Disruption in Primary Care and Patient Outcomes: Evidence from Physician Retirement

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Abstract

Most of the evidence linking primary care use with better patient outcomes is correlational in nature. In this paper, I exploit exogenous timing of primary care physician (PCP) retirement to study the causal effect of disruption in primary care on patients' health care utilization, medical costs, and health outcomes. I find that the disruption results in higher total medical costs and worsen patient health outcomes through the reduction in primary care utilization and discontinuity of care. Although on average patients find a new PCP of higher quality, this cannot offset the negative effect driven by the above-mentioned two channels. After the disruption, patients substitute primary care with more expensive specialty care and emergency care, and they use more diagnostic and imaging tests. Although there is no change in mortality, hospitalization increases due to the disruption. This evidence supports the widely-held brief that primary care is important in curbing health care costs and improving health care quality.

JEL Codes: I11, I12, I18, J63

1 Introduction

The US health care cost is the highest in the world, accounting for 18% of the GDP (CMS 2016), yet quality lags behind that of other developed countries (Kamal and Cox 2017). Many policies have been implemented with the objective to first, curb the increase in health care costs and second, to improve quality of care. Several recent policies under the Affordable Care Act (ACA) have viewed primary care as a potentially useful tool to achieve these two goals (Davis, Abrams and Stremikis 2011; Blumenthal, Abrams and Nuzum 2015). Part of the rationale for bolstering primary care relies on the widely held belief that increasing primary care utilization and maintaining continuity of care can lead to better patient health outcomes and lower health care costs (Weiss and Blustein 1996; De Maeseneer et al. 2003; Friedberg, Hussey and Schneider 2010; Phillips and Bazemore 2010; Nyweide et al. 2013; Hussey et al. 2014; Romano, Segal and Pollack 2015; Schneider and Squires 2017).[1]

However, the evidence that primary care can lead to better health care quality and lower medical costs is mainly based on associations. A causal relationship has not been convincingly established, mainly due to the lack of exogenous variations in primary care use. Only a few studies use random experiments or other plausible exogenous variations to explore the causality, but the conclusions are mixed and the evidence is segmented (Wasson et al. 1984; Pereira, Kleinman and Pearson 2003; Bailey and Goodman-Bacon 2015; Reddy et al. 2015; Bradley, Neumark and Walker 2017). In this paper, I exploit a potential random shock to primary care use, the turnover of primary care physician (PCP), to investigate the causal effect of disruption in primary care on different patient outcomes and on patients' choice of new PCP.

Two studies have used the similar idea to investigate the impact of PCP turnover on the quality of primary care, and both of them find little impact (Pereira, Kleinman and Pearson 2003; Reddy et al. 2015). However, three weaknesses make their conclusions unconvincing to be causal and hard to generalize. First, they do not show the dynamics of pre-turnover primary care use among affected and non-affected patients or any other evi-

[1]A recent study (Iizuka et al. 2017) uses a regression discontinuity design by exploiting random variations around the threshold for diabetes and find that more physician visits does not benefit patient health and thus are not cost-effective.

dence that PCP turnover is exogenous in their settings. Second, both studies occur within a well-integrated group practice/Veterans health care system, which may mitigate the shock from PCP turnover and thus attenuate the estimated effect.[2] Third, their measurement of the quality of primary care is mainly about whether patients receive recommended preventative tests by a time point. Neither of them considers broader changes in patients' health care utilization, health care costs and health outcomes.[3]

A key assumption for identifying the causal effect of disruption in primary care on patient outcomes is that there is no systematic different pre-trend in patient outcomes between patients who experience disruption in care and who do not. This assumption carries two implications: first, patients do not react to the coming PCP retirement until encountering the shock; second, PCPs' retirement/migration decision does not affect their practice behavior before departure. I show that PCP retirement is a plausible exogenous shock to patients' primary care use since it supports the assumption, but PCP migration is not. Therefore, in this paper, I rely on PCP retirement as the exogenous source of disruption in primary care.

My data are the 20% original Medicare claims from 2006 to 2015, and my sample is a panel of the elderly who entered the 20% sample in 2006, 2007 or 2008 and were included thereafter until their death. I restrict my patient sample to Medicare beneficiaries with full coverage of Medicare Part A & B and are non-movers to avoid confounding factors that may also affect patients health care utilization and patient outcomes. In addition to the directly affected primary care use, I also examine changes in other forms of health care, patients' health care costs, and patients' health outcomes. One feature of the original Medicare is that it does not limit provider network, so patients can freely choose any clinics and physicians. Given this feature, I also analyze patients' choice of new PCP in terms of PCP quality. I measure a PCP's quality following Chetty, Friedman and Rockoff (2014*a*) by estimating a PCP's value-added on four recommended preventative tests.

My main analysis focuses on a niche sample who has the best-scenario primary care use in

[2]The first study occurs in a multi-specialty group practice in Boston, and the second study is in the Veterans Health Administration (VHA). Both settings have well-integrated information system, and patients are guaranteed to have a new PCP in both settings. In the Boston-based group practice, patients can choose a new PCP or passively be assigned one. In VHA, patients cannot choose physicians but they are assigned with PCPs and other health care practitioners.

[3]Pereira, Kleinman and Pearson (2003) consider emergency department utilization and find no change.

the baseline period, i.e., a group of patients who previously maintained desired primary care use (regular visits and continuity of care) and were then informed of their PCP's departure decision on some random day.[4] This niche sample meets two conditions. First, patients stick with a single PCP before the PCP retirement. Second, patients have at least one visit to the retired PCP in the 8 quarters prior to her retirement, i.e., patients have regular primary care visits.[5] The estimates from this niche sample are likely to be the upper-bound effect of disruption in primary care, since these patients have the most desired primary care use prior to PCP retirement and tend to rely most heavily on primary care. Therefore, the shock may be particularly salient for them. In addition, I construct a matched control group who shares the same gender, sex, five-age bin, original disability status, first-observed dual eligibility status, PCP's MD status, and geographic area as the treatment group, and who maintains the best-scenario primary care use over the entire sample period.[6]

The effect of disruption in primary care on patient outcomes is estimated by an event-study model and a difference-in-difference (DID) model. Notably, primary care utilization declines permanently by about 25 percent after the shock. In the meantime, there is strong substitution towards more expensive specialty care and emergency care, with a 14 percent and a 9 percent increase each. In addition, the number of diagnostic and imaging tests also increase by 3 percent and 5 percent separately, and patients' probability of being diagnosed with a new chronic condition increases by 20 percent right after the shock. Patients' overall health status worsens, since hospitalization increases by about 3 percent, mainly driven by admissions through emergency room (ER) visits, but individual mortality has little change. Due to the increase in utilization of these expensive forms of care and medical tests, the total medical costs increase by about 6.6 percent after the disruption.

Three potential mechanisms can explain the changes in medical costs and patient health outcomes, as disruption in primary care brings three direct impacts. The first one is reduction in primary care utilization, which has been demonstrated from the data. The second one is discontinuity of care, which is self-evident as switching PCP for any reason involves a break

[4]Patients may have multiple PCPs but only one accountable PCP in a year, who accounts for the largest share of a patient's primary care services in that year. Through out this paper, without special notice, all PCPs refer to patients' accountable PCPs.

[5]Once in 8 quarters is a very low frequency requirement.

[6]The geographic area is hospital referral region (HRR) defined by the Dartmouth Atlas.

of continuity. Besides, the increase use of medical tests is partially driven by discontinuity of care, as difficulty accessing previous medical records is a main reason for overusing medical tests (Lyu et al. 2017). The last one is the change in PCP quality as patients choose a new PCP. In my sample, among the 83% of patients who find a new PCP, they end up with a PCP of higher quality. Given that most patients on average find a higher-quality new PCP, the increased total medical costs and declined health status are attributable to the reduction in primary care utilization and discontinuity of care, although I cannot disentangle the effect of each channel.

My findings support the belief that primary care is important in curbing health care costs and improving health care quality. Moreover, as the population ages, so does the physician population, and thus disruption in primary care due to PCP retirement will become more often. The current evidence also indicates that a substantial number of Medicare patients cannot cope well with PCP retirement. Therefore, policies that help patients transit smoothly is probably needed.

The rest of the paper proceeds as follows. Section 2 places my research in the context of existing literature and briefly discusses my research setup. Section 3 describes data, sample construction and summary statistics. Section 4 illustrates the empirical strategy. Section 5 shows the effect of physician turnover on patient health care utilization, costs and health. Section 6 analyzes patients' choice of PCP, and Section 7 concludes.

2 Background

I focus on primary care use and PCPs in this analysis for three reasons. First, although bolstering (desired) primary care is often endorsed by researchers and policy makers as an effective way in improving patients' health outcomes and reducing health care costs, we lack causal evidence. Second, the shock created by physician turnover may not only affect patients' well-being through changes in health care utilization, but also through a profound change in patients' choice of PCP. Unlike choosing a specialist, choosing a PCP for most patients is an active decision-making process (Tu and Lauer 2008). Therefore, I can investigate how patients choose their new PCP with a focus on PCP quality. Last, physician turnover rate is increasing over the past decade, and the turnover rate among PCPs is the highest among all types of physicians (AMGA 2014; Singleton and Miller 2015). Physician turnover is costly to clinics, but its effect on patients is less clear, especially turnover from PCPs, who usually have the closest relationship with patients and serve as the gatekeeper for patients' coordinated medical care. Therefore, it is policy-relevant to study how PCP turnover affects patients' outcomes.

2.1 Primary Care Utilization, Continuity of Care, and Patient Outcomes

Desired primary care has two necessary components (Starfield, Shi and Macinko 2005). First, patients get needed primary care regularly and timely. Second, patients maintain a long-lasting relationship with their PCP to preserve continuity of care . Sizable literature has looked at the relationship between each component and the quality and efficiency of health care, and the consensus is that both components are associated with better patient health outcomes and lower health care costs (Friedberg, Hussey and Schneider 2010; Phillips and Bazemore 2010). However, most of the existing estimation tends to suffer from selection bias and/or confounding factors.

I. Primary Care Utilization and Patient Outcomes

Most evidence on the association between primary care utilization and patient outcomes is from cross-sectional macro-level analysis.[7] Most of these studies assess a health care system's orientation toward primary care by evaluating the supply of PCPs. Across countries, Schneider and Squires (2017) show that countries with higher percentage of PCPs have less overall health care expenditure and higher quality of care. Within the US, Shi (1992, 1994) show that states with higher ratio of PCPs have better patient health outcomes. Baicker and Chandra (2004) also find that states with higher proportion of PCPs have lower overall spending and higher quality. A recent research by Koller and Khullar (2017) claims that higher proportion of primary care spending in total state-level medical spending is also

[7]In general, the utilization of primary care is relative to the utilization of specialty care among these studies.

associated with lower total medical costs.

The evidence from individual-level analysis is relatively limited, but Kronman et al. (2008) find that more primary care visits in the preceding year are correlated with less and less-costly end-of-life hospitalization. Recently, there is a study by Bradley, Neumark and Walker (2017) trying to build the causal relationship between primary care utilization and patients' overall medical spending by running a random experiment with low-income patients. They show that primary care visits increase after an incentivized initial PCP visit, and expensive emergency room visits decrease, but the overall health care spending remains the same, because people also increase other outpatient care use.[8]

II. Continuity of Care and Patient Outcomes

Continuity of care is regarded as the cornerstone of primary care use, and compared with primary care utilization, it has aroused more attention. Tons of studies have focused on the role of continuity of care in determining patient outcomes. Similar to the conclusions from the primary care utilization, most studies find that continuity of care is correlated with better patient outcomes. Specifically, studies have found that continuity of care reduces hospitalization, emergency department visits, and overall health care costs (Weiss and Blustein 1996; De Maeseneer et al. 2003; Phillips and Bazemore 2010; Nyweide et al. 2013; Hussey et al. 2014; Romano, Segal and Pollack 2015).

The most popular measurement of continuity of care is based on patients' primary care visits: the more concentrated patients' PCP visits is, the higher the continuity. However, this measurement is subject to patient selection and reverse causality, since patients who see multiple PCPs may be fundamentally different from patients who only see one PCP, for example, sicker or tougher.

A few studies have exploited plausibly exogenous variations in continuity of care, such as Pereira, Kleinman and Pearson (2003) and Reddy et al. (2015), which find no impact of PCP turnover on the quality of primary care, but later I will show that although PCP retirement is exogenous, PCP migration is not. Wasson et al. (1984) conducted a random experiment in

[8] This conclusion may not be generalized because they only observe patients health care-seeking behavior in the first six months, so the results can be biased by the initial release of low-income patients' restrained demand in the past.

an VHA General Medical Clinic with nearly 780 male patients by randomly assigning them to the treatment group with continuity of care (seeing the same PCP every visit) and to the control group without continuity of care (seeing different PCPs). They show that the group with continuity of care have fewer emergent admissions, shorter inpatient stays and higher patient satisfaction, but there is no effect on the quality and efficiency of outpatient care.

2.2 Patient Choice of Health Care Provider: PCP Quality

Many factors affect patients' choice of health care provider, and similar to choosing other normal goods/services, perceived quality is an important factor for over 60% of patients (Tu and Lauer 2008). Studies on patients' response to the quality of institutional providers are relatively abundant. As the advancement of publicly available report cards and online ranking, patients are more aware of the quality of hospitals, and several studies have shown that higher-quality hospitals do face higher patient demand (Dranove et al. 2003; Cutler, Huckman and Landrum 2004; Howard 2006; Pope 2009), but Cutler, Huckman and Landrum (2004) also find that patients respond more to lower-quality hospitals by eluding them than to higher-quality hospitals by seeking more care from them.

Public information on clinics' and individual providers' quality is relatively limited, and thus research on patients' response to physician quality is also limited. However, in recent years, more and more public information on individual providers also becomes available, and a recent study by Santos, Gravelle and Propper (2017) finds that family doctors with better evaluations attract more patients in the UK. Due to asymmetric information in the health care market, when such information is not publicly available, patients' response is uncertain. However, Biørn and Godager (2010) find that even when physician quality information is unavailable, patients can still judge general practitioners' quality and the demand for higher-quality PCPs is higher.[9] In my study, I assess PCP quality by estimating PCPs' value-added on four recommended preventative tests and test whether patients go to higher-quality PCPs.[10]

[9] They measure a PCP's quality by estimating the excessive mortality of her patients.

[10] Physician Compare is a publicly available dataset about physician information. However, it started in 2014, so the information on most of the retired PCPs in my sample cannot be found, and thus I cannot construct physician quality based on information from Physician Compare.

2.3 Quasi-natural Experiment arising from Movers/Turnover

To obtain causal estimation, ideally we want to have a random experiment or exogenous variations from social programs, but when these are unavailable, studies have exploited naturally occurring exogenous sources of variations, and one example is migration/turnover.

The first series of papers exploit the effect on movers themselves. Song et al. (2010) and Finkelstein, Gentzkow and Williams (2016) analyze patients' health care utilization before and after migration to disentangle the influences from environmental factors and individual factors in determining health care utilization. Molitor (2018) compares cardiologists' practice intensity before and after migration to estimate environmental effect on physicians' practice style.

Another literature, on the other hand, looks at how teacher/physician turnover (migration and retirement) affects the remaining students/patients' well-being. Chetty, Friedman and Rockoff (2014*b*) exploit teacher turnover to estimate how teacher quality affect students' life-time earnings. Tu (2017) exploits specialist turnover to examine the effect of specialists' practice intensity on patients' health care utilization and health outcomes. Pereira, Kleinman and Pearson (2003) and Reddy et al. (2015) explore the effect of PCP turnover on patients' quality of primary care, but unlike turnover of primary school teachers and specialists, I find that not all sources of PCP turnover are plausibly exogenous, as patient outcomes exhibit bizarre pattern prior to PCP migration.

Statistics of Physician Turnover

The average annual physician turnover rate is 6.7 percent in 2012, and the turnover rate among nurse practitioners and physician assistants, who also often serve as primary care practitioners (PCP), is even higher of 12.6 percent (AMGA 2014).[11] PCP turnover is the third most common source of disruption in primary care, after patients' voluntary switch of PCP and patients' switch of health insurance plan.[12] As the physician population ages, turnover rate is expected to be even higher. Therefore, studying the disruption in primary

[11] This paper uses a broad concept of PCP, i.e., not only including physicians with specialty in general practice, family medicine, general internal medicine, and geriatrics, but also including non-physicians such as nurse practitioners and physician assistants who assume the role of a patient's PCP.

[12] Based on the author's own calculation from the Medicare data.

care arising from PCP turnover itself is relevant for a substantial number of patients.

2.4 Conceptual Framework

Since I want to estimate the causal effect of primary care use on patient well-being, an ideal experiment would be that patients are randomly assigned into two groups, one with (desired) primary care, and one without primary care.[13] As I do not have this experiment, instead, I exploit the disruption in primary care arising from PCP turnover to mimic such an experiment from the opposite direction, i.e., focusing on a group of patients who initially had desired primary care use and were then removed from the primary care "treatment" by an exogenous shock. Analyzing this counter-example can also shed light on the importance of primary care.

In my main analysis, I focus on a group of patients who had the textbook example of primary care use before the disruption – having an extending stable, long-term clinical relationship with a primary-care type practitioner (Donaldson et al. 1996; Friedberg, Hussey and Schneider 2010) – to avoid confounding factors that may bias the baseline. Unlike a well-specified real experiment, the primary care "treatment" patients receive before the disruption might not be clean. Although a forced switch due to PCP turnover is conceptually not correlated with unobserved idiosyncratic errors and is thus plausibly exogenous, a voluntary switch decided by patients themselves is probably not. Besides, some patients may stop having regular primary care visits long before the disruption. Both voluntary switch and non-regular visits may affect patient outcomes prior to the disruption, and thus bias the estimated effect due to a contaminated baseline. Therefore, my main analysis sample excludes patients who had any voluntary switch or who stopped visiting a PCP more than 8 quarters prior to the PCP departure. Using this niche sample comes with a loss of generalizability. The estimated effect is likely to be an upper bound, because the selected group of patients represent the best scenario of primary care use prior to the disruption.[14]

In addition, the disruption due to PCP turnover is not perfect in estimating a precise

[13]But the control group can have specialty care, emergency care, and inpatient care.

[14]In the robustness analysis, I relax these two restrictions on the baseline sample, and the effect is smaller but still significant.

effect due to a specific channel, because it brings three direct impacts simultaneously. First, it breaks the existing continuity of care. Second, it results in a forced switch of PCP, so quality of new and former PCPs might be different. Third, it may decrease utilization of primary care and/or shift primary care towards other forms of care. Since the first and the third channel are expected to change in the same direction, even if there is an effect of disruption in primary care on patient outcomes, it is difficult to disentangle the effect of each of them.[15]

3 Data, Sample, and Summary Statistics

3.1 Data

This paper uses 2006—2015 20% Medicare original/fee-for-service (FFS) beneficiary summary file and claim files on Medicare Part A (inpatient), Part B (outpatient and carrier), and Part D (prescription drug). The same data source has been used by several studies, such as Finkelstein, Gentzkow and Williams (2016), Tu (2017), Molitor (2018). The data have detailed information of patients' health care utilization, costs, and health status, but are limited in individual demographic characteristics. Therefore, I link the Medicare data with the 2010 American Community Survey (ACS) through zip code/ZCTA to obtain patients' neighborhood characteristics. To identify non-movers in the patient sample and to identify PCP migration, patients' residence zip codes and physician's practice zip codes are grouped into hospital service areas (HSA) and hospital referral regions (HRR) following the definition from Dartmouth Atlas.[16]

3.2 Exogenous Source of PCP Turnover: PCP Retirement

Unlike many of the existing studies focusing on patient-driven disruption in primary care, this paper exploits the disruption driven by the physician side. There are two main sources

[15] The direction of PCP quality is unclear, if it also goes to the same direction, then we cannot disentangle all of the three.

[16] There are 3,436 HSAs and 306 HRRs in the US. The data can be downloaded from: http://www.dartmouthatlas.org/tools/downloads.aspx

for physician turnover: physician retirement and physician migration. I construct work trajectory for each primary care-type practitioner using her national provider identifier (NPI), service date, and service zip code from Medicare carrier claims.[17] Physician retirement date is the last date a physician filed a claim by 2014, and physician migration date is the last date a physician filed a claim in her previous location of practice. The location of practice I used is HRR, similar to Finkelstein, Gentzkow and Williams (2016), Molitor (2018), and Tu (2017). Figure 1 displays the distribution of PCP retirement and migration dates. As expected, most PCP turnover occurs in December.

A key assumption for identifying the causal effect of disruption in primary care on patient outcomes is that there is no systematic different pre-trend in patient outcomes between patients who experience disruption and who do not. This assumption, for one thing, implies that patients hardly anticipate PCP turnover (until receiving PCPs' notice of departure), so that they do not react until encountering the shock; and for another, it implies that PCPs' retirement/migration decision does not affect their medical treatment before departure, and more critically, PCP turnover cannot be a result of their worsening performance.

Conceptually, both types of PCP turnover would create a random shock to patients' primary care use, since physician turnover is normally due to physicians' personal reasons and is thus independent of patient characteristics. However, as shown in Figure 5, patients taken care by migrated PCPs exhibit different pre-trend in the mortality rate and underlying health status from patients seen by retired PCPs and remaining PCPs.[18] In addition, as shown by Figure 4, the increasing trend in imaging tests ordered for patients seeing migrated PCPs implies that migrated PCPs may have abnormal practice behavior before migration.[19] Given that the no pre-trend assumption does not hold for patients seeing migrated PCPs, my analysis only relies on the exogenous source – PCP retirement.

[17]There was a reform of provider ID in early 2007, which converted previous unique provider identification numbers (UPINs) to NPIs. I use the UPIN to NPI crosswalk from the NBER website to covert physician identifiers into NPIs. For those UPINs with no information from the NBER crosswalk, I derive the correspondence from the Medicare data I have.

[18]In addition, the unexpected high mortality rate among patients seeing migrated PCPs cannot be explained by any group-specific characteristics; instead, it seems to be correlated with characteristics of migrated PCPs.

[19]Although the tests are not necessarily ordered by PCPs, research finds that PCPs account for the most of imaging tests for patients (Ayoola, Rosenkrantz and Duszak 2017).

3.3 Patient Sample

My basic patient sample is a panel of elderly original Medicare beneficiaries who were included in the 20% random sample since 2006, 2007, or 2008 until 2015 (or until their death). Two broad restrictions are applied to the sample to avoid disruption in primary care due to other confounding factors. First, I keep patients with full coverage of Medicare Part A (inpatient care) and Part B (outpatient care), because patients with partial coverage are very likely to only use covered health care services, and patients with no coverage can be fundamentally different from their insured counterparts in terms of health status, health care utilization, and/or other aspects. Second, I limit my patient sample to non-movers, who lived in the same HSA for all of the observed years, in order to eliminate disruption in care due to moving and to avoid geographic factors that influence patients' health care utilization (Song et al. 2010; Finkelstein, Gentzkow and Williams 2016).

In addition, since this paper looks at primary care use and disruption due to PCP behavior, a necessary condition for being included in the sample is that patients have at least one accountable PCP over the sample period. Patients may have multiple PCPs in a year but only one accountable PCP, who accounts for the largest proportion of patients' primary care costs (and/or services) in a year (CMS 2017). Throughout this paper, without specific illustration of other/secondary PCPs, PCPs all refer to accountable PCPs.

Patients may have up to 10 different accountable PCPs over the sample period, and there are two types of switching PCP. The first type is a forced switch due to PCP retirement, i.e., patients start seeing a new PCP no earlier than 30 days prior to the former PCP's departure. This 30-day deviation from PCP departure date is due to the 30-day departure notice of physicians required by many states, such as California and Texas (Wall 2005). Figure 2 and Figure 3 demonstrate the existence of this 30-day rule. The second type is a voluntary switch decided by patients themselves, i.e, patients start seeing a new PCP when their former PCP stays and does not have any notice of departure. Patients whose first-observed forced switch occurred between 2010 and 2012 form the potential treatment group, and patients who did not have forced switch over the sample period are the potential control group.[20]

[20]As illustrated above, since PCP migration is an endogenous source of disruption, I only keep patients

As illustrated in the conceptual framework, my main analysis sample (treatment group) is a group of patients who had desired primary care use prior to the disruption and suddenly experienced PCP retirement. This niche sample satisfies two conditions in the baseline period. First, they did not have any voluntary switch of PCP before their forced switch. Second, they had at least 1 visit to the retired PCP in the 8 quarters prior to PCP retirement.[21] In addition, I build a matched control group who share the same gender, race, 5-year age bin, original disability status, first-observed dual eligibility status, PCP MD indicator, and HRR as the treatment group, and who maintain the desired primary care use all over the sample period.

Sample used in the Robustness Analysis

In my robustness analysis, I relax the two limitations that I impose on the baseline period, allowing for irregular visits and a weaker patient-PCP relationship. Since these patients do not maintain desired primary care use and encounter disruptions (by themselves) anyway, the effect on them is expected to be smaller.

3.4 Summary Statistics

Table 1 shows characteristics of patients in the treatment and control group. In general, the treatment and the control group are similar, although due to the large sample size, almost all characteristics are statistically significantly different. The treatment group is slightly sicker than the control group, because the share of the dual eligible and the disabled are higher in the treatment group. Besides, the treatment group is more likely to live in rural areas.

I also compare my main analysis sample with the original Medicare population and the basic patient sample. Compared with the original Medicare population, the basic sample of patients who have full insurance coverage, are non-movers, and have PCP visits are sicker, which is as expected due to adverse-selection in the insurance market and selection into seeking primary care. In addition, as expected, both the treatment and the control group are healthier than the basic sample, since they are the patients who tend to have desired

whose forced switch is due to PCP retirement. In addition, in both groups, patients seeing PCPs who had shorter than 505 days (5 percentile) of stays and who had fewer than 80 days (5 percentile) with claims filed are excluded.

[21] This is a very broad requirement for regular primary care visits.

primary care.

4 Empirical Strategy

My empirical strategy uses the variations from when (and which) PCP retired to quantify the effect of disruption in primary care on patient outcomes. Two findings support the key assumption for identification – the timing of PCP retirement is not correlated with time-varying factors that affect the changes in patient outcomes. First, as shown in Figure 2 and Figure 3, most patients do not alter their health care-seeking behavior beforehand.[22] Second, as shown in Figure 4, retired PCPs do not alter their practice behavior, so that the pre-retirement medical treatment remains the same. In addition, the distribution of PCP retirement dates is smooth over all years (Figure 1).[23]

Therefore, my main estimation is based on a flexible event-study model (Jacobson, LaLonde and Sullivan 1993), equation (1), and a difference-in-difference (DID) model, equation (2).

$$y_{ikt} = \alpha_i + \sigma_t + \sum_{k=-8}^{k=-2} \eta_k 1(t - t_i^* = k) + \sum_{k=0}^{k=11} \beta_k 1(t - t_i^* = k) + \gamma \cdot X_{it} + \varepsilon_{ikt} \tag{1}$$

y_{ikt} represents patient outcomes of health care utilization, procedures and diagnosis, medical costs, and health outcomes in each relative quarter k. In the analysis of patients' choice of PCP, y_{ikt} represents the quality of patients' chosen PCP. The descriptions and details of these outcome variables are illustrated below. On the right-hand side, $1(t-t_i^* = k)$ takes 1 when the quarter is -8,...0,...11 quarters relative to the timing of PCP retirement t_i^*. $t - t_i^* >= 11$ are captured by $1(t - t_i^* >= 11)$, and $t - t_i^* <= -8$ are captured by $1(t - t_i^* <= -8)$. The relative quarter right before PCP retirement ($k = -1$) is set to be the reference.[24] X_{it} includes time-varying individual characteristics, such as age, disability, dual eligibility, number of ever-diagnosed chronic conditions, and predicted Hierarchical Condition

[22] In fact, there is a slightly downward trend in primary care utilization, but compared with the decline right after the shock, the pre-trend only affects the results slightly.

[23] The potential effect from 2008 economic recession is minimal.

[24] However, for specialty care, emergency care, and secondary PCP visit, the increase started since relative quarter -1, so the reference quarter is -2 for these three outcomes.

Categories (HCC) risk score. α_i are patient fixed effects, and σ_t are calendar quarter fixed effects.

η_k's describe the evolution of outcome y_{it} among eventually treated patients before the shock after adjusting for model covariates. They allow a direct evaluation of the assumption that physician retirement is unrelated to pre-turnover changes in y_{it}, i.e., no pre-trend. β_k are coefficients of interest, estimating the average treatment effect of disruption in primary care on the treated patients.

$$y_{it} = \alpha_i + \sigma_t + \beta \cdot Disrupt_i * 1(t > t_i^*) + \gamma \cdot X_{it} + \varepsilon_{it} \tag{2}$$

In the DID specification (Equation (2)), the matched control group is also included in estimation. $Disrupt_i$ indicates whether patient i experienced PCP retirement at time t_i^*, and $1(t > t_i^*)$ groups all post-event quarters together with a single indicator. The other variables are the same as the event-study model. Using an DID framework has three advantages. First, by lumping together all relative quarters in the pre- and post-period, the estimate will be tighter. Second, adding a control group can avoid bias from time-varying unobserved factors that affect both groups. Third, DID makes it easier to interpret a result with a single average effect.

For analysis on all outcome variables except for mortality, I keep patients' outcomes in every relative quarter, as individual fixed effects can handle the changes in sample composition and avoid under-identification problem in the event-study model (Borusyak and Jaravel 2017).[25] For analysis on individual mortality, as individual fixed effects cannot be used, I restrict the sample to the balanced window of relative quarter -8 to relative quarter 11 to deal with the influences from changes in sample composition.

The following part describes outcome variables y_{it} that I use to assess the changes in patient outcomes and in patients' choice of PCP.

I. Patient outcomes

For most of the patient outcomes, I consider the aggregate change in average cost and de-

[25] Balanced sample and individual fixed effects with only the treatment group can lead to under-identification problem.

compose changes into the extensive margin (whether patients have the outcome) and the intensive margin (costs conditional on having the outcome). To avoid influences from inflation, all costs are measured in 2010 USD.

A. Health care utilization

The effect on health care utilization examines the direct effect of disruption on primary care use and the substitution effect towards specialty care and emergency care (ER use). Besides, I look at the change in prescription drug use. For primary care use, I look at the changes in patients' visit/payment to accountable PCP and to other secondary PCPs. For specialty care, I use cardiology as a representative example, since cardiologist is the type of specialist that Medicare patients visit most frequently for consultation purposes.[26] For both primary care use and specialty care use, I only consider physician visits in outpatient settings to avoid the increase in physician visits due to more inpatient admissions.[27]

B. Procedure use and diagnosis

I look at patients' utilization of diagnostic tests and imaging tests to examine if the disruption in primary care leads to higher utilization of (unnecessary) expensive medical tests. Difficulty of accessing previous medical records is one of the main reasons that physicians overuse medical tests (Lyu et al. 2017). As one negative outcome of discontinuity of care is the potential failure in smoothly transferring patient information between physicians (Reddy et al. 2015), it is worth of examining whether medical test utilization increases after the disruption. In addition, given the evidence that more medical tests can lead to more diagnosis (Lu-Yao et al. 2002) and patients' diagnosis can change after moving (Song et al. 2010), I investigate if there is any change in patients' diagnosed chronic condition.

C. Total medical costs

Total medical costs are calculated for each patient by adding up all payments from all claim

[26] According to the author's calculation, visits to cardiologists account for over 10% in all types of specialist visits, following visits to clinical laboratory and diagnostic radiologists.

[27] Outpatient settings are physician's office, hospital outpatient, federally qualified health center and rural health clinic, as used by Dartmouth Atlas 2018: http://www.dartmouthatlas.org/data/table.aspx?ind=170.

files. All of the cost measures include three components: Medicare payment, beneficiary payment (deductible and copay), and payment from other payers. The costs from Medicare claims capture a large proportion of a person's overall medical costs, since hospital care (32%), physician and clinical Services (20%), and prescription drugs (10%) are the most costly parts among one's all medical costs, and they are all included by Medicare claims.

D. Health outcomes

I look at individual mortality, which is an ultimate measure of health status, and I also use hospitalization as an intermediate measurement of health status. In addition to total hospitalization, I look at hospitalization separately by physician referral and through ER. Besides, I analyze hospitalization due to ambulatory care-sensitive conditions (ACSC), since PCPs are thought to be responsible for inpatient admissions due to these conditions (Gao et al. 2014). ACSC-led admissions are divided into admissions caused by acute and chronic conditions. Acute ACSCs are bacterial pneumonia, urinary tract infection and dehydration, and chronic ACSCs include chronic obstructive pulmonary disease (COPD), diabetes and heart failure. Admissions due to acute ACSCs are relevant for all patients, and the admissions due to a chronic ACSC are only relevent for patients who had that chronic condition.

II. Choice of PCP: PCP quality

Ideally, I would have objective measures such as physician's medical school attended and teaching hospital affiliation to evaluate PCP quality. However, such physician-level data are only publicly available since 2014, so I do not have this information for retired PCPs.[28] Therefore, I derive PCP quality measures based on their patient pool from the claim data. I follow the empirical strategy used by Chetty, Friedman and Rockoff (2014*a*) to estimate a PCP's value-added on four recommended preventative tests: annual Hemoglobin A1c test for diabetics, lipid test for diabetics, annual flu immunization, and biannual mammography for females aged 65-69 (Baicker and Chandra 2004).

[28] American Medical Association's Physician Masterfile has such information, however, the price is intimidating.

$$P_{it} = P^*_{it} - \beta \cdot X_{it} = \mu_{jt} + \varepsilon_{it} \tag{3}$$

μ_{jt} is PCP j's value-added on a procedure in year t and is the key variable of interest.[29] β is estimated through adding physician fixed effects μ_p in equation (4):

$$P^*_{it} = \mu_p + \beta \cdot X_{it} \tag{4}$$

P^*_{it} indicates whether a patient i receives a recommended procedure in year t or not. X_{it} includes patients' 5-year age bin, race, gender, HRR, and the lagged use of this procedure in the past year.[30] μ_{jt} is the best linear predictor of j's mean residual procedure in year t using mean residual procedure in other years:

$$\hat{\mu}_{jt} = \sum_{s \neq t} \phi_s \overline{P}_{js} = \vec{\phi}^{-s} \vec{P}_j^{-s} \tag{5}$$

where $\overline{P}_{js}$ is the mean residual procedure among all patients treated by PCP j in year s that estimated from equation (3), and ϕ_s minimizes the difference between $\overline{P}_{jt}$ and the prediction of it using mean residual procedures from other years other than t:

$$\vec{\phi} = \underset{\{\phi_1, \ldots \phi_{t-1}, \phi_{t+1}, \ldots \phi_T\}}{\operatorname{argmin}} \sum_j (\overline{P}_{jt} - \sum_{s \neq t} \phi_s \overline{P}_{js})^2 \tag{6}$$

For all of the four estimated PCP value-added on different procedures, the higher the value-added is, the higher-quality the PCP is. The variations for a PCP's quality over years are small. The estimation of patients' choice of PCP still follows equation (1) and (2), which can partially test if longer searching process can generate better choice.

5 Results: Effect on Patient Outcomes

This section shows the effect of disruption in primary care on patients' health care utilization, medical costs and health outcomes. Graphical evidence from event studies and regression

[29] The subscript for procedure is omitted.

[30] The lagged control is not included in the estimation of value-added on mammography due to not enough years of data.

results from DID and event studies are presented. In most regression tables, columns (1)-(3) are estimations from DID, and columns (4)-(6) are estimations from event studies. Column (1) and (4) show aggregate effect, column (2) and (5) are changes at the extensive margin, and column (3) and (6) are changes in the intensive margin.

5.1 Primary Care Utilization

Notably as shown in Figure 6, there is an abrupt reduction in primary care utilization. In the first quarter right after PCP retirement, the decline is almost 40% of the average baseline level. Although it goes up since the second quarter, the primary care utilization never goes back to the previous level. The disruption results in a permanently 25% decrease in primary care utilization. Conditional on having visit to a new PCP, the cost increases sharply in the first several visits and then goes back to the previous level.

Table 2 shows results from regressions. Overall, the average cost per quarter decreases by 20 dollars, which is a 26% decrease. This decline is mainly driven by the extensive margin, as the share of patients regularly seeing accountable PCPs per quarter decreases by 13 percentage points, which is a 24% decline. Although the conditional cost increases in the first two quarters after the event, its effect on the aggregate cost is trivial.

Although patients only have one accountable PCP each year, they may also visit other PCPs as a secondary source of primary care. Figure 7 and Table 3 demonstrate the changes in patients' utilization of primary care from other PCPs. There is a big increase (6 percent) in other primary care utilization right after the retirement of accountable PCP, which is an over 50% increase. In fact, the change has already started in the quarter right before PCP retirement, with an 15% increase in the share of patients having other PCP visit.[31] However, this increase is only temporary, as the trend declines sharply since the second post-quarter, and after two years the effect totally disappears.

By construction, only patients who have an accountable PCP can have other PCPs (as a secondary source of primary care). Therefore, the temporary increase in other primary

[31] The increase started before PCP retirement is not surprising, as many PCPs notice their patients of departure earlier than 30 days prior to their scheduled retirement date. Therefore, patients may react to PCP retirement once they receive the departure notice.

care use indicates that more patients have a temporary second source of primary care after the disruption. These secondary PCPs can be PCPs that patients initially visit after the shock and then abandon, or can be PCPs that patients visit simultaneously as a supplement to their new accountable PCP. No matter which is the dominant cause of the increase, the increase in other PCP visits reflects the searching cost of finding a new reliable (accountable) PCP.

5.2 Substitution towards Other Health Care Utilization

As primary care utilization declines after the disruption, I investigate if there is any substitution from primary care towards specialty care and emergency care. For specialty care, I use cardiology as an example, since this is the most frequently used specialty care for consultation purposes. Figure 8 and Table 4 demonstrate the increase in cardiology care use. The shift towards specialty care is fairly permanent. In the first post-year, cardiology care increases by 12%. Then, although utilization decreases, the increase still maintains at 8%. Although the increase in cardiologist visits (0.02) is much smaller than the decrease in PCP visits (0.13), since cardiologist visit (217 USD) is much more expensive than primary care visit (143 USD), the cost increase in cardiology care is not neglectable. Similarly to patients' other primary care visits, Figure 8 indicates that patients already responded to PCP retirement by increasing specialty care use in the last quarter of former PCP's stay.

Then I examine changes in emergency care, since previous research shows that primary care use can reduce ER visits (Whittaker et al. 2016; Bradley, Neumark and Walker 2017). Figure 9 and Table 5 imply that there is a slight increase in ER utilization. The share of patients with at least one ER visit per quarter increases by 4.3%. However, as ER visit is very expensive (about $1,700 per quarter), the overall cost increase in emergency care ($14.7 USD) is higher than the overall cost increase in cardiology care ($5.2 USD). In addition, the increase in emergency care cost and cardiology care cost almost offset the decrease in primary care cost ($19.9 USD).

Finally, I look at the change in prescription drug utilization, as shown in Figure 10 and Table 6. In general, there is almost no effect on prescription drug use. The only detectable change is that there is a 3% decrease in prescription drug cost conditional on having part D claims in the quarter right after PCP retirement.

5.3 Medical Tests and Diagnosis

Unnecessary medical tests and treatments cost $200 billion annually (News 2017). Although there is no research yet revealing what percentage of the unnecessary costs can be attributed to discontinuity of care, discontinuity of care can potentially increase the use of medical tests due to the imperfect information transmission between physicians (Reddy et al. 2015). In a recent survey (Lyu et al. 2017), physicians report that 24.9% of medical tests are unnecessary, top among different kinds of overtreatment. Among the most cited reasons for overtreatment, difficulty accessing medical records ranks the third, with 38.2% votes.

Figure 12, Table 7 and Table 8 illustrate the changes in medical test utilization. Both the number of diagnostic and imaging tests increase after the disruption, with the increase in imaging tests more evident. Overall, the number of imaging tests increases by 4.8%, and the increase in diagnostics tests is 3%. As expected, the increase is bigger in the first year after disruption and then decreases gradually, but still, the utilization of medical tests is higher than that in the baseline period.

Finding a new diagnosis might be beneficial to patient health if the disease is found in time and necessary treatment is applied. However, the cost-effectiveness of finding a new disease is ambiguous. Previous research has shown that finding a chronic disease through preventative tests does not lead to better patient outcomes but increase costs (Lu-Yao et al. 2002; Iizuka et al. 2017). In addition, Song et al. (2010) have shown that diagnosis might be subject to physician's diagnostic intensity, and coding with a diagnosis does not necessarily mean a patient really have that condition. In my study, I simply document whether there is an increase in new diagnosis without claiming the cost-benefit of it. Figure 13 and Table 9 depict the change. In the first three quarters after the disruption, there is an over 20% increase in the likelihood of being diagnosed with a new chronic condition, although there is little change in the intensive margin. Later on, the increase becomes modest, but still persists until three years after the disruption. In addition, notice that there is a slightly downward trend prior to PCP retirement, it is hard to claim whether the increased probability of being diagnosed with a new disease is the remedy of former PCP's negligence or is endogenous to new physician's practice behavior.

5.4 Total Medical Costs

Figure 14 and Table 10 illustrate the changes in total medical costs. At the extensive margin, there is a slight decrease in the share of patients who have any medical cost per quarter, but the magnitude is very small, only around 1 percentage point. However, conditional on having any medical cost, the total per capita costs increase by over 200 dollars per quarter, which is a 7.5% increase relative to the baseline period. Therefore, total medical costs increase after the disruption in primary care, which is consistent with previous findings from correlation analysis (Phillips and Bazemore 2010).

5.5 Patient Health Outcomes

I. Hospitalization

Hospitalization is an intermediate health outcome, and if hospitalization increases, the cost increase will be tremendous. One reason for bolstering primary care use is that it can prevent hospital admissions (Parchman and Culler 1994; Gao et al. 2014). Therefore, it is necessary to look at how hospitalization changes after the disruption in primary care.

Figure 15 and Table 11 show that hospitalization increases by about 8% after the disruption, and there is no change of the conditional costs. Although the increase in hospitalization is smaller than the increase in specialty care and emergency care, due to the high cost of inpatient care, the cost increase is the biggest for hospitalization. Figure 16 decomposes hospitalization into to the two main admission sources, and it is clearly that the increase in overall hospitalization is mainly driven by admissions through ER.

Figure 17 and Table 12 examine hospitalization due to ambulatory care-sensitive conditions (ACSC), as ACSC-led hospitalization is often used as a measure of primary care quality (Indicators 2001). Except for hospitalization due to acute ACSCs, which has an 7% increase, there is basically no change in hospitalization due to COPD, diabetes, and heart failure among patients who have those conditions.

II. Mortality

Mortality is a crude measurement of individual health and is a drastic outcome. Even though PCP retirement can have negative effect on patients' health outcomes, except for some outliers at the borderline, it seems very unlikely that a disruption can cause an immediate plummet in patients' health and thus lead to fatal outcomes. Similar to Tu (2017), I find that there is essentially no change in mortality, as shown by Figure 18 and Table 13.

6 Results: Choice of PCP – PCP Quality

The above section indicates that the disruption in primary care results in higher medical costs and worse patient health status through two underlying channels: the reduction in primary care and discontinuity of care. However, in addition to these two channels, the disruption due to PCP retirement also naturally leads to patients' switch of PCP, and thus the quality of new PCPs and former PCPs can be potentially different, which in turn can affect the efficiency of treatment (Doyle, Ewer and Wagner 2010).

Whether patients can find a new PCP of higher quality is an open question, since many internal and external factors can affect patients' choice of a PCP, and physician quality is just one factor (Harris (2003); Victoor et al. 2012; Tu and Lauer 2008). An advantage of the original Medicare is that there is no limitation in provider network, so patients face fewer constraints and are thus more likely to reveal their actual preference in making choices. I hypothesize that patients can find a new PCP of higher quality for three reasons. First, as patients get older and sicker, then tend to be more health literature by accumulated experience, and health literacy improves their decision-making. Second, although a forced switch can be harmful, it also forces patients to overcome inertia and review their current medical needs, so they may choose a new PCP with better fit. Third, Biørn and Godager (2010) show that patients are able to judge PCP quality even if there is no publicly available information of PCP and when asymmetric information exists.

In fact, not all patients in my sample find a new PCP: 13% of patients did not find a new PCP by 2015. 70% of patients find a new PCP within a year, and the rest 17% find a new PCP within five years. My PCP quality measures are PCP value-added on four recommended procedures, and the average quality is computed only when patients have at least one PCP visit in a quarter.[32]

Figure 19 and Table 14 reveal patients' choice. In general, patients are able to find a new PCP of higher quality. New PCPs have higher quality on diabetes management, with value-added on relevant tests increase by over 100%. New PCPs also seem to have better performance on flu vaccination, although the effect is not significant. Unlike the previous three measures, new PCPs have lower value-added on mammography, but this quality measure is irrelevant for most patients as neither they are female nor their age is under 70. In addition, there is no evidence that searching longer will lead to a better PCP.

7 Conclusion

The US health care system is expensive, and Medicare alone accounts for 3.6% of the GDP (CMS 2016; Martin et al. 2017). Better care, smarter spending, and healthier people are the main goals for the recent health care reform (CMS 2015). Advocates for bolstering primary care claim that the under-investment in primary care is one of the reasons for the unsatisfactory performance of the US health care system (Schneider and Squires 2017), and several recent policies under the ACA, such as increasing reimbursement for primary care services and building a comprehensive primary care system (Davis, Abrams and Stremikis 2011; Taylor et al. 2015), have used primary care as a lever for a more efficient and effective health care system.

In this paper, I have exploited a naturally occurring source of disruption in primary care - PCP retirement - to examine how disruption in primary care affects the Medicare population's health care utilization, health care costs, and health outcomes. If the widely held belief is true, then the exogenous disruption in primary care would lead to higher health care costs and worsen health outcomes. In fact, my findings are consistent with this belief. In addition, I find that the main drivers for the increased costs and deteriorated health outcomes are the reduction in primary care utilization (and the shift towards specialty care

[32]I.e., for patients who do not find a new PCP, only pre-quarters with PCP visit(s) are kept for analysis. The results are similar if I only keep patients who have both former and new PCPs.

and emergency care) and discontinuity of care. On the contrary, quality difference between new and former PCPs cannot explain the worsening patient outcomes, as on average new PCPs have higher quality. However, the potential positive effect from increased PCP quality is far away from offsetting the negative effect brought by the two main drivers.

In my main analysis, the baseline sample is a group of patients who follow most closely of the textbook example of primary care use – regular visits and stable patient-physician relationship, and thus the estimated effect is likely to be the upper bound. In reality, many people cannot maintain the desired primary care use, and thus the effect of disruption in primary care is not as detrimental as that on my main analysis sample, which is shown in the robustness analysis.

A limitation of this study is that I cannot disentangle the effect from the two drivers, since reduction in primary care utilization and discontinuity of care occur simultaneously.[33] Nevertheless, since both are essential components of desired primary care use, the evidence still demonstrates the importance of primary care in curbing health care costs and improving health status.

In addition to providing causal evidence on the importance of primary care use, this paper also demonstrates the effect of PCP retirement on patient outcomes. As the population ages, so does the physician population, and thus PCP retirement is expected to become more common. The findings indicate that a substantial number of patients cannot cope well with PCP retirement. Therefore, relevant assistance is needed from governments, social organizations or communities.

[33]Extended discontinuity of care is possible for the treatment group since settling down with a new PCP may some involve trial and error.

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Figures

Figure 1: Distribution physician turnover dates

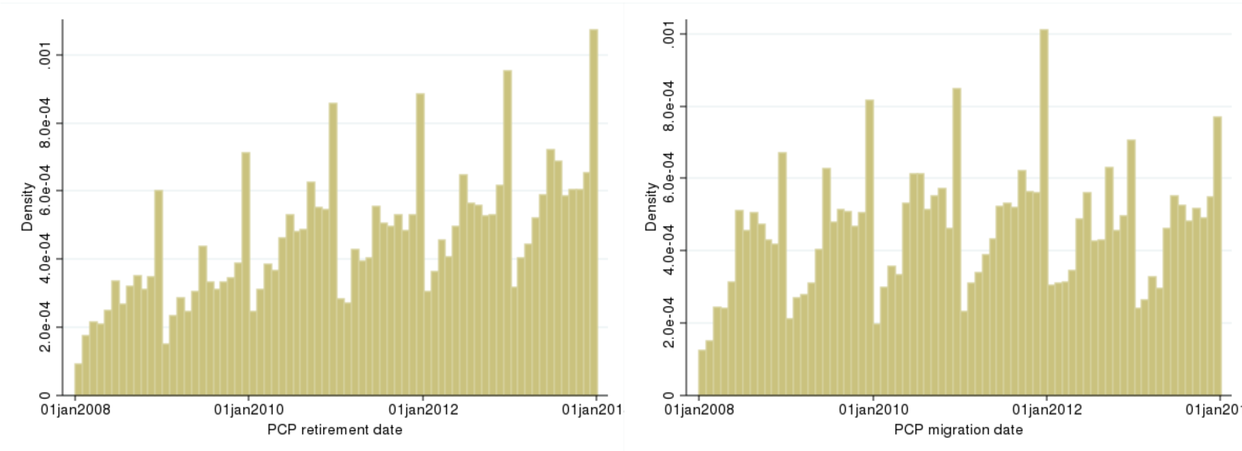


Figure 2: Patients' switch rate by quarter

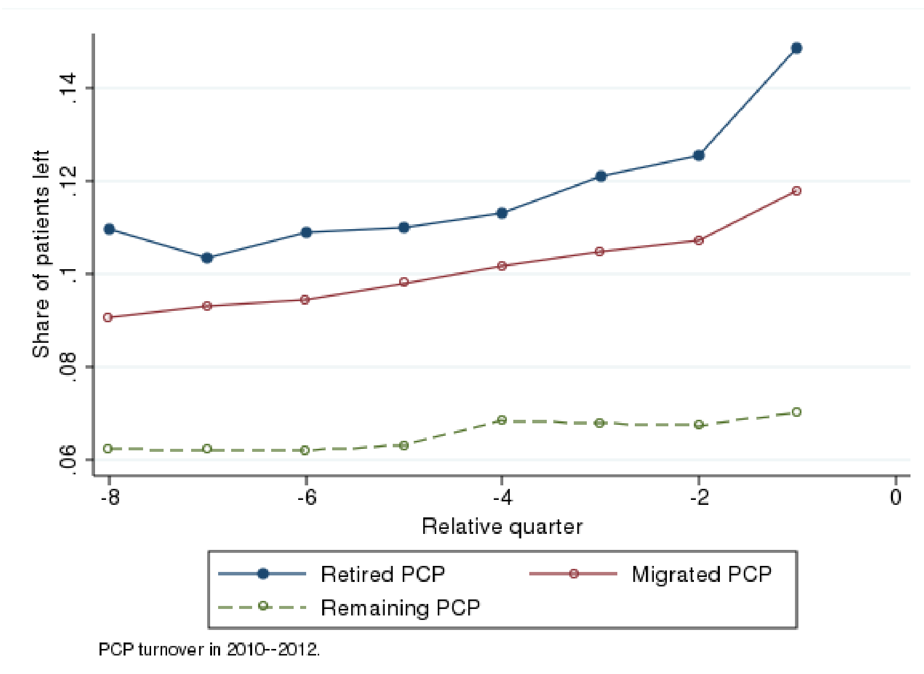


Figure 3: Distribution of patients' switch date (PCP retired)

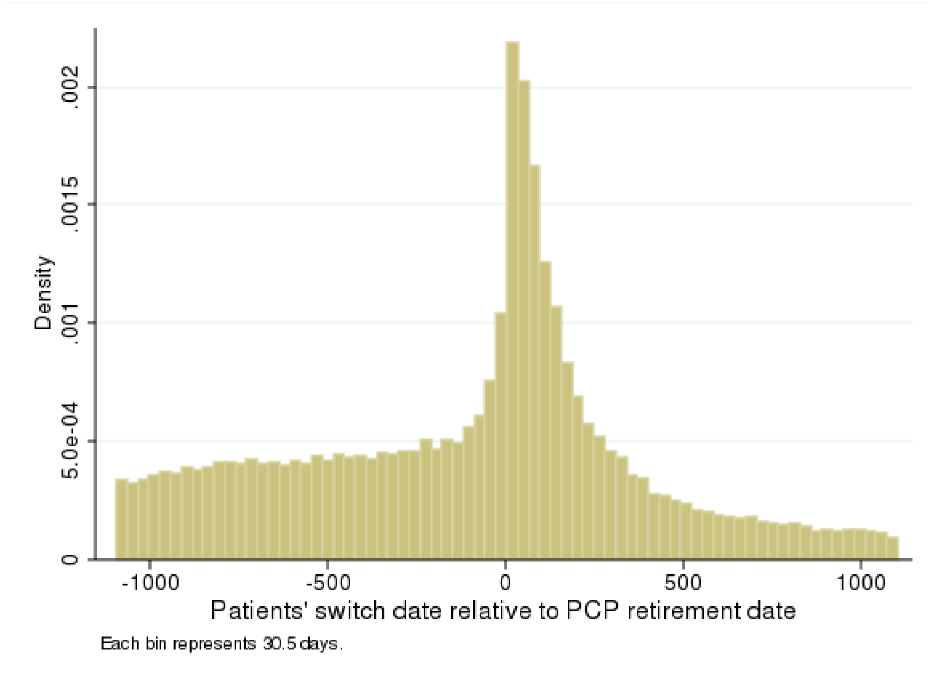


Figure 4: Overall medical test use by patients seeing different types of PCPs

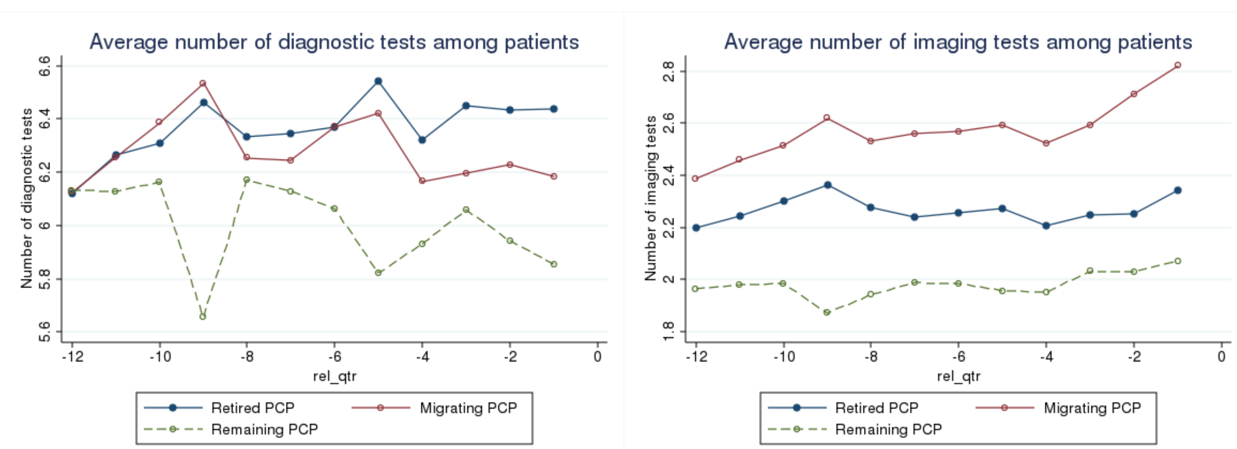


Figure 5: Raw mortality rate and patients' risk scores

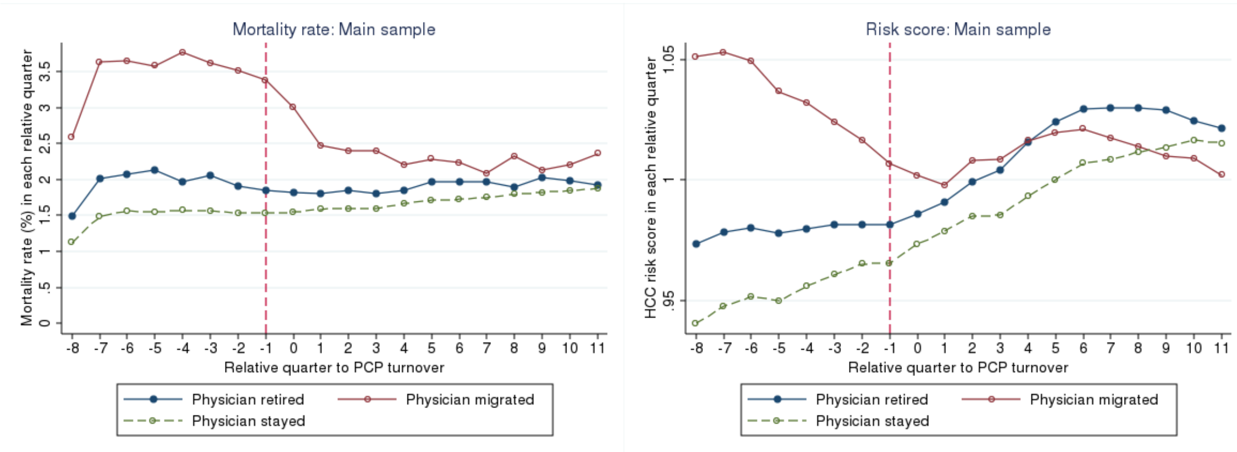


Figure 6: Accountable primary care utilization

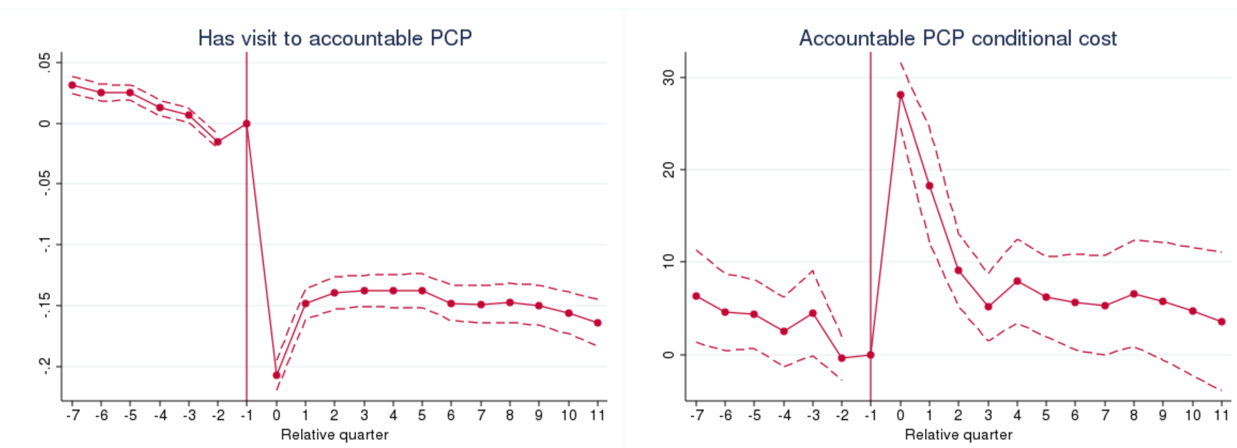


Figure 7: Other primary care utilization

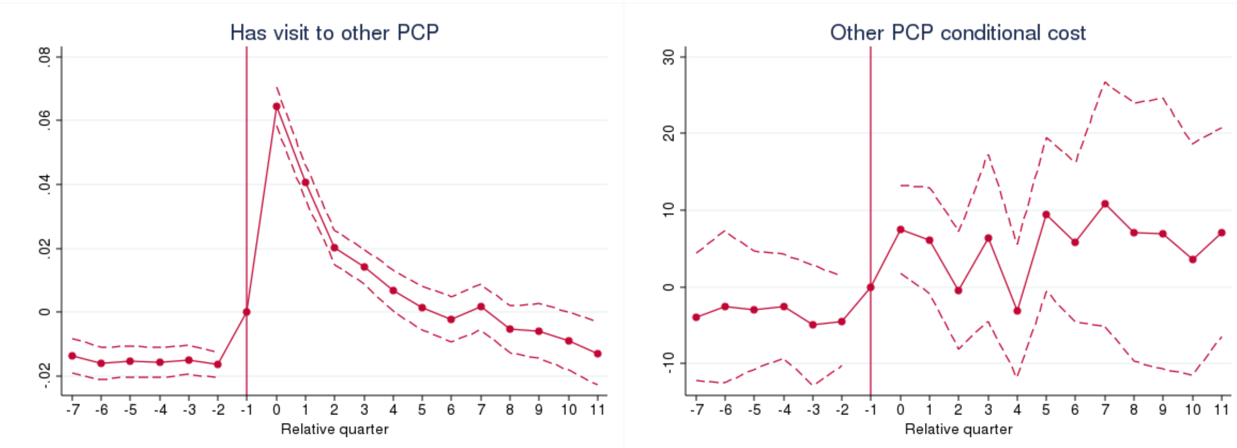


Figure 8: Specialty care utilization – Cardiology

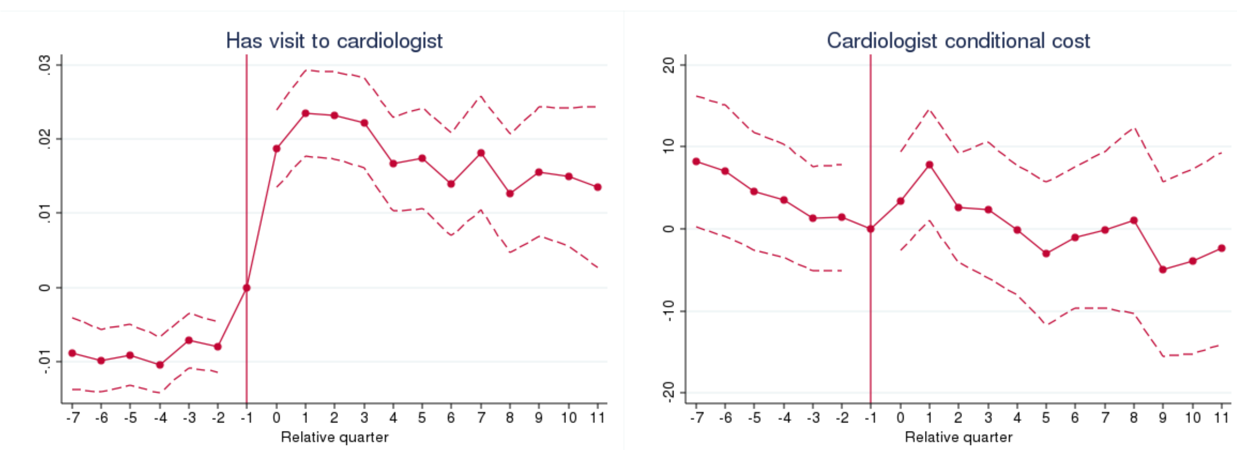


Figure 9: Emergency room utilization

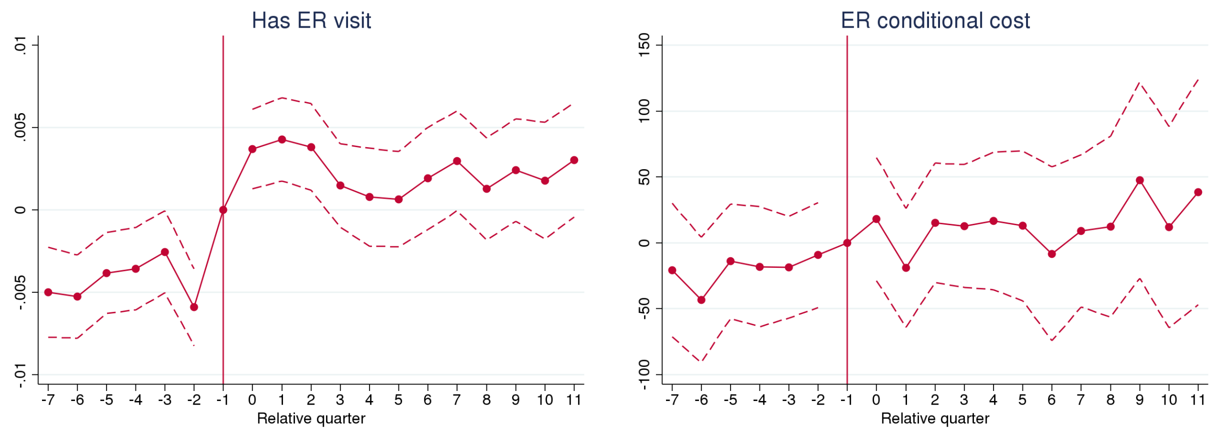


Figure 10: Prescription drug use

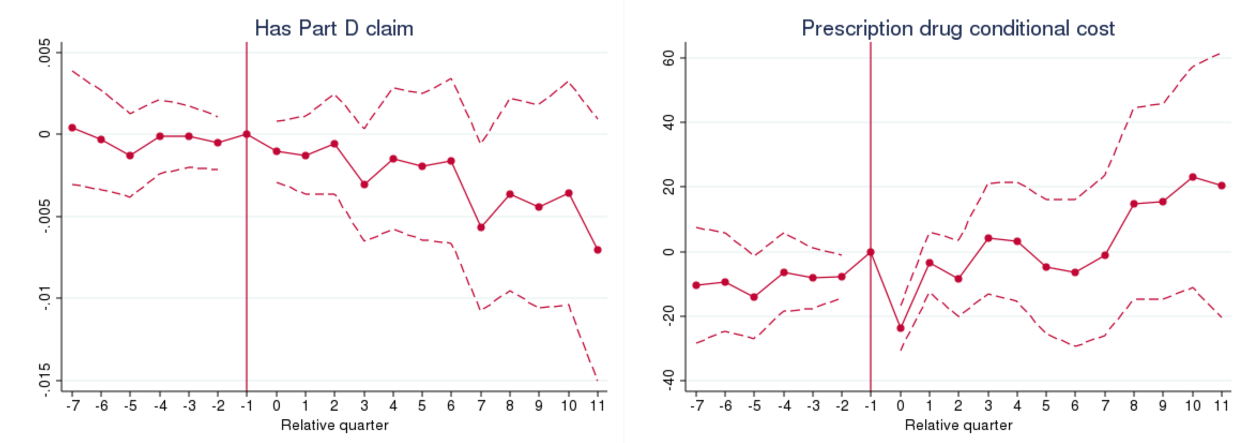


Figure 11: Diagnostic and imaging test

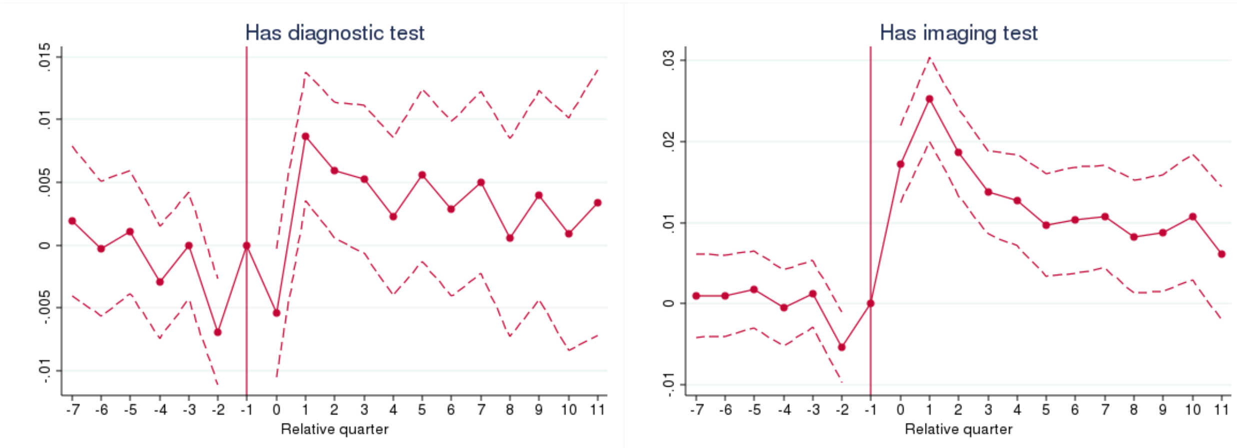


Figure 12: Number of diagnostic and imaging test

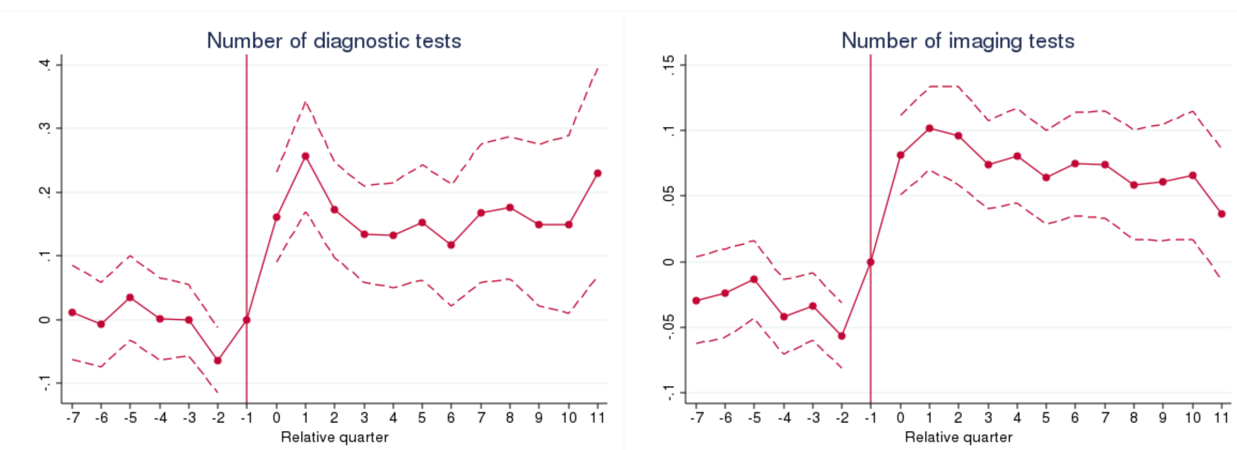


Figure 13: Diagnosed with new chronic conditions

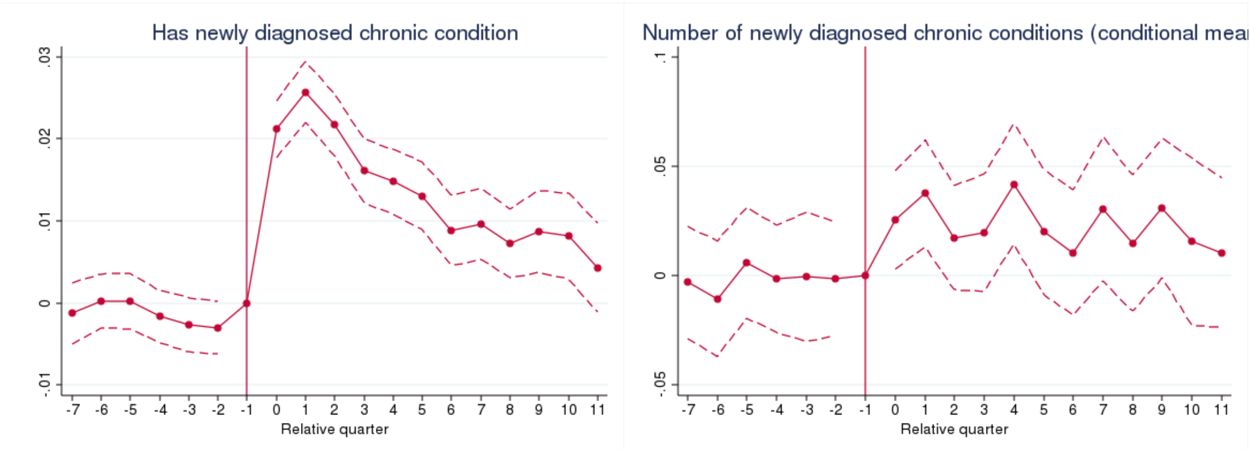


Figure 14: Total health care costs

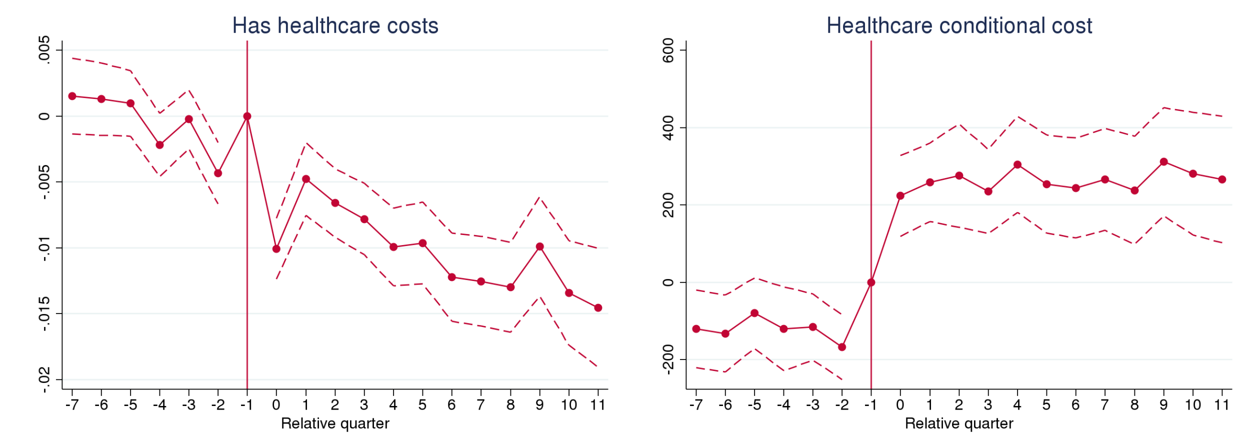


Figure 15: Hospitalization

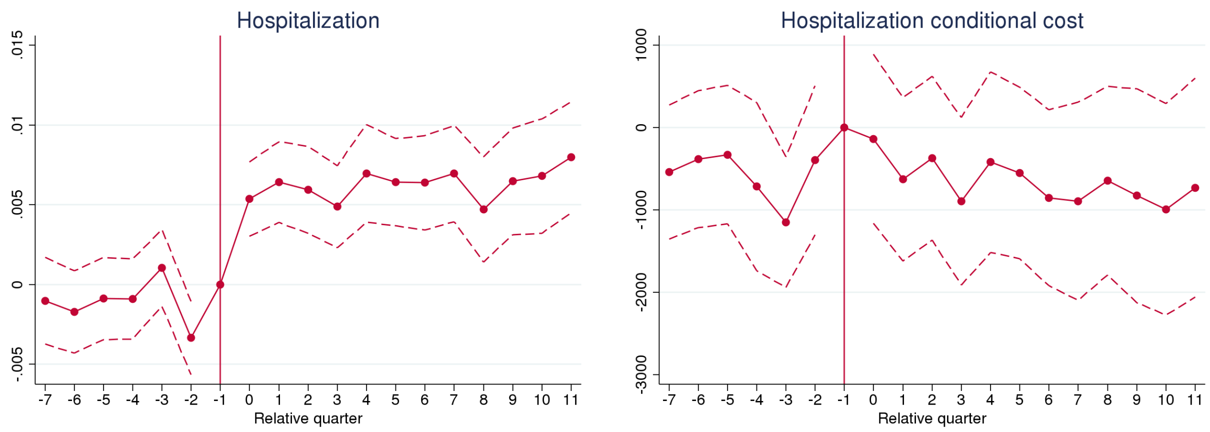


Figure 16: Hospitalization due to different admitting sources

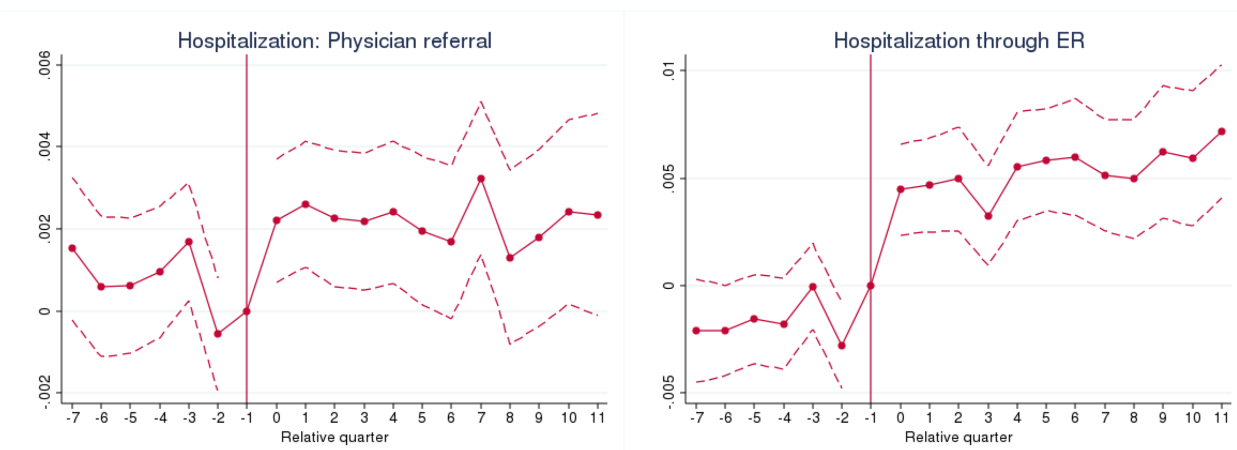


Figure 17: Admissions due to ACSC

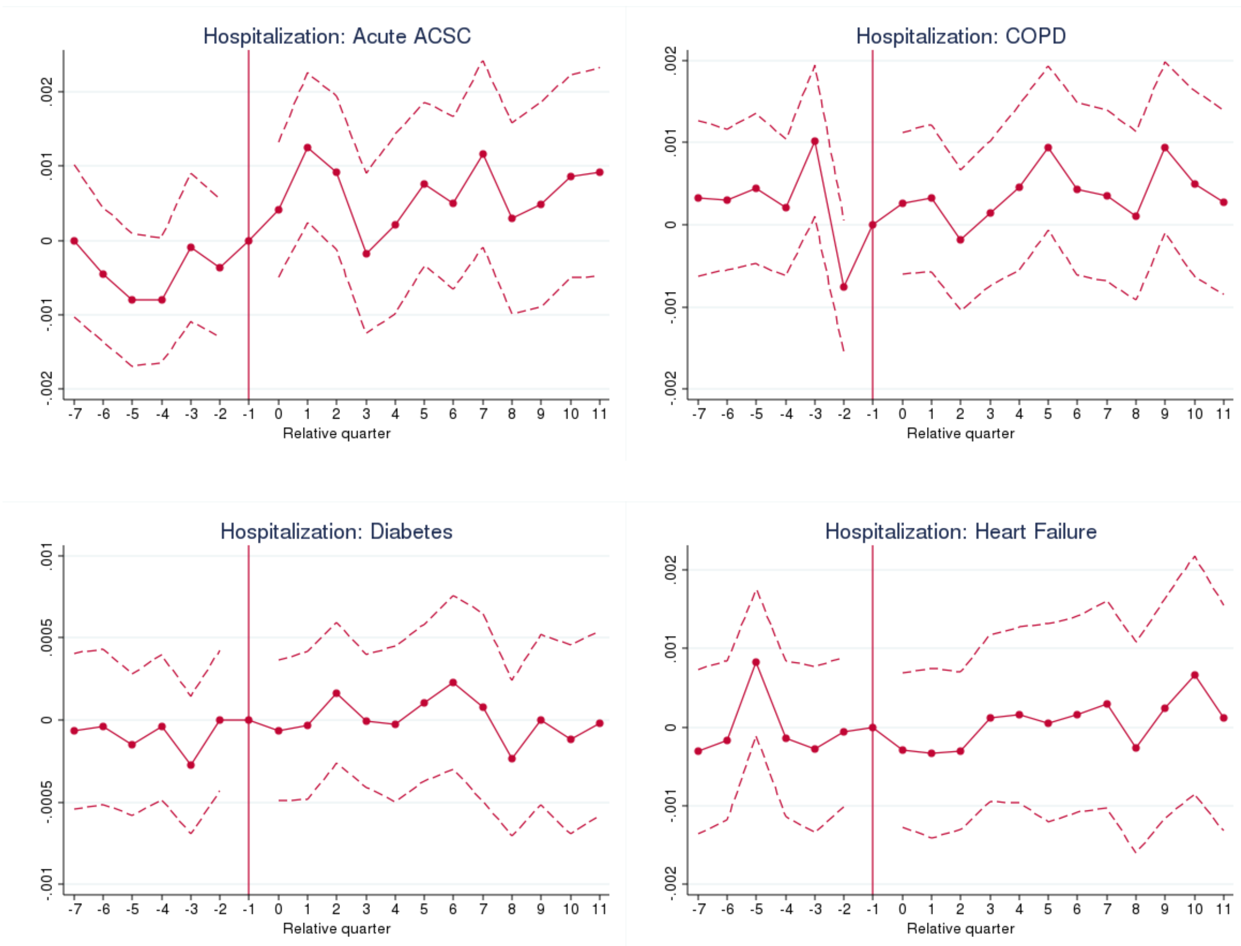


Figure 18: Mortality

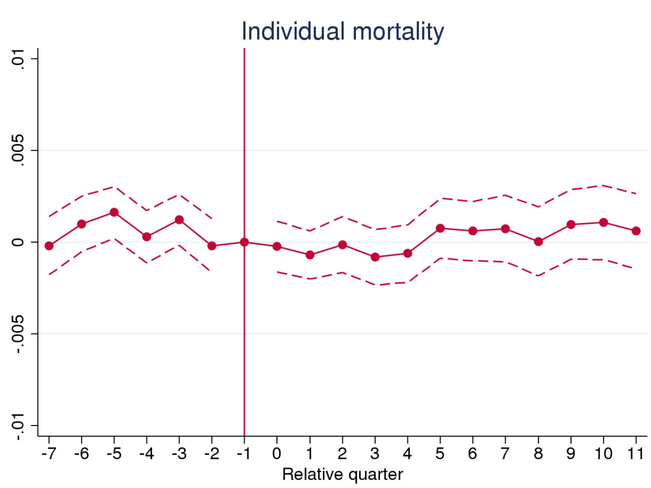
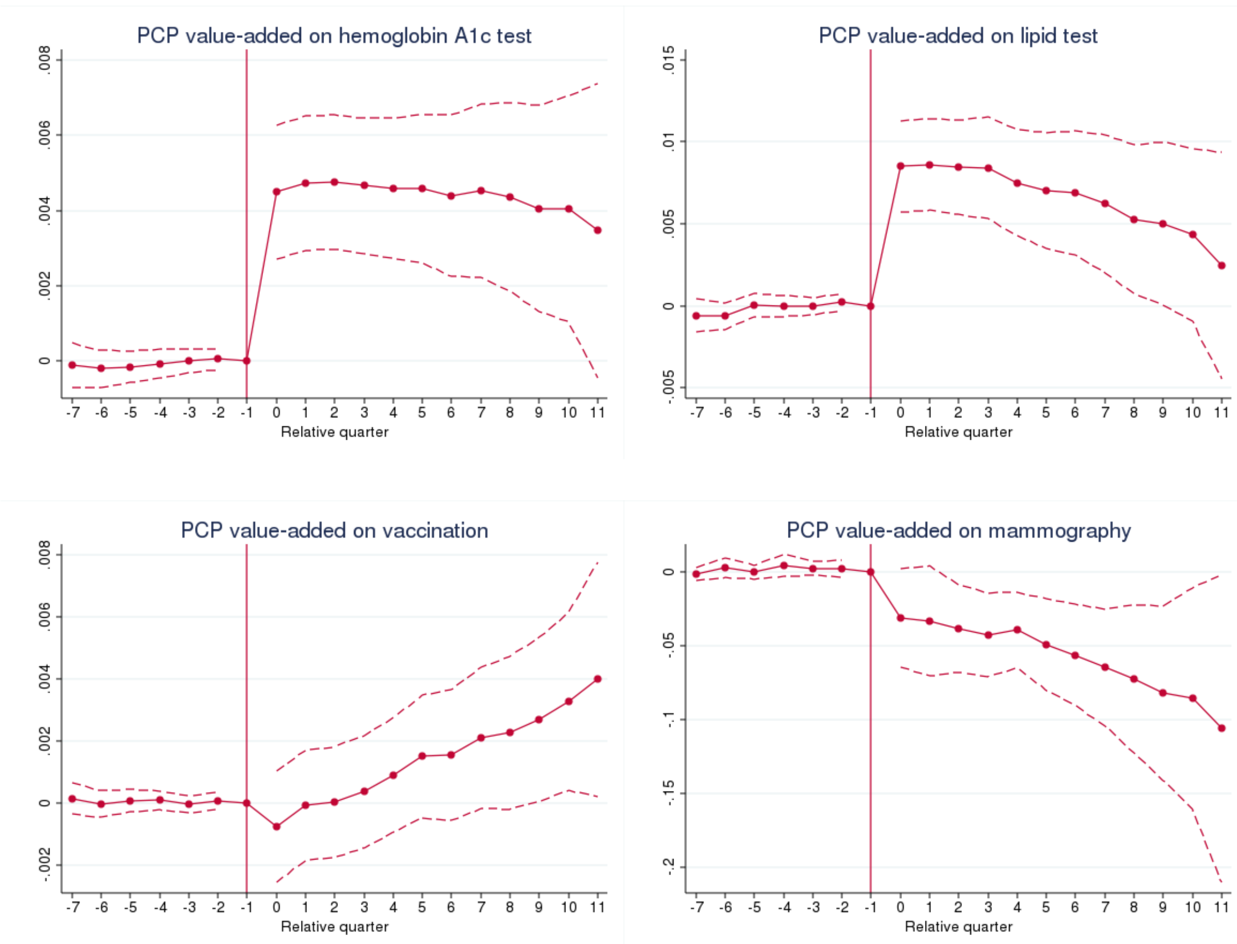


Figure 19: PCP quality



Tables

Table 1: Summary statistics of patients

	65+ original Medicare	Basic sample	Treatment	Control	Difference
Individual-level characteristics					
Age in 2006	74.68	74.55	74.06	74.00	*
Male	0.43	0.42	0.44	0.44	
White	0.88	0.89	0.88	0.89	***
Black	0.07	0.07	0.07	0.07	***
Dual eligible (FY)	0.11	0.11	0.10	0.10	***
Originally disabled	0.07	0.08	0.08	0.07	**
No. of CCs (FY)	3.06	3.38	3.21	3.24	***
HCC score (FY)		0.92	0.87	0.86	*
Retired PCP is MD			0.95	0.96	***
No. of quarters with retired PCP			15.03	14.11	***
Zip-level characteristics					
Mean HH income	71546	70865	71414	70540	***
Median HH income	56838	56351	56418	56166	***
Population	25042	24644	24453	24702	***
Share of rural population	0.25	0.25	0.26	0.25	***
Share of white	0.71	0.72	0.71	0.72	***
Share of elderly	0.15	0.16	0.15	0.15	**
Share of vacant house	0.11	0.11	0.11	0.11	**
Number of patients	5,081,201	3,303,027	83,040	1,035,724	

[1] Basic sample satisfy these conditions: aged 65 and over, original Medicare, full coverage of Part A & B, non-movers, and having at least 1 PCP identified.
[2] Difference shows the t-test results for the mean of treatment and control group. *** p<0.01, ** p<0.05, * p<0.1
[3] FY indicates the variable is measured when individuals are first observed in the data.

Table 2: Primary care use: Accountable PCPs

	(1) Avg cost	(2) Has visit	(3) Cond cost	(4) Avg cost	(5) Has visit	(6) Cond cost
Treatment	-19.9435***	-0.1343***	4.6216***			
	(1.6711)	(0.0058)	(1.2955)			
Quarters -8-				3.7587**	0.0247***	1.1848
				(1.8866)	(0.0041)	(2.6410)
Quarters -7 to -5				6.1347***	0.0254***	2.6302
				(1.4271)	(0.0029)	(1.7436)
Quarters -4 to -2				1.9237*	0.0013	1.0994
				(1.0008)	(0.0026)	(1.3993)
Quarters 0 to 3				-17.6337***	-0.1566***	16.1979***
				(1.6170)	(0.0059)	(1.7721)
Quarters 4 to 7				-16.6508***	-0.1409***	10.1844***
				(1.8683)	(0.0064)	(1.9002)
Quarters 8 to 11+	-18.2583***	-0.1534***	11.0501***			
				(2.1783)	(0.0075)	(2.6219)
Observations	4,119,970	4,119,970	2,284,603	2,174,157	2,174,157	1,093,014
R-squared	0.0036	0.0196	0.0020	0.0030	0.0268	0.0017
Number of id	154,185	154,185	154,111	82,729	82,729	79,120
Quarter FE	yes	yes	yes	yes	yes	yes
Individual FE	yes	yes	yes	yes	yes	yes
Time-varying controls	yes	yes	yes	yes	yes	yes
Mean of dep.	78.16	0.548	142.6	70.50	0.496	142.1

Standard errors are clustered at the HRR level.
*** p<0.01, ** p<0.05, * p<0.1

Table 3: Primary care use: Secondary PCPs

	(1) Avg cost	(2) Has visit	(3) Cond cost	(4) Avg cost	(5) Has visit	(6) Cond cost
Treatment	3.0037***	0.0262***	3.4774*			
	(0.3151)	(0.0015)	(1.7831)			
Quarters -8-				-2.2436***	-0.0226***	-6.5545
				(0.6874)	(0.0025)	(4.3181)
Quarters -7 to -5				-1.2643**	-0.0156***	-2.7602
				(0.5401)	(0.0019)	(3.5781)
Quarters -4 to -2				-1.3268***	-0.0141***	-3.7411
				(0.3516)	(0.0016)	(2.7965)
Quarters 0 to 3				4.1854***	0.0309***	4.9741**
				(0.4327)	(0.0020)	(2.4248)
Quarters 4 to 7				1.7475***	0.0079***	4.7685
				(0.6381)	(0.0024)	(4.6655)
Quarters 8 to 11+				1.5109	0.0021	4.6327
				(1.2983)	(0.0031)	(7.7754)
Observations	4,724,294	4,724,294	528,690	2,420,429	2,420,429	274,989
R-squared	0.0019	0.0116	0.0007	0.0022	0.0146	0.0010
Number of id	160,455	160,455	120,136	81,825	81,825	62,633
Quarter FE	yes	yes	yes	yes	yes	yes
Individual FE	yes	yes	yes	yes	yes	yes
Time-varying controls	yes	yes	yes	yes	yes	yes
Mean of dep.	11.80	0.111	106.1	11.94	0.113	105.9

Standard errors are clustered at the HRR level.
*** p<0.01, ** p<0.05, * p<0.1

Table 4: Specialty care use: Cardiology

	(1) Avg cost	(2) Has visit	(3) Cond cost	(4) Avg cost	(5) Has visit	(6) Cond cost
treatment	4.9482***	0.0217***	3.4466*			
	(0.6751)	(0.0022)	(2.0452)			
Quarters -8-				-1.2978	-0.0075***	3.2989
				(0.9643)	(0.0023)	(4.6556)
Quarters -7 to -5				-0.9091	-0.0076***	5.5966
				(0.8082)	(0.0018)	(4.1976)
Quarters -4 to -2				-1.4487**	-0.0064***	1.1288
				(0.7240)	(0.0015)	(3.5738)
Quarters 0 to 3				5.4998***	0.0212***	3.8048
				(1.0078)	(0.0024)	(3.6401)
Quarters 4 to 7				3.9895***	0.0175***	-0.7017
				(1.1495)	(0.0027)	(4.4457)
Quarters 8 to 11+				3.8434***	0.0163***	-2.1746
				(1.4476)	(0.0035)	(5.6155)
Observations	4,883,134	4,883,134	854,770	2,439,966	2,439,966	437,970
R-squared	0.0024	0.0141	0.0140	0.0022	0.0161	0.0126
Number of id	162,487	162,487	113,351	82,353	82,353	57,722
Quarter FE	yes	yes	yes	yes	yes	yes
Individual FE	yes	yes	yes	yes	yes	yes
Time-varying controls	yes	yes	yes	yes	yes	yes
Mean of dep.	37.70	0.174	217.0	38.59	0.178	216.4

Standard errors are clustered at the HRR level.
*** p<0.01, ** p<0.05, * p<0.1

Table 5: Emergency care use

	(1) Avg cost	(2) Has visit	(3) Cond cost	(4) Avg cost	(5) Has visit	(6) Cond cost
Treatment	14.6652***	0.0042***	45.5438***			
	(2.0993)	(0.0006)	(11.9878)			
Quarters -8-				-25.0025***	-0.0121***	-56.9539*
				(5.1541)	(0.0016)	(32.5561)
Quarters -7 to -5				-10.3194**	-0.0046***	-28.5054
				(4.0317)	(0.0013)	(28.5673)
Quarters -4 to -2				-9.3001***	-0.0031**	-11.2054
				(3.5581)	(0.0012)	(22.6890)
Quarters 0 to 3				9.7972***	0.0058***	20.5339
				(3.6496)	(0.0013)	(23.5212)
Quarters 4 to 7				9.8043**	0.0049***	22.6529
				(4.8323)	(0.0016)	(30.2125)
Quarters 8 to 11+				6.6590	0.0045***	28.1270
				(6.1199)	(0.0018)	(42.1456)
Observations	4,828,292	4,828,292	476,192	2,441,425	2,441,425	247,144
R-squared	0.0506	0.0361	0.0851	0.0534	0.0382	0.0864
Number of id	164,188	164,188	133,918	82,458	82,458	68,017
Quarter FE	yes	yes	yes	yes	yes	yes
Individual FE	yes	yes	yes	yes	yes	yes
Time-varying controls	yes	yes	yes	yes	yes	yes
Mean of dep.	170.2	0.0981	1735	177.4	0.101	1765

Standard errors are clustered at the HRR level.
*** p<0.01, ** p<0.05, * p<0.1

Table 6: Prescription drug use

	(1) Avg cost	(2) Has visit	(3) Cond cost	(4) Avg cost	(5) Has visit	(6) Cond cost
Treatment	1.1269	-0.0028*	8.2952			
	(3.2712)	(0.0015)	(6.0800)			
Quarters -8-				-0.8213	-0.0013	-6.4364
				(6.0824)	(0.0026)	(10.8410)
Quarters -7 to -5				-4.0321	-0.0012	-9.6871
				(3.5866)	(0.0015)	(6.7560)
Quarters -4 to -2				-2.7615	-0.0006	-6.6703*
				(1.9820)	(0.0009)	(3.8974)
Quarters 0 to 3				-5.4294**	-0.0010	-9.2399**
				(2.6109)	(0.0012)	(4.5607)
Quarters 4 to 7				-3.4574	-0.0012	-5.6729
				(4.9247)	(0.0022)	(8.7965)
Quarters 8 to 11+				7.5749	-0.0028	13.6345
				(7.2328)	(0.0028)	(13.5007)
Observations	4,792,700	4,792,700	2,335,036	2,450,998	2,450,998	1,209,369
R-squared	0.0093	0.0824	0.0065	0.0090	0.0798	0.0061
Number of id	162,686	162,686	105,002	82,840	82,840	53,990
Quarter FE	yes	yes	yes	yes	yes	yes
Individual FE	yes	yes	yes	yes	yes	yes
Time-varying controls	yes	yes	yes	yes	yes	yes
Mean of dep.	315.7	0.487	648.6	322.2	0.492	654.5

Standard errors are clustered at the HRR level.
*** p<0.01, ** p<0.05, * p<0.1

Table 7: Diagnostic tests

	(1) No. tests	(2) Has test	(3) Cond no. tests	(4) No. tests	(5) Has test	(6) Cond no. tests
Treatment	0.1146***	0.0055***	0.1616***			
	(0.0250)	(0.0016)	(0.0379)			
Quarters -8-				-0.0170	-0.0001	-0.0719
				(0.0428)	(0.0029)	(0.0712)
Quarters -7 to -5				0.0179	0.0015	0.0097
				(0.0303)	(0.0023)	(0.0504)
Quarters -4 to -2				-0.0191	-0.0030*	0.0002
				(0.0242)	(0.0018)	(0.0394)
Quarters 0 to 3				0.1781***	0.0030	0.2662***
				(0.0327)	(0.0023)	(0.0462)
Quarters 4 to 7				0.1304***	0.0025	0.1735***
				(0.0385)	(0.0029)	(0.0557)
Quarters 8 to 11+				0.1686***	0.0002	0.2396***
				(0.0561)	(0.0037)	(0.0825)
Observations	4,737,379	4,737,379	2,419,004	2,421,464	2,421,464	1,360,364
R-squared	0.0583	0.1521	0.0053	0.0181	0.0189	0.0114
Number of id	162,686	162,686	160,434	82,840	82,840	82,036
Quarter FE	yes	yes	yes	yes	yes	yes
Individual FE	yes	yes	yes	yes	yes	yes
Time-varying controls	yes	yes	yes	yes	yes	yes
Mean of dep.	3.672	0.510	7.193	4.030	0.562	7.174

Standard errors are clustered at the HRR level.
*** p<0.01, ** p<0.05, * p<0.1

Table 8: Imaging tests

	(1) No. tests	(2) Has test	(3) Cond no. tests	(4) No. tests	(5) Has test	(6) Cond no. tests
Treatment	0.0542***	0.0104***	0.0832***			
	(0.0064)	(0.0010)	(0.0154)			
Quarters -8-				-0.1175***	-0.0091***	-0.2070***
				(0.0158)	(0.0025)	(0.0344)
Quarters -7 to -5				-0.0263*	0.0002	-0.0759**
				(0.0137)	(0.0021)	(0.0338)
Quarters -4 to -2				-0.0458***	-0.0020	-0.1002***
				(0.0111)	(0.0018)	(0.0264)
Quarters 0 to 3				0.0907***	0.0193***	0.0759**
				(0.0144)	(0.0021)	(0.0325)
Quarters 4 to 7				0.0810***	0.0126***	0.0941***
				(0.0156)	(0.0026)	(0.0328)
Quarters 8 to 11+				0.0635***	0.0106***	0.0706*
				(0.0198)	(0.0032)	(0.0403)
Observations	4,737,379	4,737,379	1,524,185	2,421,464	2,421,464	871,954
R-squared	0.0622	0.0802	0.0374	0.0362	0.0182	0.0376
Number of id	162,686	162,686	159,354	82,840	82,840	81,648
Quarter FE	yes	yes	yes	yes	yes	yes
Individual FE	yes	yes	yes	yes	yes	yes
Time-varying controls	yes	yes	yes	yes	yes	yes
Mean of dep.	1.054	0.322	3.275	1.186	0.360	3.296

Standard errors are clustered at the HRR level.
*** p<0.01, ** p<0.05, * p<0.1

Table 9: Diagnosed with new chronic condition

	(1) No. CCs	(2) Has new CC	(3) Cond CCs	(4) No. CCs	(5) Has new CC	(6) Cond CCs
Treatment	0.0184***	0.0138***	0.0237***			
	(0.0010)	(0.0007)	(0.0041)			
Quarters -8-				-0.0148***	-0.0091***	-0.0212
				(0.0026)	(0.0018)	(0.0130)
Quarters -7 to -5				-0.0011	-0.0014	-0.0048
				(0.0022)	(0.0015)	(0.0113)
Quarters -4 to -2				-0.0034*	-0.0029**	-0.0021
				(0.0020)	(0.0014)	(0.0114)
Quarters 0 to 3				0.0304***	0.0220***	0.0269***
				(0.0021)	(0.0015)	(0.0099)
Quarters 4 to 7				0.0205***	0.0138***	0.0311***
				(0.0025)	(0.0017)	(0.0117)
Quarters 8 to 11+				0.0154***	0.0101***	0.0245*
				(0.0030)	(0.0021)	(0.0139)
Observations	4,737,379	4,737,379	482,533	2,421,464	2,421,464	253,738
R-squared	0.0053	0.0034	0.0108	0.0057	0.0037	0.0115
Number of id	162,686	162,686	153,324	82,840	82,840	78,466
Quarter FE	yes	yes	yes	yes	yes	yes
Individual FE	yes	yes	yes	yes	yes	yes
Time-varying controls	yes	yes	yes	yes	yes	yes
Mean of dep.	0.130	0.102	1.278	0.134	0.105	1.278

Standard errors are clustered at the HRR level.
*** p<0.01, ** p<0.05, * p<0.1

Table 10: Total medical costs

	(1) Avg cost	(2) Has cost	(3) Cond cost	(4) Avg cost	(5) has cost	(6) Cond cost
Treatment	165.0751***	-0.0063***	205.9234***			
	(20.8257)	(0.0007)	(23.5022)			
Quarters -8-				-293.4684***	-0.0031**	-326.5684***
				(52.0736)	(0.0014)	(58.2689)
Quarters -7 to -5				-73.6133*	0.0004	-96.9450**
				(38.9192)	(0.0011)	(43.1451)
Quarters -4 to -2				-115.7419***	-0.0026***	-128.2569***
				(36.3817)	(0.0010)	(40.1851)
Quarters 0 to 3				207.7134***	-0.0068***	240.1776***
				(44.8124)	(0.0010)	(48.8717)
Quarters 4 to 7				204.8257***	-0.0096***	242.4472***
				(50.2734)	(0.0013)	(54.8770)
Quarters 8 to 11+				230.0393***	-0.0110***	277.6829***
				(59.8928)	(0.0016)	(64.8150)
Observations	4,791,189	4,791,189	4,338,691	2,450,222	2,450,222	2,235,597
R-squared	0.0436	0.0388	0.0434	0.0532	0.0331	0.0534
Number of id	162,686	162,686	162,674	82,840	82,840	82,837
Quarter FE	yes	yes	yes	yes	yes	yes
Individual FE	yes	yes	yes	yes	yes	yes
Time-varying controls	yes	yes	yes	yes	yes	yes
Mean of dep.	2497	0.905	2759	2573	0.911	2823

Standard errors are clustered at the HRR level.
*** p<0.01, ** p<0.05, * p<0.1

Table 11: Hospitalization

	(1) Avg cost	(2) Hospitalized	(3) Cond cost	(4) Avg cost	(5) Hospitalized	(6) Cond cost
treatment	26.4572**	0.0019***	27.8306			
	(13.3317)	(0.0005)	(170.5953)			
Quarters -8-				-243.8516***	-0.0085***	-1,063.7874**
				(38.1607)	(0.0014)	(420.8537)
Quarters -7 to -5				-65.5600**	-0.0011	-434.4894
				(28.6004)	(0.0011)	(363.4354)
Quarters -4 to -2				-82.8083***	-0.0010	-763.2057**
				(27.8554)	(0.0010)	(376.9551)
Quarters 0 to 3				60.4742*	0.0056***	-450.4449
				(35.6038)	(0.0010)	(447.3288)
Quarters 4 to 7				82.4651**	0.0063***	-545.1726
				(38.5005)	(0.0012)	(479.1703)
Quarters 8 to 11+				88.9118**	0.0062***	-576.0121
				(43.9921)	(0.0015)	(551.6765)
Observations	4,638,457	4,638,457	295,023	2,393,268	2,393,268	153,310
R-squared	0.0358	0.0461	0.0234	0.0362	0.0479	0.0237
Number of id	157,154	157,154	112,309	80,832	80,832	57,953
Quarter FE	yes	yes	yes	yes	yes	yes
Individual FE	yes	yes	yes	yes	yes	yes
Time-varying controls	yes	yes	yes	yes	yes	yes
Mean of dep.	917.1	0.0632	14505	933.1	0.0636	14676

Standard errors are clustered at the HRR level.
*** p<0.01, ** p<0.05, * p<0.1

Table 12: Hospitalization due to ACSCs

	(1) Acute	(2) Diabetes	(3) COPD	(4) Heart Failure	(5) Acute	(6) Diabetes	(7) COPD	(8) Heart Failure
Treatment	0.0005***	0.0000	-0.0001	-0.0001				
	(0.0002)	(0.0001)	(0.0002)	(0.0004)				
Quarters -8-					-0.0013***	-0.0000	-0.0012	-0.0024***
					(0.0004)	(0.0003)	(0.0007)	(0.0008)
Quarters -7 to -5					-0.0004	-0.0000	-0.0004	-0.0008
					(0.0004)	(0.0003)	(0.0007)	(0.0007)
Quarters -4 to -2					-0.0004	-0.0001	-0.0003	-0.0004
					(0.0004)	(0.0003)	(0.0006)	(0.0006)
Quarters 0 to 3					0.0006	0.0002	0.0007	0.0001
					(0.0004)	(0.0003)	(0.0006)	(0.0007)
Quarters 4 to 7					0.0006	0.0002	0.0007	0.0012
					(0.0005)	(0.0003)	(0.0007)	(0.0008)
Quarters 8 to 11+					0.0005	0.0000	0.0002	0.0008
					(0.0006)	(0.0004)	(0.0008)	(0.0010)
Observations	4,786,162	2,089,105	1,641,923	1,903,630	2,445,762	1,079,765	859,915	1,004,534
R-squared	0.0067	0.0006	0.0028	0.0083	0.0073	0.0006	0.0028	0.0084
Number of id	162,160	71,886	60,064	70,889	82,571	36,974	31,162	36,936
Quarter FE	yes	yes	yes	yes	yes	yes	yes	yes
Individual FE	yes	yes	yes	yes	yes	yes	yes	yes
Time-varying controls	yes	yes	yes	yes	yes	yes	yes	yes
Mean of dep.	0.00681	0.00143	0.00674	0.00975	0.00691	0.00147	0.00639	0.00954

Standard errors are clustered at the HRR level.
*** p<0.01, ** p<0.05, * p<0.1

Table 13: Mortality

	(1) Death	(2) Death with pair FE	(3) Death
Treatment	-0.0002	0.0006*	
	(0.0003)	(0.0003)	
Quarters -8-			-0.0070***
			(0.0008)
Quarters -7 to -5			-0.0001
			(0.0006)
Quarters -4 to -2			0.0005
			(0.0006)
Quarters 0 to 3			-0.0013**
			(0.0006)
Quarters 4 to 7			-0.0009
			(0.0007)
Quarters 8 to 11+			-0.0008
			(0.0008)
PCP retire	-0.0022***	-0.0030***	
	(0.0002)	(0.0003)	
Observations	2,601,302	2,601,302	1,551,054
R-squared	0.0333	0.0253	0.0332
Quarter FE	yes	yes	yes
HRR FE	yes	yes	yes
Individual controls	yes	yes	yes
Mean of dep.	0.0196	0.0196	0.0200
Number of pair		81,151	
Pair FE		yes	

Standard errors are clustered at the HRR level.
*** p<0.01, ** p<0.05, * p<0.1

Table 14: PCP quality

	(1) A1c test	(2) Lipid test	(3) Vaccination	(4) Mammography	(5) A1c test	(6) Lipid test	(7) Vaccination	(8) Mammography
Treatment	0.0050***	0.0096***	0.0002	-0.0288				
	(0.0009)	(0.0014)	(0.0009)	(0.0181)				
Quarters -8-					-0.0006	-0.0026*	0.0017**	-0.0187*
					(0.0009)	(0.0015)	(0.0007)	(0.0111)
Quarters -7 to -5					-0.0003	-0.0009	0.0005	-0.0055
					(0.0004)	(0.0006)	(0.0003)	(0.0040)
Quarters -4 to -2					-0.0001	-0.0002	0.0002	-0.0000
					(0.0002)	(0.0003)	(0.0001)	(0.0016)
Quarters 0 to 3					0.0047***	0.0089***	-0.0003	-0.0335*
					(0.0009)	(0.0014)	(0.0009)	(0.0175)
Quarters 4 to 7					0.0047***	0.0080***	0.0009	-0.0417***
					(0.0009)	(0.0016)	(0.0009)	(0.0145)
Quarters 8 to 11+					0.0042***	0.0056**	0.0022*	-0.0713***
					(0.0012)	(0.0022)	(0.0012)	(0.0246)
Observations	2,235,889	2,235,889	2,269,185	2,028,127	1,047,820	1,047,820	1,076,664	886,317
R-squared	0.0077	0.0102	0.0006	0.0005	0.0081	0.0114	0.0018	0.0010
Number of id	150,244	150,244	152,810	141,969	76,285	76,285	78,072	72,833
Quarter FE	yes	yes	yes	yes	yes	yes	yes	yes
Individual FE	yes	yes	yes	yes	yes	yes	yes	yes
Time-varying controls	yes	yes	yes	yes	yes	yes	yes	yes
Mean of dep.	0.00420	0.00845	0.00849	-0.0124	0.000298	0.00282	0.00337	-0.0101

Standard errors are clustered at the HRR level.
*** p<0.01, ** p<0.05, * p<0.1

Appendix 1 Sample Composition

Table A1 shows the summary statistics of the remaining sample after each restriction. As expected, individuals with (full coverage of) original Medicare are more likely to be older, white and have more chronic conditions. In addition, they are more likely to live in rural areas with more white people and elderly people. Movers and non-movers are fairly similar. Patients with primary care use or not are also similar. Although patients with PCP(s) are more likely to be originally disabled, but their risk score is a little lower than patients without PCP(s). The sample shrinks as I gradually impose a new restriction. In the end, my basic sample is 65% of total elderly original Medicare population.

Table A1: Sample composition

	Over 65	Original Medicare	Full part A & B	Non-movers	Has a PCP (basic sample)
Individual-level demographics					
Age in 2006	74.03	74.68	75.31	75.27	74.55
Male	0.43	0.43	0.42	0.42	0.42
White	0.85	0.88	0.90	0.89	0.89
Black	0.08	0.07	0.06	0.07	0.07
Dual eligible (FY)	0.11	0.11	0.11	0.11	0.11
Originally disabled	0.07	0.07	0.07	0.07	0.08
No. of CCs (FY)	2.49	3.06	3.40	3.40	3.38
HCC score (FY)				0.97	0.92
Zip-level characteristics					
Mean HH income	70555	71546	70927	70477	70865
Median HH income	56297	56838	56354	56023	56351
Population	26608	25042	24496	24420	24644
Share of rural population	0.22	0.25	0.26	0.26	0.25
Share of white	0.68	0.71	0.72	0.72	0.72
Share of elderly	0.15	0.15	0.16	0.16	0.16
Share of vacant house	0.11	0.11	0.12	0.11	0.11
N	8,110,762	5,081,201	4,458,823	3,860,296	3,303,027
		100%	87.75%	75.97%	65.00%

[1] FY indicates the variable is measured when individuals are first observed in the data.

Appendix 2 Robustness Analysis

In my main analysis, I restrict the sample to patients who initially had desired primary care, which is the best-case scenario for the baseline period, and thus the effect of disruption is expected to be maximal on them. In this section, I relax the two restrictions I impose on the baseline sample, i.e., allowing patients to have endogenous disruptions in primary care before PCP retirement.

Table A2 depicts the robustness sample. Compared with my main analysis sample, they are sicker, older, have shorter relationship with PCPs, and are more likely to see non-physician primary care practitioners. Similar to the difference between the treatment and control group in the main analysis sample, the treatment group is still worse off than the control group, which indicates that using a matched control group is important.

Table A2: Summary statistics of patients

	Treatment	Control	Difference
Individual-level characteristics			
Age in 2006	74.76	74.45	***
Male	0.44	0.42	***
White	0.88	0.90	***
Black	0.07	0.06	***
Dual eligible (FY)	0.12	0.10	***
Originally disabled	0.08	0.08	***
No. of CCs (FY)	3.44	3.36	***
HCC score (FY)	0.96	0.91	***
Retired PCP is MD	0.87	0.90	***
No. of quaters with retired PCP	13.11	13.30	***
Zip-level characteristics			
Mean HH income	71181	71220	
Median HH income	56214	56675	***
Population	24569	24883	***
Share of rural population	0.26	0.25	***
Share of white	0.71	0.72	***
Share of elderly	0.15	0.16	***
Share of vacant house	0.11	0.11	***
Number of patients	165,302	2,425,187	

[1] Difference shows the t-test results for the mean of treatment and control group. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

[2] FY indicates the variable is measured when individuals are first observed in the data.

Table A3 to Table A15 display estimates using the robustness sample. Overall, the evidence supports my hypothesis, i.e., the effect of disruption due to PCP retirement has a smaller effect on this not well-behaved sample. However, there are a few noticeable differences in estimated effect. First, unlike that of the main analysis sample, the conditional cost of primary care declines after the disruption. Therefore, although the decline in primary care utilization is smaller, the overall cost reduction is about the same as the main analysis sample. Second, although hospitalization only increases slightly (and significantly at 10% level), the conditional costs of hospitalization increases. Therefore, the drivers for the increase in hospitalization costs are different compared with the main sample. In addition, hospitalization due to COPD increase by 5%. Finally, the mortality rate decreases for the robust sample by about 7%, which implies that disruption due to PCP retirement actually has a positive impact on individual health status among those not well-behaved patients.

Table A3: Primary care use: Accountable PCPs

	(1) Avg cost	(2) Has visit	(3) Cond cost	(4) Avg cost	(5) Has visit	(6) Cond cost
treatment	-24.32***	-0.0990***	-16.00***			
	(1.66)	(0.0042)	(1.58)			
Quarters -8-				2.1726	0.0119***	1.6739
				(2.0426)	(0.0031)	(3.2016)
Quarters -7 to -5				5.4456***	0.0112***	5.2341**
				(1.6261)	(0.0024)	(2.3842)
Quarters -4 to -2				2.0133*	-0.0030	2.7774
				(1.1392)	(0.0020)	(1.8084)
Quarters 0 to 3				-26.7791***	-0.1239***	-13.3813***
				(2.1287)	(0.0042)	(2.6906)
Quarters 4 to 7				-25.8406***	-0.1069***	-18.2533***
				(2.3978)	(0.0049)	(3.1675)
Quarters 8 to 11+				-27.9691***	-0.1131***	-20.5246***
				(2.6023)	(0.0057)	(3.4947)
Observations	7,837,176	7,837,176	4,087,724	3,849,420	3,849,420	1,880,977
R-squared	0.00	0.0148	0.00	0.0028	0.0195	0.0012
Number of id	319,549	319,549	297,898	161,144	161,144	149,949
Quarter FE	yes	yes	yes	yes	yes	yes
Individual FE	yes	yes	yes	yes	yes	yes
Time-varying controls	yes	yes	yes	yes	yes	yes
Mean of dep.	76.55	0.516	148.3	72.75	0.483	150.7

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A4: Primary care use: Secondary PCPs

	(1) Avg cost	(2) Has visit	(3) Cond cost	(4) Avg cost	(5) Has visit	(6) Cond cost
Treatment	1.2664***	0.0159***	-0.6510			
	(0.3028)	(0.0013)	(1.5648)			
Quarters -8-				-2.0140**	-0.0141***	-9.4389*
				(0.7987)	(0.0017)	(5.4069)
Quarters -7 to -5				-1.2908**	-0.0109***	-5.0014
				(0.5805)	(0.0014)	(4.1613)
Quarters -4 to -2				-1.1339***	-0.0102***	-3.7198
				(0.3351)	(0.0013)	(2.4055)
Quarters 0 to 3				2.2532***	0.0209***	0.5056
				(0.3602)	(0.0015)	(2.3610)
Quarters 4 to 7				0.2693	0.0036**	-0.6164
				(0.5343)	(0.0018)	(3.7544)
Quarters 8 to 11+				0.0503	-0.0011	-0.3163
				(0.9432)	(0.0024)	(5.7342)
Observations	8,879,803	8,879,803	1,087,803	4,391,627	4,391,627	529,597
R-squared	0.0016	0.0114	0.0005	0.0020	0.0130	0.0007
Number of id	320,424	320,424	240,203	162,204	162,204	120,552
Quarter FE	yes	yes	yes	yes	yes	yes
Individual FE	yes	yes	yes	yes	yes	yes
Time-varying controls	yes	yes	yes	yes	yes	yes
Mean of dep.	13.39	0.122	110.0	13.02	0.120	108.9

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A5: Specialty care use: Cardiology

	(1) Avg cost	(2) Has visit	(3) Cond cost	(4) Avg cost	(5) Has visit	(6) Cond cost
Treatment	4.3099***	0.0194***	4.4824***			
	(0.5821)	(0.0018)	(1.4974)			
Quarters -8-				-1.4768**	-0.0070***	2.3377
				(0.7147)	(0.0018)	(3.7172)
Quarters -7 to -5				-1.6220***	-0.0075***	1.9618
				(0.6078)	(0.0014)	(3.1402)
Quarters -4 to -2				-2.0041***	-0.0068***	-1.2674
				(0.5928)	(0.0012)	(2.8966)
Quarters 0 to 3				4.3179***	0.0188***	0.9581
				(0.8388)	(0.0018)	(3.0754)
Quarters 4 to 7				3.3677***	0.0171***	-2.0525
				(0.8829)	(0.0022)	(3.4041)
Quarters 8 to 11+				4.0715***	0.0187***	-0.2130
				(1.1129)	(0.0027)	(4.3872)
Observations	8,967,136	8,967,136	1,642,907	4,435,256	4,435,256	832,148
R-squared	0.0024	0.0124	0.0138	0.0021	0.0136	0.0124
Number of id	323,027	323,027	222,858	163,492	163,492	112,479
Quarter FE	yes	yes	yes	yes	yes	yes
Individual FE	yes	yes	yes	yes	yes	yes
Time-varying controls	yes	yes	yes	yes	yes	yes
Mean of dep.	39.79	0.182	218.7	40.60	0.186	217.8

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A6: Emergency care use

	(1) Avg cost	(2) Has visit	(3) Cond cost	(4) Avg cost	(5) Has visit	(6) Cond cost
Treatment	4.4789**	0.0017***	20.3453**			
	(1.7609)	(0.0005)	(9.3385)			
Quarters -8-				-6.5843*	-0.0016	-31.6244
				(3.6806)	(0.0013)	(23.9010)
Quarters -7 to -5				-4.2570	-0.0004	-31.1014
				(3.1859)	(0.0011)	(21.7223)
Quarters -4 to -2				-6.6249**	-0.0009	-29.8433*
				(2.7847)	(0.0010)	(17.2737)
Quarters 0 to 3				2.9918	0.0035***	-3.2786
				(2.7510)	(0.0009)	(17.2645)
Quarters 4 to 7				0.2226	0.0020*	-14.8874
				(3.8397)	(0.0012)	(22.8861)
Quarters 8 to 11+				-1.9019	0.0006	11.7959
				(5.1661)	(0.0014)	(31.5159)
Observations	8,973,749	8,973,749	1,006,325	4,437,523	4,437,523	499,215
R-squared	0.0500	0.0356	0.0816	0.0506	0.0362	0.0823
Number of id	323,608	323,608	271,937	163,777	163,777	137,670
Quarter FE	yes	yes	yes	yes	yes	yes
Individual FE	yes	yes	yes	yes	yes	yes
Time-varying controls	yes	yes	yes	yes	yes	yes
Mean of dep.	199.0	0.112	1784	198.6	0.112	1778

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A7: Prescription drug use

	(1) Avg cost	(2) Has visit	(3) Cond cost	(4) Avg cost	(5) Has visit	(6) Cond cost
Treatment	-0.8950	-0.0015	-2.7312			
	(2.4848)	(0.0011)	(4.4657)			
Quarters -8-				-1.4822	0.0009	-10.0130
				(4.4351)	(0.0019)	(8.3480)
Quarters -7 to -5				-1.8835	0.0002	-8.0990
				(2.9137)	(0.0012)	(5.8281)
Quarters -4 to -2				-2.8138	0.0001	-7.2469**
				(1.7237)	(0.0006)	(3.5615)
Quarters 0 to 3				-7.0244***	-0.0003	-14.2160***
				(2.1094)	(0.0009)	(4.3620)
Quarters 4 to 7				-5.8396	0.0011	-15.6146**
				(3.9062)	(0.0018)	(7.8757)
Quarters 8 to 11+				2.5985	0.0023	-4.2097
				(5.8799)	(0.0022)	(11.6283)
Observations	9,018,847	9,018,847	4,431,625	4,456,851	4,456,851	2,191,968
R-squared	0.0093	0.0788	0.0062	0.0091	0.0757	0.0062
Number of id	325,342	325,342	210,240	164,684	164,684	106,067
Quarter FE	yes	yes	yes	yes	yes	yes
Individual FE	yes	yes	yes	yes	yes	yes
Time-varying controls	yes	yes	yes	yes	yes	yes
Mean of dep.	341.3	0.491	695.4	345.2	0.491	703.8

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A8: Diagnostic tests

	(1) No. tests	(2) Has test	(3) Cond no. tests	(4) No. tests	(5) Has test	(6) Cond no. tests
Treatment	-0.0217	0.0002	-0.0241			
	(0.0201)	(0.0013)	(0.0309)			
Quarters -8-				0.0283	-0.0015	0.0363
				(0.0308)	(0.0022)	(0.0499)
Quarters -7 to -5				0.0370	-0.0014	0.0656*
				(0.0235)	(0.0017)	(0.0387)
Quarters -4 to -2				0.0034	-0.0044***	0.0385
				(0.0194)	(0.0014)	(0.0313)
Quarters 0 to 3				0.1032***	0.0018	0.1528***
				(0.0229)	(0.0016)	(0.0350)
Quarters 4 to 7				0.0523*	0.0018	0.0559
				(0.0305)	(0.0021)	(0.0466)
Quarters 8 to 11+				0.0759*	0.0007	0.0898
				(0.0448)	(0.0027)	(0.0661)
Observations	8,909,669	8,909,669	5,115,714	4,405,871	4,405,871	2,501,676
R-squared	0.0059	0.0068	0.0032	0.0056	0.0063	0.0030
Number of id	325,342	325,342	321,237	164,684	164,684	162,392
Quarter FE	yes	yes	yes	yes	yes	yes
Individual FE	yes	yes	yes	yes	yes	yes
Time-varying controls	yes	yes	yes	yes	yes	yes
Mean of dep.	4.274	0.574	7.445	4.244	0.568	7.476

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A9: Imaging tests

	(1) No. tests	(2) Has test	(3) Cond no. tests	(4) No. tests	(5) Has test	(6) Cond no. tests
Treatment	0.0214***	0.0040***	0.0320***			
	(0.0056)	(0.0009)	(0.0103)			
Quarters -8-				-0.0185	-0.0030	-0.0225
				(0.0143)	(0.0019)	(0.0290)
Quarters -7 to -5				-0.0013	0.0004	-0.0120
				(0.0118)	(0.0015)	(0.0270)
Quarters -4 to -2				-0.0317***	-0.0028*	-0.0611***
				(0.0098)	(0.0015)	(0.0227)
Quarters 0 to 3				0.0441***	0.0102***	0.0330
				(0.0099)	(0.0015)	(0.0231)
Quarters 4 to 7				0.0314***	0.0061***	0.0266
				(0.0117)	(0.0019)	(0.0254)
Quarters 8 to 11+				0.0100	0.0045*	-0.0121
				(0.0142)	(0.0024)	(0.0294)
Observations	8,909,669	8,909,669	3,375,561	4,405,871	4,405,871	1,668,737
R-squared	0.0119	0.0045	0.0152	0.0125	0.0046	0.0160
Number of id	325,342	325,342	320,348	164,684	164,684	162,043
Quarter FE	yes	yes	yes	yes	yes	yes
Individual FE	yes	yes	yes	yes	yes	yes
Time-varying controls	yes	yes	yes	yes	yes	yes
Mean of dep.	1.317	0.379	3.476	1.324	0.379	3.498

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A10: Diagnosed with new chronic condition

	(1) No. CCs	(2) Has new CC	(3) Cond CCs	(4) No. CCs	(5) Has new CC	(6) Cond CCs
Treatment	0.0068***	0.0058***	0.0098***			
	(0.0007)	(0.0005)	(0.0028)			
Quarters -8-				-0.0004	-0.0012	0.0066
				(0.0021)	(0.0014)	(0.0095)
Quarters -7 to -5				0.0028	0.0005	0.0129
				(0.0018)	(0.0012)	(0.0088)
Quarters -4 to -2				-0.0008	-0.0020*	0.0100
				(0.0016)	(0.0011)	(0.0085)
Quarters 0 to 3				0.0199***	0.0138***	0.0247***
				(0.0014)	(0.0011)	(0.0072)
Quarters 4 to 7				0.0123***	0.0081***	0.0223***
				(0.0017)	(0.0011)	(0.0083)
Quarters 8 to 11+				0.0079***	0.0050***	0.0147
				(0.0021)	(0.0014)	(0.0101)
Observations	8,911,712	8,911,712	960,619	4,405,871	4,405,871	479,897
R-squared	0.0048	0.0031	0.0102	0.0052	0.0034	0.0106
Number of id	325,342	325,342	304,438	164,684	164,684	153,550
Quarter FE	yes	yes	yes	yes	yes	yes
Individual FE	yes	yes	yes	yes	yes	yes
Time-varying controls	yes	yes	yes	yes	yes	yes
Mean of dep.	0.139	0.108	1.293	0.141	0.109	1.292

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A11: Total medical costs

	(1) Avg cost	(2) has cost	(3) Cond cost	(4) Avg cost	(5) Has cost	(6) Cond cost
Treatment	45.50***	-0.0054***	65.39***			
	(14.26)	(0.0005)	(15.58)			
Quarters -8-				15.26	-0.0022**	19.82
				(40.58)	(0.0010)	(44.65)
Quarters -7 to -5				69.61**	-0.0014*	74.26**
				(31.50)	(0.0008)	(34.75)
Quarters -4 to -2				-13.81	-0.0035***	-12.17
				(26.70)	(0.0007)	(29.27)
Quarters 0 to 3				95.93***	-0.0051***	117.71***
				(25.25)	(0.0008)	(27.63)
Quarters 4 to 7				47.89	-0.0060***	70.02**
				(31.96)	(0.0010)	(35.07)
Quarters 8 to 11+				37.69	-0.0062***	64.63
				(41.29)	(0.0013)	(44.52)
Observations	9,009,317	9,009,317	8,187,853	4,455,391	4,455,391	4,052,221
R-squared	0.05	0.0366	0.05	0.05	0.0307	0.05
Number of id	325,342	325,342	325,222	164,684	164,684	164,629
Quarter FE	yes	yes	yes	yes	yes	yes
Individual FE	yes	yes	yes	yes	yes	yes
Time-varying controls	yes	yes	yes	yes	yes	yes
Mean of dep.	2911	0.908	3205	2954	0.908	3252

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A12: Hospitalization

	(1) Avg cost	(2) Has visit	(3) Cond cost	(4) Avg cost	(5) Has visit	(6) Cond cost
Treatment	35.93***	0.0007*	231.22**			
	(9.95)	(0.0004)	(113.23)			
Quarters -8-				-39.8541	0.0003	-360.3523
				(27.9391)	(0.0011)	(319.3460)
Quarters -7 to -5				10.4812	0.0017**	-133.0632
				(22.3416)	(0.0009)	(280.1215)
Quarters -4 to -2				-32.5735	0.0002	-368.4124
				(20.2191)	(0.0008)	(256.9073)
Quarters 0 to 3				33.1944*	0.0022***	8.7781
				(19.9509)	(0.0007)	(284.9369)
Quarters 4 to 7				22.2040	0.0018**	-202.5861
				(22.3572)	(0.0009)	(321.9697)
Quarters 8 to 11+				8.7920	0.0008	-227.2415
				(27.3372)	(0.0011)	(356.6090)
Observations	8,792,472	8,792,472	647,223	4,345,879	4,345,879	321,735
R-squared	0.03	0.0456	0.02	0.0336	0.0464	0.0205
Number of id	316,821	316,821	237,067	160,238	160,238	119,910
Quarter FE	yes	yes	yes	yes	yes	yes
Individual FE	yes	yes	yes	yes	yes	yes
Time-varying controls	yes	yes	yes	yes	yes	yes
Mean of dep.	1093	0.0732	14926	1111	0.0735	15117

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A13: Hospitalization due to ACSCs

	(1) Acute	(2) Diabetes	(3) COPD	(4) Heart Failure	(5) Acute	(6) Diabetes	(7) COPD	(8) Heart Failure
Treatment	0.0002	0.0001	0.0004**	0.0002				
	(0.0001)	(0.0001)	(0.0002)	(0.0003)				
Quarters -8-					-0.0003	-0.0001	-0.0002	-0.0007
					(0.0003)	(0.0004)	(0.0003)	(0.0006)
Quarters -7 to -5					0.0001	-0.0003	0.0001	-0.0003
					(0.0002)	(0.0005)	(0.0006)	(0.0007)
Quarters -4 to -2					-0.0003	-0.0001	-0.0002	-0.0002
					(0.0003)	(0.0002)	(0.0004)	(0.0005)
Quarters 0 to 3					0.0002	0.0001	0.0005	-0.0004
					(0.0003)	(0.0002)	(0.0004)	(0.0005)
Quarters 4 to 7					0.0000	0.0001	0.0008*	0.0004
					(0.0004)	(0.0002)	(0.0005)	(0.0006)
Quarters 8 to 11+					-0.0001	-0.0002	0.0006	0.0004
					(0.0004)	(0.0003)	(0.0006)	(0.0007)
Observations	8,998,145	3,875,128	3,274,880	3,825,232	4,446,337	1,921,536	1,617,147	1,896,699
R-squared	0.0069	0.0005	0.0024	0.0076	0.0071	0.0005	0.0026	0.0078
Number of id	324,084	142,971	129,252	154,373	164,010	72,784	65,944	78,968
Quarter FE	yes	yes	yes	yes	yes	yes	yes	yes
Individual FE	yes	yes	yes	yes	yes	yes	yes	yes
Time-varying controls	yes	yes	yes	yes	yes	yes	yes	yes
Mean of dep.	0.00826	0.00180	0.00733	0.0108	0.00835	0.00187	0.00738	0.0110

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A14: Mortality

	(1) Death	(2) Death	(3) Death
Treatment	-0.0037***	-0.0013***	
	(0.0002)	(0.0002)	
Quarters -8-			-0.0057***
			(0.0007)
Quarters -7 to -5			-0.0040***
			(0.0006)
Quarters -4 to -2			-0.0022***
			(0.0004)
Quarters 0 to 3			-0.0048***
			(0.0005)
Quarters 4 to 7			-0.0063***
			(0.0005)
Quarters 8 to 11+			-0.0072***
			(0.0006)
Retire	0.0050***	0.0049***	
	(0.0002)	(0.0003)	
Observations	4,740,557	4,740,557	2,927,709
R-squared	0.0325	0.0254	0.0360
Quarter FE	yes	yes	yes
HRR FE	yes	yes	yes
Individual controls	yes	yes	yes
Mean of dep.	0.0185	0.0185	0.0213
Number of pair		158,890	
Pair FE		yes	

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A15: PCP quality

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	A1c test	Lipid test	Vaccination	Mammography	A1c test	Lipid test	Vaccination	Mammography
Treatment	0.0042***	0.0080***	0.0014**	-0.0152				
	(0.0006)	(0.0009)	(0.0006)	(0.0115)				
Quarters -8-					-0.0005	-0.0018*	0.0003	-0.0140*
					(0.0006)	(0.0010)	(0.0005)	(0.0077)
Quarters -7 to -5					-0.0004	-0.0010**	-0.0002	-0.0037
					(0.0003)	(0.0004)	(0.0002)	(0.0031)
Quarters -4 to -2					-0.0001	-0.0004	-0.0002	-0.0004
					(0.0001)	(0.0002)	(0.0001)	(0.0015)
Quarters 0 to 3					0.0039***	0.0075***	0.0008	-0.0214*
					(0.0006)	(0.0010)	(0.0006)	(0.0111)
Quarters 4 to 7					0.0042***	0.0071***	0.0016**	-0.0263***
					(0.0007)	(0.0011)	(0.0007)	(0.0093)
Quarters 8 to 11+					0.0042***	0.0059***	0.0026***	-0.0453***
					(0.0009)	(0.0015)	(0.0009)	(0.0154)
Observations	3,976,270	3,976,270	4,052,638	3,578,811	1,797,593	1,797,593	1,851,472	1,555,960
R-squared	0.0037	0.0052	0.0009	0.0002	0.0059	0.0083	0.0016	0.0004
Number of id	291,121	291,121	295,760	275,789	144,823	144,823	148,231	137,527
Quarter FE	yes	yes	yes	yes	yes	yes	yes	yes
Individual FE	yes	yes	yes	yes	yes	yes	yes	yes
Time-varying controls	yes	yes	yes	yes	yes	yes	yes	yes
Mean of dep.	0.00436	0.00722	0.00611	-0.0210	0.00181	0.00345	0.00296	-0.0169

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$