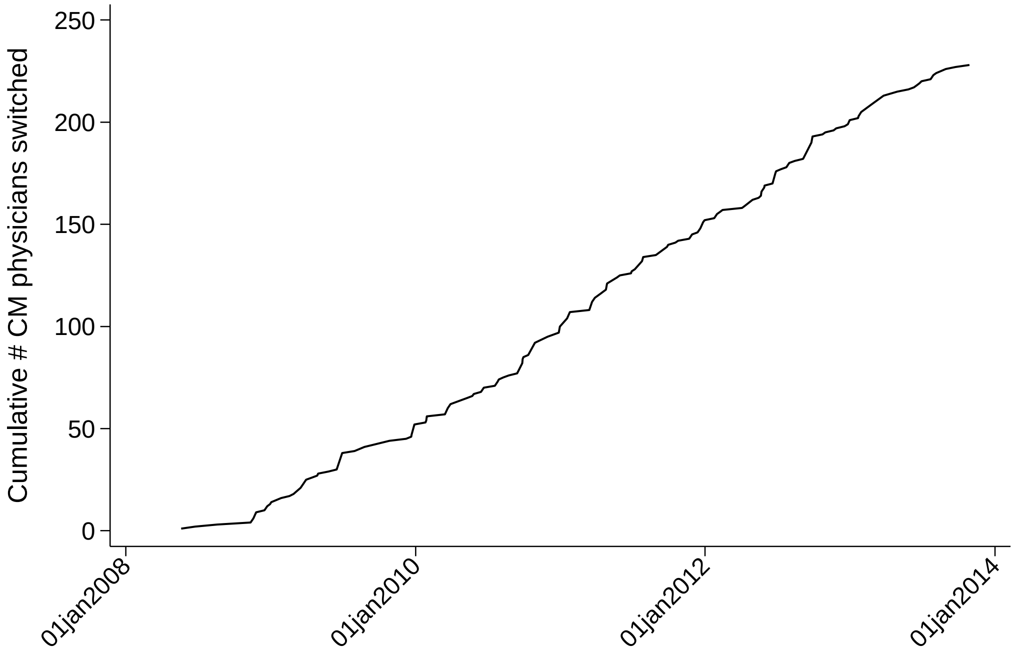
Notes: Table presents balance tests of covariates for the matched sample. We use coarsened exact matching to match patients whose physician switches to concierge medicine (CM) during our sample period to patients whose physicians switches to the same concierge medicine company after our sample period. TFhe final row performs an omnibus balance test, including the variables that are not used in matching.

Appendix Table B6. Sample Sizes by Event Time (Quarters)

Event time	All	Stayers	Leavers	<6 chronic conditions	6+ chronic conditions	Low predicted spending	High predicted spending
-8	4,250	1,649	2,601	2,482	1,768	2,436	1,789
-7	4,647	1,793	2,854	2,754	1,893	2,719	1,899
-6	4,819	1,852	2,967	2,901	1,918	2,857	1,928
-5	4,829	1,860	2,969	2,954	1,875	2,888	1,899
-4	4,760	1,818	2,942	2,932	1,828	2,891	1,828
-3	4,562	1,764	2,798	2,735	1,827	2,792	1,732
-2	4,735	1,804	2,931	2,851	1,884	2,902	1,791
-1	4,965	1,895	3,070	3,001	1,964	3,033	1,881
0	5,264	1,987	3,277	3,298	1,966	3,207	1,989
1	5,320	2,006	3,314	3,360	1,960	3,242	2,003
2	4,930	1,866	3,064	3,117	1,813	3,020	1,841
3	4,625	1,768	2,857	2,926	1,699	2,839	1,718
4	4,233	1,594	2,639	2,689	1,544	2,599	1,567
5	4,027	1,512	2,515	2,567	1,460	2,444	1,512
6	3,797	1,378	2,419	2,449	1,348	2,302	1,429
7	3,488	1,289	2,199	2,277	1,211	2,130	1,297
8	3,464	1,256	2,208	2,254	1,210	2,157	1,259
9	3,383	1,302	2,081	2,078	1,305	2,124	1,236
10	3,498	1,367	2,131	2,148	1,350	2,203	1,269
11	3,618	1,438	2,180	2,215	1,403	2,273	1,320
12	3,394	1,304	2,090	2,071	1,323	2,123	1,241
13	3,291	1,291	2,000	2,037	1,254	2,062	1,199
14	2,798	1,100	1,698	1,716	1,082	1,757	1,018
15	2,863	1,158	1,705	1,777	1,086	1,819	1,019
16	2,881	1,112	1,769	1,767	1,114	1,853	1,003

Notes: Table presents sample sizes of matched samples for quarters relative to the switch. Expected health spending is calculated from a LASSO regression as described in the text. Low predicted spending is classified as below-median expected spending (across all Medicare beneficiaries) and high predicted spending is classified as above-median expected spending (across all Medicare beneficiaries).

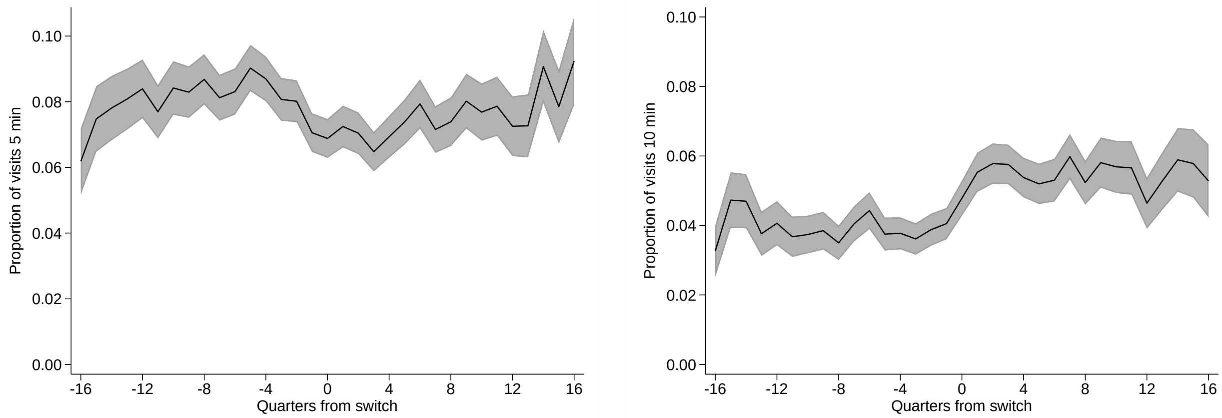
Appendix Figure B1. Timing of Physician Switches to CM



Notes: Appendix Figure B1 plots the cumulative number of physicians within the analysis sample who have switched to concierge medicine as of the date on the x-axis.

Appendix Figure B2. Distribution of 5-minute and 10-minute visits

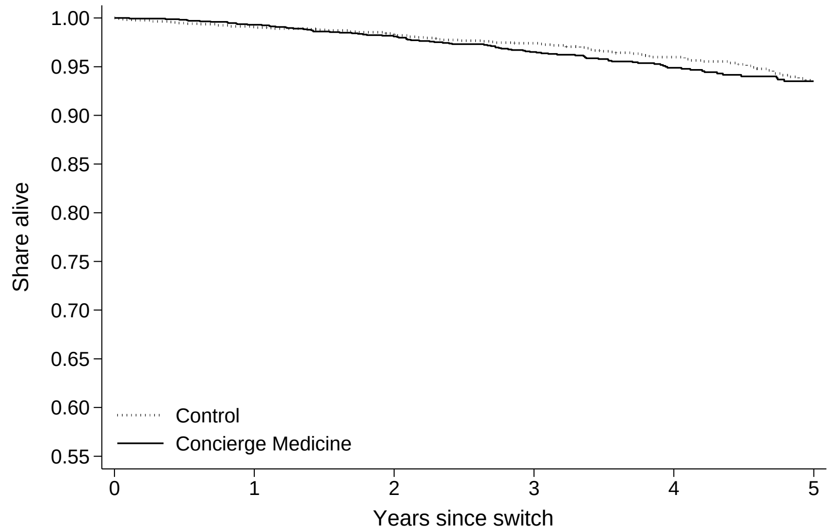
(a) 5-minute visits (CPT code 99211) (b) 10-minute visits (CPT code 99212)



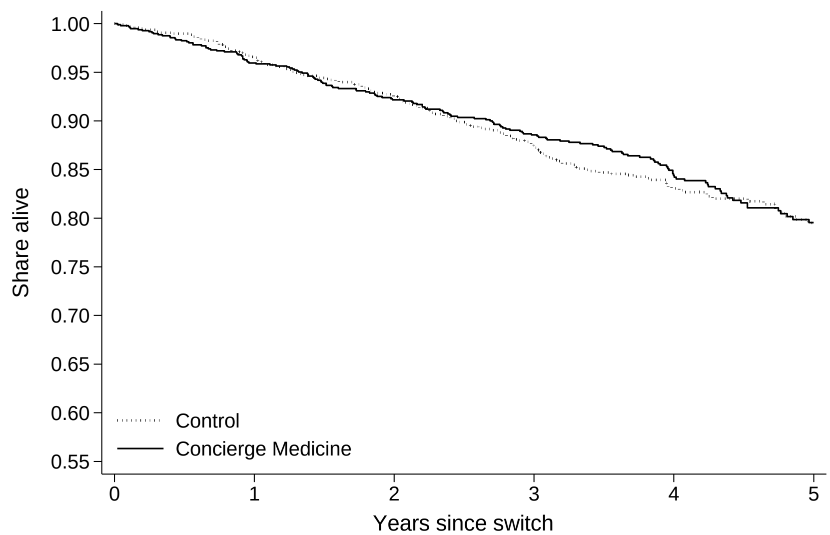
Notes: Panel (a) plots the average proportion of 5-minute visits (CPT code 99211) among established patients and Panel (b) plots the average proportion of 10-minute visits (CPT code 99212). Both are restricted to patients who stay with the concierge physician to remove differences in the composition of patients before and after the switch.

Appendix Figure B3. Mortality by baseline chronic conditions

(a) 0-5 chronic conditions



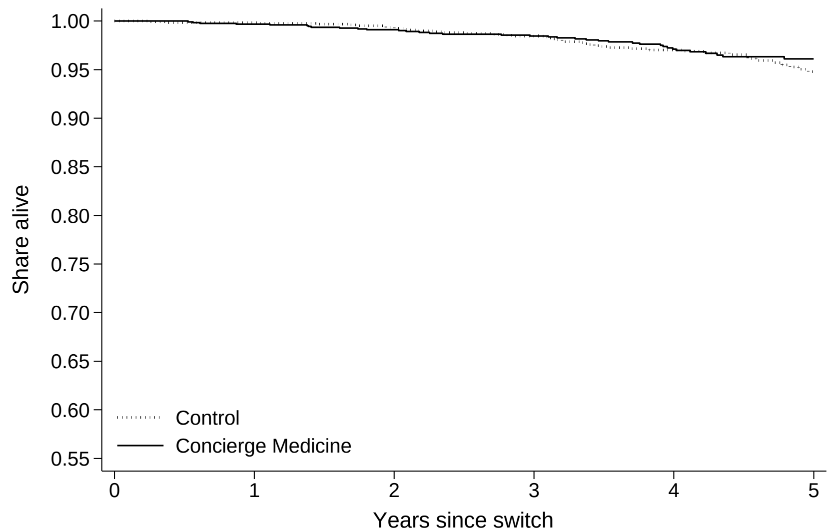
(b) 6 or more chronic conditions



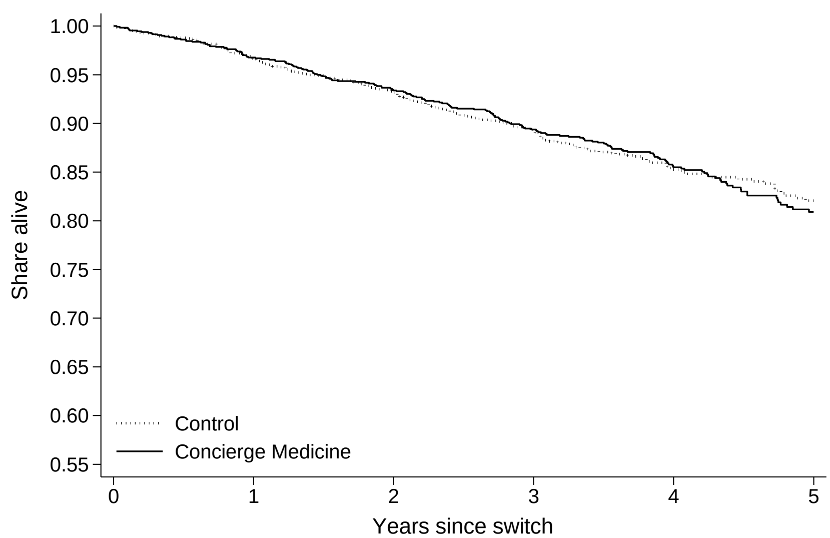
Notes: This figure plots Kaplan-Meier survival curves for patients whose physician switches to concierge medicine (solid line) and their matched controls (dotted line), splitting the sample by the number of chronic conditions diagnosed in the year prior to the switch. The curves denote the fraction of patients who are alive as a function of the number of years since the physician's switch to concierge medicine. Control patients are assigned the switch date corresponding to the concierge physician of their match. The area between the solid and dotted lines over the entire period represents the difference in number of months alive between groups.

Appendix Figure B4. Mortality by baseline expected spending

(a) Below median spending

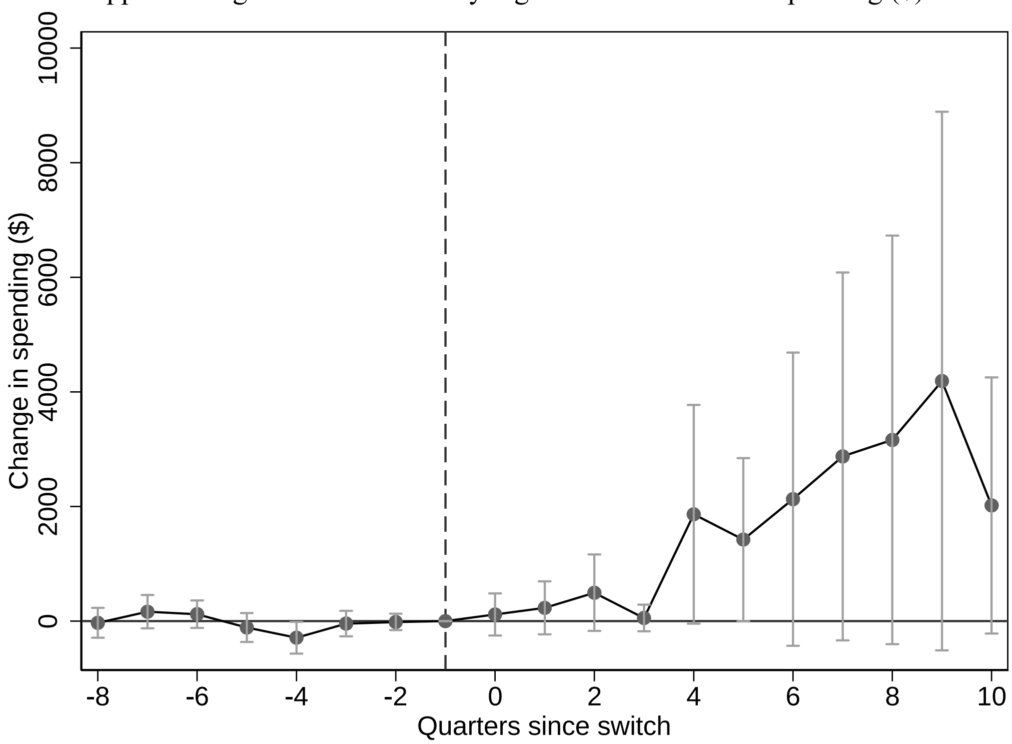


(b) Above median spending



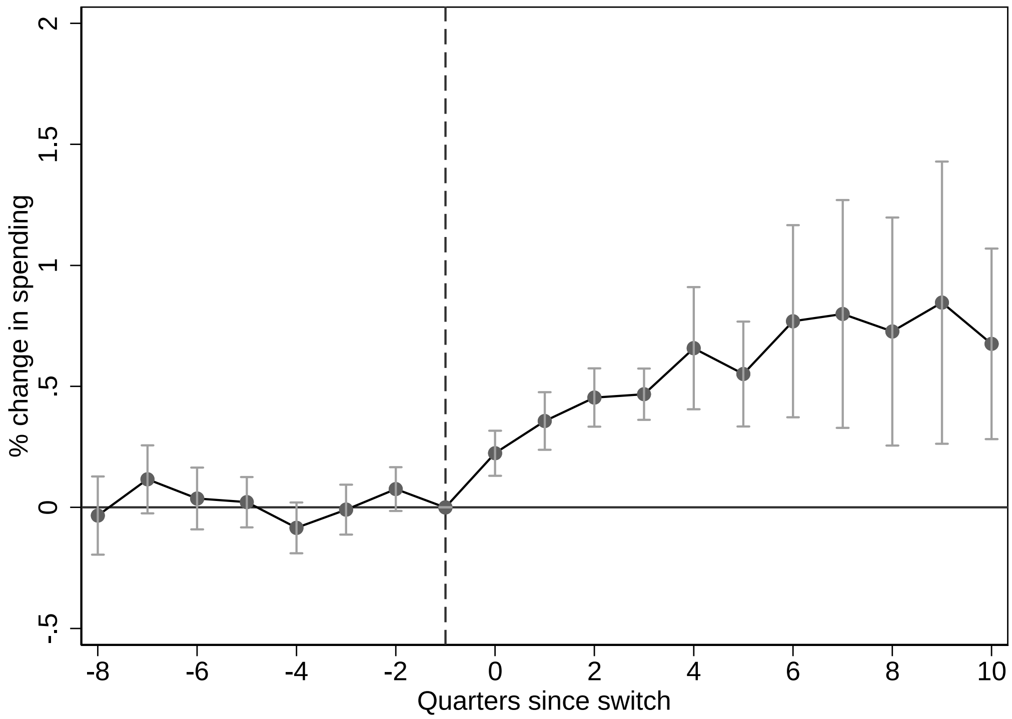
Notes: This figure plots Kaplan-Meier survival curves for patients whose physician switches to concierge medicine (solid line) and their matched controls (dotted line), splitting the sample by expected health spending in the year prior to the switch. Expected health spending is calculated from a LASSO regression as described in the text. The curves denote the fraction of patients who are alive as a function of the number of years since the physician's switch to concierge medicine. Control patients are assigned the switch date corresponding to the concierge physician of their match. The area between the solid and dotted lines over the entire period represents the difference in number of months alive between groups.

Appendix Figure B5. Event-study regressions: total health spending ($)



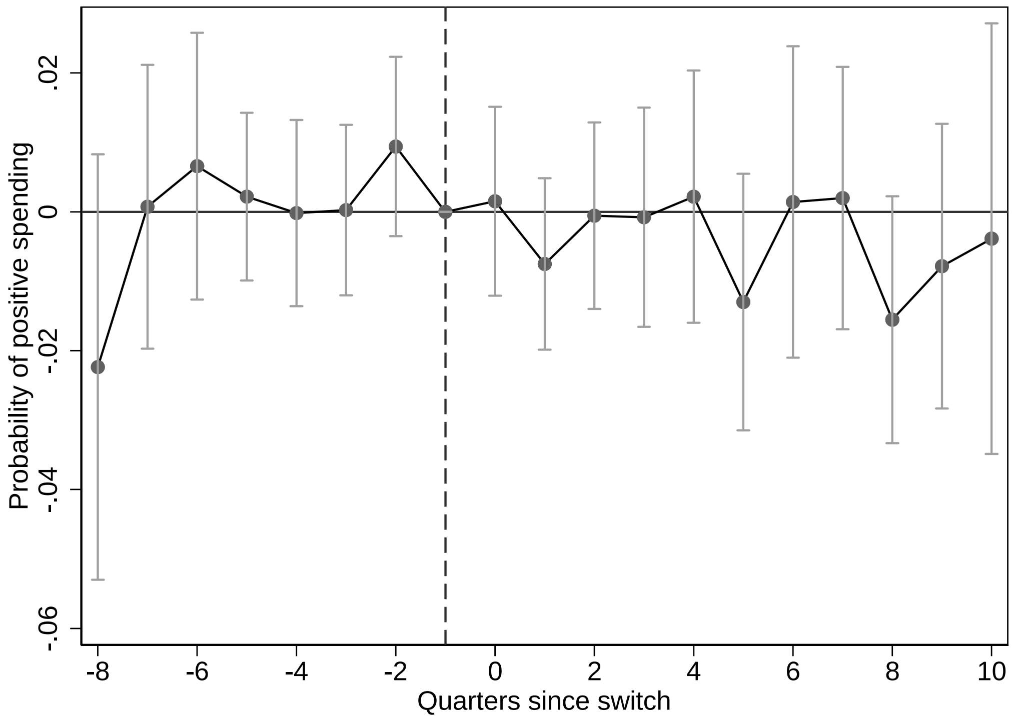
Notes: Figure plots results of estimating equation (2) in the text using the methods of de Chaisemartin and D'Haultfoeuille (2020) on the matched sample. Dependent variable is total health spending at the quarterly level. Spending is top-coded (winsorized) at the 99th percentile. The top percentile is defined across only treatment and control groups within each year. Standard errors are calculated via bootstrapping 100 times. Control patients are assigned the switch date corresponding to the concierge physician of their match.

Appendix Figure B6. Event-study regressions: total health spending with membership fee (%)



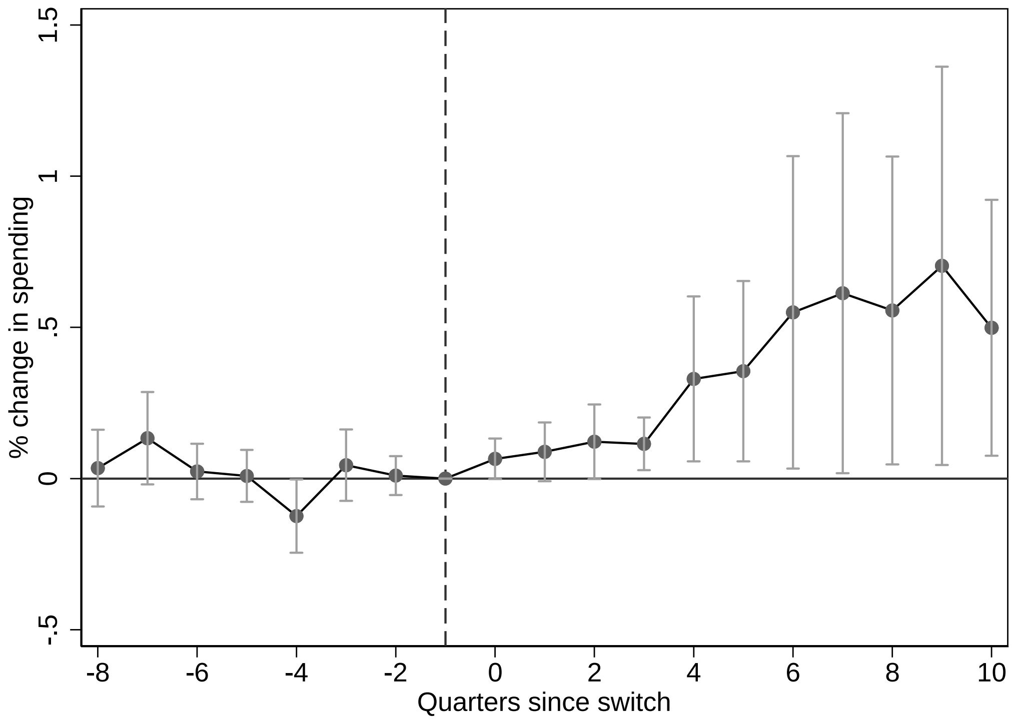
Notes: Figure plots results of estimating equation (2) in the text using the methods of de Chaisemartin and D'Haultfoeuille (2020) on the matched sample. Dependent variable is the inverse hyperbolic sine of total health spending at the quarterly level. The retainer fee is added for stayers for the months between the switch and the month of their last observed claim with the concierge physician. Standard errors are calculated via bootstrapping 100 times. Control patients are assigned the switch date corresponding to the concierge medicine physician of their match.

Appendix Figure B7. Positive total health spending



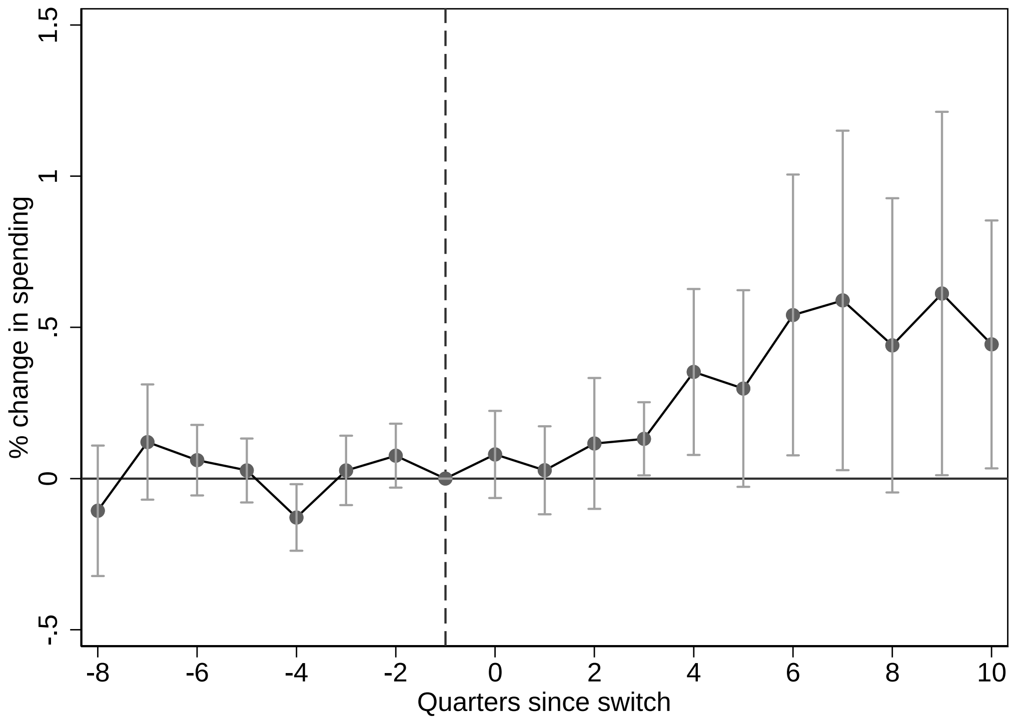
Notes: Figure plots results of estimating equation (2) in the text using the methods of de Chaisemartin and D'Haultfoeuille (2020) on the matched sample. Dependent variable is an indicator for having positive total health spending, excluding the membership fee paid by stayers. Standard errors are calculated via bootstrapping 100 times. Control patients are assigned the switch date corresponding to the concierge medicine physician of their match.

Appendix Figure B8. Log total health spending (%)



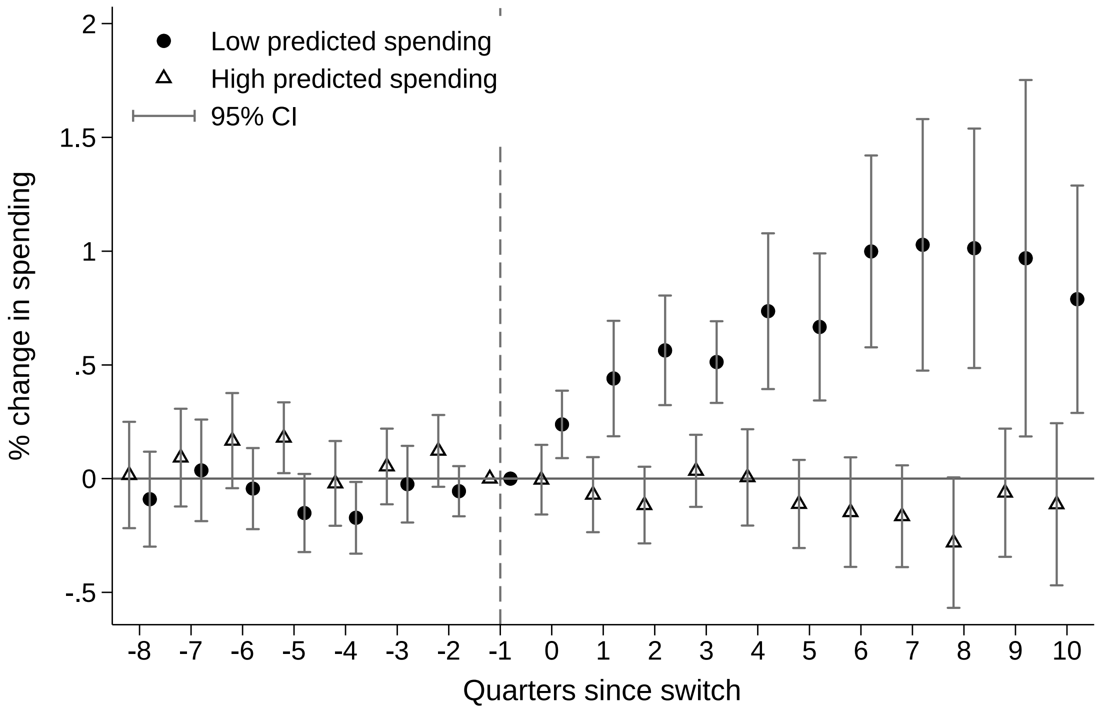
Notes: Figure plots results of estimating equation (2) in the text using the methods of de Chaisemartin and D'Haultfoeuille (2020) on the matched sample. Dependent variable is the log of total health spending, inclusive of the membership fee, among those with positive spending. Standard errors are calculated via bootstrapping 100 times. Control patients are assigned the switch date corresponding to the concierge medicine physician of their match.

Appendix Figure B9. Event-study regressions: total health spending (%), clustering by patient



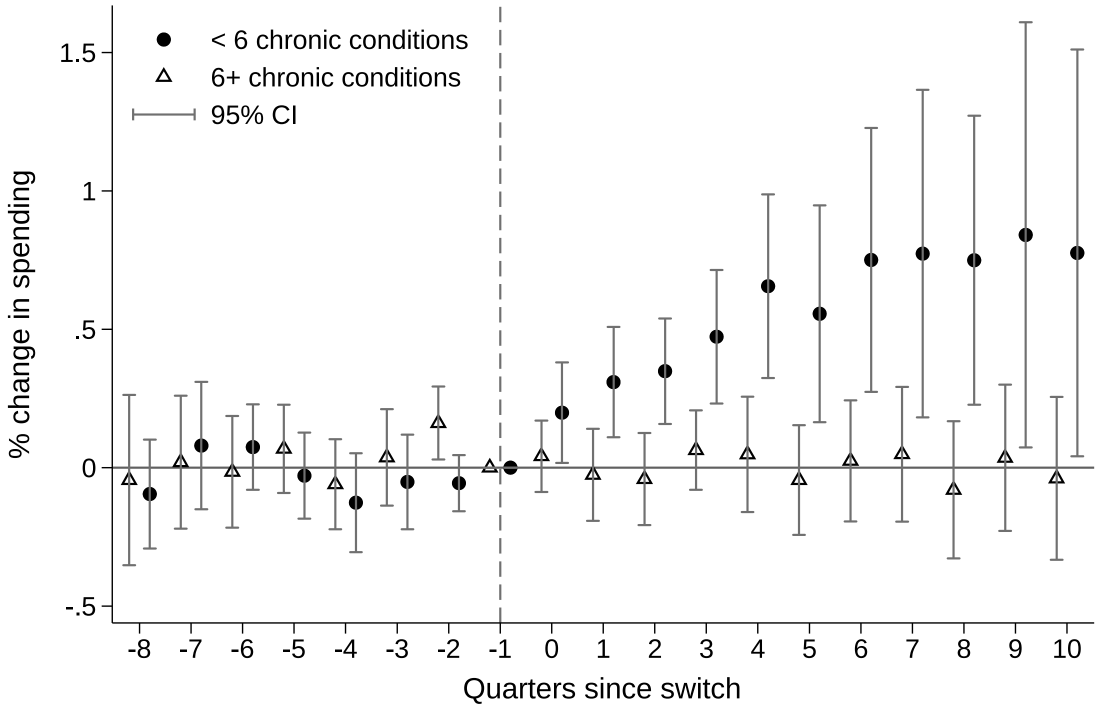
Notes: Figure plots results of estimating equation (2) in the text using the methods of de Chaisemartin and D'Haultfoeuille (2020) on the matched sample. Dependent variable is the inverse hyperbolic sine of total health spending at the quarterly level. Standard errors are calculated via bootstrapping 100 times and are clustered by physician. Control patients are assigned the switch date corresponding to the concierge medicine physician of their match.

Appendix Figure B10. Total health spending (%) by predicted health spending at baseline



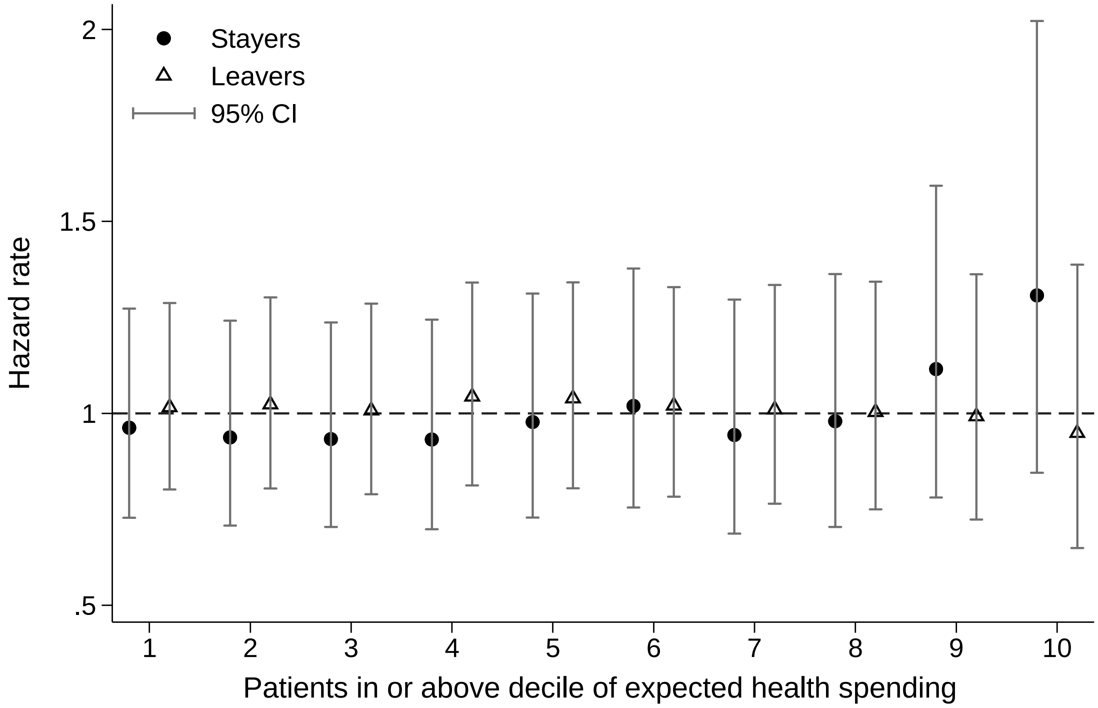
Notes: Figure plots results of estimating equation (2) in the text using the methods of de Chaisemartin and D'Haultfoeuille (2020) on the matched sample, split by expected health spending in the year prior to the switch. Expected health spending is calculated from a LASSO regression as described in the text. Low predicted spending is classified as below-median expected spending and high predicted spending is classified as above-median expected spending. Dependent variable is the inverse hyperbolic sine of total health spending at the quarterly level. Standard errors are calculated via bootstrapping 100 times. Control patients are assigned the switch date corresponding to the concierge physician of their match.

Appendix Figure B11. Total health spending (%) by chronic conditions at baseline



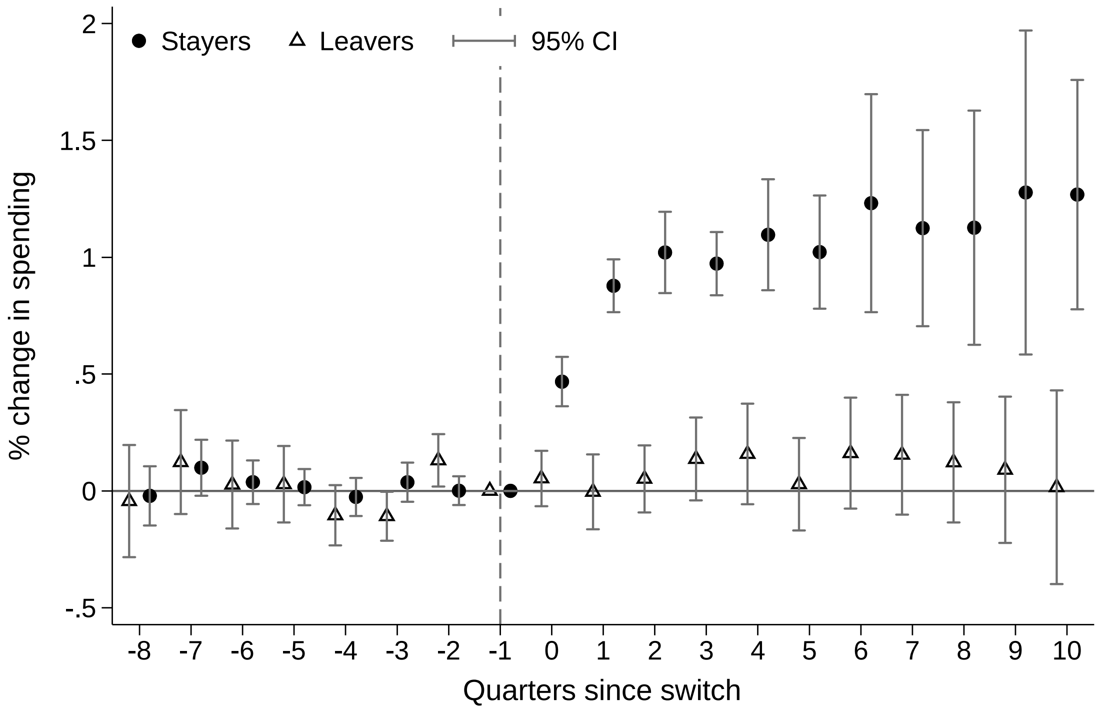
Notes: Figure plots results of estimating equation (2) in the text using the methods of de Chaisemartin and D'Haultfoeuille (2020) on the matched sample, split by the number of diagnoses chronic conditions in the year prior to the switch. Dependent variable is the inverse hyperbolic sine of total health spending at the quarterly level. Standard errors are calculated via bootstrapping 100 times. Control patients are assigned the switch date corresponding to the concierge physician of their match.

Appendix Figure B12. Cox model estimates stratified by stayers vs. leavers, and deciles of expected health spending



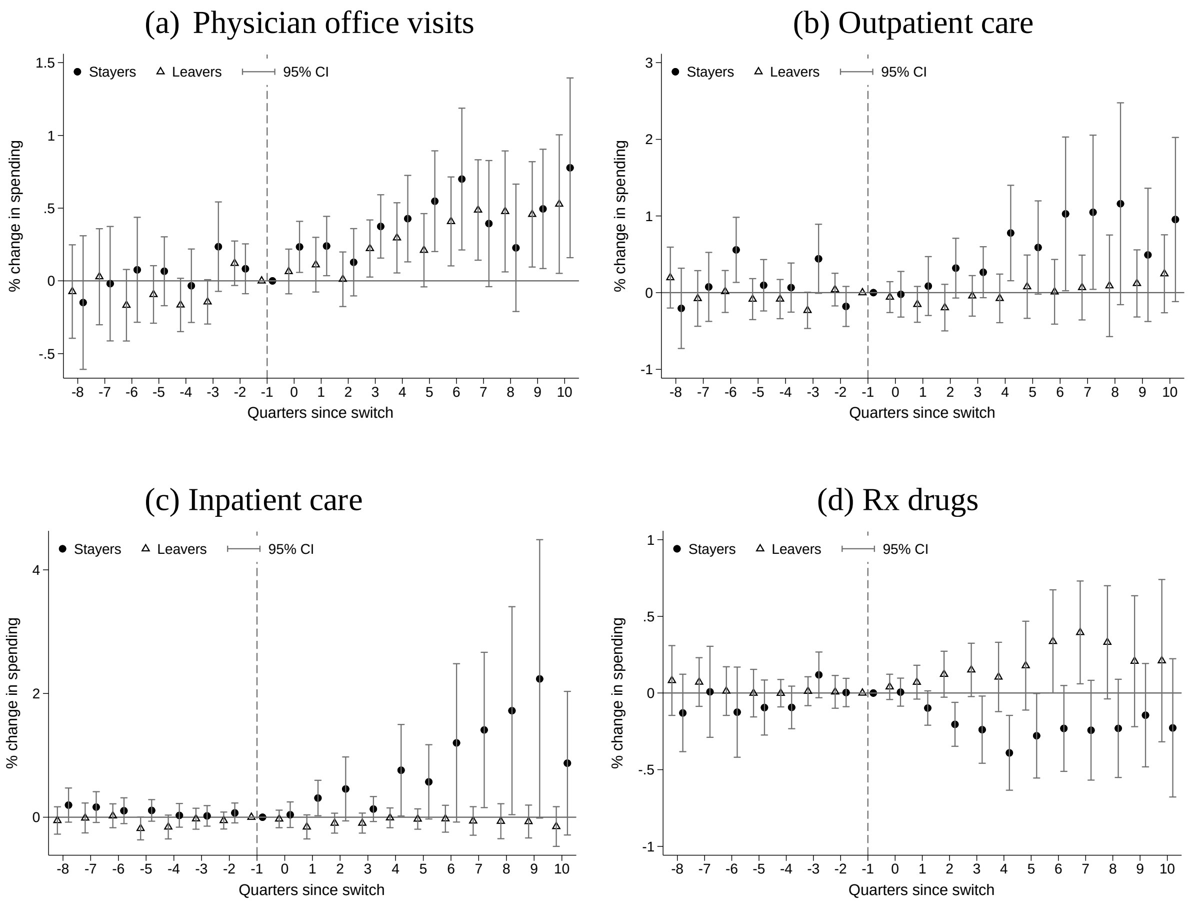
Notes: Figure plots results from estimating the Cox survival models in equation (1) on the matched sample. Each point is the estimate from a separate regression that compares treated units to their matched controls. Hazard estimates from the regressions of stayers are shown in circles and results for leavers are shown in triangles. Each regression is run on patients who are in or above the decile of expected costs listed on the x-axis, ranging from 1 (lowest spending decile) to 10 (highest spending decile). Control patients are assigned the switch date corresponding to the concierge physician of their match.

Figure B13. Event-study regressions: total health spending (%) by stayers vs. leavers, with membership fee



Notes: Figure plots results of estimating equation (2) in the text using the methods of de Chaisemartin and D'Haultfoeuille (2020) on the matched sample. Separate regressions are run for stayers (circles) and leavers (triangles). Dependent variable is the inverse hyperbolic sine of total health spending at the quarterly level. Standard errors are calculated via bootstrapping 100 times. The membership fee is included for stayers. Control patients are assigned the switch date corresponding to the concierge physician of their match.

Appendix Figure B14. Spending by service type for stayers vs. leavers



Notes: Figure plots results of estimating equation (2) in the text using the methods of de Chaisemartin and D'Haultfoeuille (2020) on the matched sample. Dependent variable is the inverse hyperbolic sine of health spending at the quarterly level, split by type of service. Standard errors are calculated via bootstrapping 100 times. Control patients are assigned the switch date corresponding to the concierge physician of their match. The membership fee is excluded from physician office spending. Outpatient care includes claims for care submitted by institutional outpatient providers, including hospital outpatient departments, rural health clinics, renal dialysis facilities, outpatient rehabilitation facilities, comprehensive outpatient rehabilitation facilities, federally qualified health centers, and community mental health centers. Outpatient care excludes physician office visits.