Political polarization in medicine*

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Abstract

Political polarization is increasingly affecting policymaking, but how is it influencing professional decision-making? This paper studies the differences in medical practice between Republican and Democratic physicians over 1999-2019. It links physicians in the Medicare claims data with their campaign contributions to determine their party alignment. In 1999, there were no partisan differences in medical expenditure per patient. By 2019, Republican physicians are now spending 13% more, or $70 annually per patient. We analyze four potential sources of this partisan difference: practice characteristics (i.e., specialization and location), patient composition, preferences for financial gain, and beliefs about appropriate care. Even among physicians in the same specialty and location treating patients for the same condition, Republican physicians spend 6% more, especially on elective procedures. Using a movers design, we also find large partisan differences for treating the same patient. We find no evidence that these partisan differences are driven by profit incentives. Instead, the evidence points to diverging beliefs. Republican physicians adhere less to clinical guidelines, consistent with their reported beliefs in prior surveys. The timing of the divergence matches the politicization of evidence-based medicine in Congress. These results suggest that political polarization may lead to partisan differences in the beliefs and behavior of practitioners.

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1 Introduction

Americans now live in a society where more issues are becoming polarized along party lines (Gentzkow, 2016; Pew Research Center, 2019). In recent decades, political partisanship has played a dominant role in determining which policies are enacted into law (McCarty, 2019; DellaVigna and Kim, 2023; Canen et al., 2020, 2023). The medical field has not been spared (Patashnik et al., 2020; Oberlander, 2024). Figure 1 shows the rise in polarization for both health and non-health policies at the federal and state levels. As medicine has become politicized, even more so since the COVID pandemic, public health experts have flagged the imposing influence of political polarization on health policy (Blendon et al., 2016; Findling et al., 2022). But could political differences have spread beyond how medicine is governed, and now into how medicine is *practiced*?

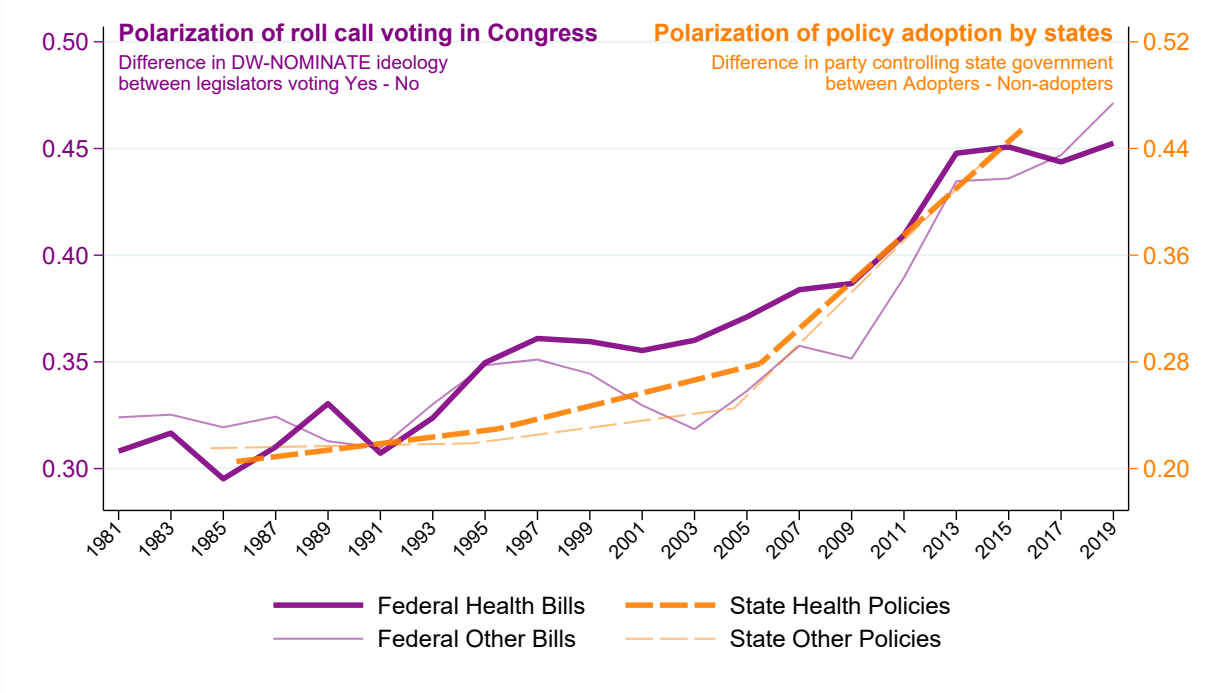
Clinically, patients should receive the optimal treatment for their health condition, regardless of whether their physician is a Republican or Democrat. Physicians, however, vary greatly in how they practice medicine (Chandra et al., 2011; Badinski et al., 2024). They differ in their skills and specialization (Chandra and Staiger, 2007; Chan et al., 2022), their beliefs on appropriate treatments (Cutler et al., 2019), and their sensitivity to prices (Clemens and Gottlieb, 2014; Song et al., 2014). In hypothetical vignette surveys, Republican and Democratic physicians recommend different treatments for politicized health issues (Hersh and Goldenberg, 2016). Yet for all the recent politicization of medical issues, it remains unclear whether there are now widespread partisan differences in real-stakes medical decisions.

This paper studies the differences between Republican and Democratic physicians in medical practice over 1999-2019. It links the campaigns contribution records for 28% of the physicians (N=308,749) in the Medicare claims data and tracks their party alignment over time (Bonica et al., 2014; Bonica, 2023). Since the vast majority donate to only one party (if any), Republican and Democratic physicians are readily distinguishable. Only those who have contributed are included in the sample, starting from their first contribution.

The key finding in this paper is that there are now large differences between Republican and Democratic physicians in medical spending per patient. Importantly, there were no such differences two decades prior. In 1999, Republican and Democratic physicians have similar average levels of utilization per patient. By 2019, Republican physicians now spend around 13% more (s.e.=2), or \$70 (s.e.=9) per patient over the year. Aggregated over millions of encounters between physicians and patients each year, this difference amounts to billions of dollars in annual public healthcare spending for additional tests, imaging, and surgeries. The U.S. is already an outlier in healthcare expenditures, of which an estimated 30% is

considered wasteful (Skinner, 2011; Doyle Jr. et al., 2017). Whether this extra expenditure is inefficient or medically necessary depends on the source of the partisan divergence.

Figure 1: Political polarization in federal and state policymaking



This figure shows the trends in political polarization for congressional roll call voting and state policy adoption over the 1980s-2010s. For congressional roll call votes (left axis), we calculate the absolute difference in the median DW-NOMINATE ideology between legislators who voted for each bill versus those who voted against the bill. DW-NOMINATE scores range from -1 (liberal) to 1 (conservative) and have two dimensions; we average the differences in both dimensions. The figure shows the four-year moving average in the DW-NOMINATE difference across the bills. The bills categorized under the Health policy area by the Congressional Research Service are shown separately. Roll call voting data and legislator DW-NOMINATE ideology scores are from voteview.com (Lewis et al., 2024). For state policy adoption (right axis), we calculate the absolute difference in the average party controlling the state government between states that have adopted each policy versus those that have not. States under unified Democratic control (i.e., Democratic governor and both state chambers controlled by the Democratic party) are assigned a party score of -1, states with a divided government a score of 0, and states under unified Republican control a score of 1. For policies that reach over 24 adopters (half the contiguous U.S. states), we compare the first 24 adopters to the rest. The figure shows the average difference in party control across policies for each decade. State policy adoption data are from DellaVigna and Kim (2023).

What are the potential sources of differences in medical practice between Republican and Democratic physicians? We derive four main theories from a simple model of physician decision-making based on prior literature (Chandra and Skinner, 2012; Finkelstein et al., 2016; Cutler et al., 2019; Badinski et al., 2024). The first potential source comes from *practice characteristics*, which include specialization and location. For example, Republicans may disproportionately select into high-utilization fields, such as cardiology (specialization),

or work in environments with different liability risk, resource constraints, and peer effects (location). The second is *patient composition*, in that Republican physicians may see patients who are sicker or prefer more aggressive treatments. The third is *preferences for financial gain*, or their weight on profit incentives. The fourth is their *beliefs about appropriate care*, regarding which treatments are warranted for a given condition.

We evaluate the evidence for each theory through four testable predictions. First, if the partisan difference comes from imbalances in specialization and location, then there should be no difference between physicians with the same specialty who treat patients from the same location for the same medical condition. For this analysis, we conduct a decomposition with specialty-location-diagnosis fixed effects. Second, if the difference is due to patient composition, then the difference should disappear when Republican and Democratic physicians are treating the same patient. We study patients who move and consequently see new physicians who are aligned with a different party. Third, if Republican physicians provide more treatments because they have stronger preferences for financial gain, then they should also respond more strongly to financial incentives. We revisit two research designs from the medical literature that feature an adjustment to the profit margin. Fourth, if Republican physicians believe that certain treatments carry more benefits, then they should perform the treatments more frequently. We rely on prior survey evidence to identify those treatments.

We begin with a decomposition that accounts for practice characteristics. The decomposition framework corrects for partisan imbalances in the number of physicians in each specialty-location-diagnosis group, and also categorizes the within-group differences into the extensive and intensive margins for various treatment categories. The extensive margin measures which services physicians choose to treat their patients, for example, deciding between physical therapy or knee replacement for osteoarthritis. Conditional on selecting a treatment, the intensive margin is the number of times it is administered. This decomposition also adjusts for differences in observable characteristics, including patient age, physician gender, and medical school graduation year.

The decomposition finds that even after controlling for practice characteristics, Republican physicians are now spending 6% more (s.e.=0.6) on patients with the same condition, with most of the difference in the extensive margin of treatment choice. For example, a Republican physician and a Democratic physician who are trained in the same specialty see patients from the same hospital referral region with the same diagnosis, such as knee arthritis. In this case, the Republican physician is significantly more likely to give the patient a knee replacement. In general, the partisan differences are concentrated in elective procedures, which depend more on the physician or patient's discretion, such as knee replacements

and cataract surgery (Clemens and Gottlieb, 2014).

After considering practice characteristics, we move onto the role of patient composition, using patients who move across hospital referral regions. We compare patient movers who go from seeing majority Democratic physicians at their origin to majority Republican physicians at their destination, against those who switch the other way from seeing majority Republican to majority Democratic physicians. This event study design estimates the partisan differences while holding the patient fixed, along with the patient's preferences and unobserved health conditions.

Even for the same patient, there are large partisan differences in treatment choice. The patient movers display similar pre-trends, but then after moving, the patients who then see mostly Republican physicians experience a significant uptick in their utilization relative to those who see mostly Democratic physicians. The patients who see mostly Republican physicians are also diagnosed with more conditions and have a higher chance of receiving a procedure (e.g., surgery), especially elective procedures.

Patient composition is also determined by the matching between patients and physicians, which cannot be resolved with patient movers alone. To account for non-random patient selection, we introduce physician movers and estimate the three-way fixed effects model from Badinski et al. (2024). The model provides fixed-effects estimates for both the physician as well as the patient. With these estimates, we can compute counterfactuals that negate any endogenous matching. We find that accounting for patient selection adjusts the partisan difference by only a small amount.

After ruling out practice characteristics and patient composition, the explanations that remain involve physician "practice style", which in our model is due to either preferences for financial gain or beliefs about appropriate care. The three-way fixed effects model cannot distinguish between these two explanations, but it does provide physician-level estimates of practice style, measured by their individual fixed effects. These estimates can pinpoint when the partisan divergence in practice styles began, and whether it originated from the entry of less aggressive Democratic physicians or more aggressive Republican physicians.

The divergence in practice styles first appears with the Republican physicians that began donating to the party during the second W. Bush term in 2004. Before then, the early Republican and Democratic physicians have similar practice styles. Over the next two decades, Democratic physicians entering the sample consistently have slightly less aggressive practice styles relative to the nonpartisan contributors. However, the Republican physicians who started contributing after 2004 have significantly more aggressive practice styles than either the Democratic or nonpartisan physicians who began donating at the same time. The divergence has further deepened with the more recent cohorts who started contributing in

the Obama and Trump years.

Which of the two remaining theories best explain the divergence in practice style — preferences for financial gain, or beliefs about appropriate care? To weigh the evidence for the former, we re-examine two research designs from the medical literature and find that Republican physicians do not respond more to financial incentives. The first design features a sharp change in the reimbursement rate for certain chemotherapy drugs in 2005 (Jacobson et al., 2010). The second is motivated by the tendency of physicians to order more MRI scans after acquiring a machine (Baker, 2010). In both cases, Republican physicians, even those who started contributing in more recent years, respond to financial incentives no more than their Democratic counterparts.

Without a leading explanation thus far, we arrive at the fourth and final factor: differences in beliefs about appropriate care. Previous studies indicate that physician beliefs play an important role in determining which treatments patients receive. Cutler et al. (2019) elicit physician beliefs on the efficacy of different treatments through a vignette survey, and find that these beliefs can explain 60% of regional variation in end-of-life health expenditures. For partisan differences in beliefs, we rely on a 2015 survey by Patashnik et al. (2020), which finds that Republican physicians place more value on physician autonomy and less on clinical guidelines. We look for corresponding partisan differences in the provision of low-value care as defined by the clinical guidelines, such as imaging for lower back pain. For comparison, we also examine partisan differences in preventive services, such as flu shots and annual wellness visits, which are typically considered high-value.

We find that the partisan differences in beliefs do predict corresponding differences in medical practice, which supports a beliefs-based explanation for the partisan divergence. In line with their beliefs, Republican physicians provide more low-value services that are discouraged by clinical guidelines. We also find that Republican physicians are more likely to try chemotherapy on patients with poor-prognosis cancer within their final two weeks of life, which is ultimately detrimental to the patients and implies that the additional medical care is not necessarily targeted to cases that warrant more aggressive treatment. In contrast to low-value care, there is no partisan difference in the provision of preventive services. These patterns indicate that the excess utilization provided by Republican physicians may be inefficient.

The partisan differences in low-value care are greater among the post-2004 contributors, aligning with both the timing of the divergence in practice style as well as the politicization of evidence-based medicine in Congress (Patashnik et al., 2020). During the second W. Bush term, Comparative Effectiveness Research (CER), which began as a bipartisan effort to fund research into which drugs and treatments are most effective, began losing

Republican support. The Obama administration then prioritized CER, and in response, Republican politicians characterized it as government overreach (Patashnik et al., 2020). Consistent with its public shift on evidence-based medicine, the Republican party began to attract physicians who practice more aggressively beyond the recommended guidelines from clinical studies. Ultimately, the modal physicians from the two parties now appear to differ in what they consider appropriate care and how they practice medicine.

While we cannot determine the source of physician beliefs, we do discover that the more recent contributors are also more segregated in their medical school training. In particular, the medical schools that have attracted more Republicans among the post-2004 contributors are in more Republican-leaning counties, have lower average MCAT scores, and have previously graduated physicians who go on to practice more aggressively. The causal relationships, if any, are unclear; these correlation between practice style and medical school characteristics could reflect training effects or selection. Nevertheless, this segregation in training makes the current divergence in beliefs more likely to be reinforced.

Related literature These results contribute to the literature on political polarization, particularly regarding health policies and behaviors. Among the elites, health policies that in prior decades passed with bipartisan support have become sharply polarized, such as the initial Medicaid program as opposed to its expansion in the Affordable Care Act (DellaVigna and Kim, 2023; Oberlander, 2024). Among the masses, Republicans and Democrats have not only diverged in their ideology (Pew Research Center, 2019), but are now at odds in what facts they believe in (Alesina et al., 2020), what they think of each other (Gentzkow, 2016), and even how they navigate a pandemic (Allcott et al., 2020), with real consequences on their health (Wallace et al., 2023). Since the COVID pandemic, trust in the government's handling of public health policies has also fractured along partisan lines (Findling et al., 2022), even among physicians (Goidel et al., 2024).

The results add to a recent body of evidence documenting partisan differences in professional decision-making. Regarding physicians, previous research has found that they recommend different treatments on vignette surveys for politicized issues such as abortion (Hersh and Goldenberg, 2016) and exhibit partisan bias in evaluating scientific evidence on COVID treatments (Levin et al., 2023). Partisan differences have also been demonstrated in variety of other professions, such as credit analysts (Kempf and Tsoutsoura, 2021), portfolio managers (Meeuwis et al., 2022), judges (Gormley et al., 2024; Cohen and Dehejia, 2024), loan officers (Dagostino et al., 2023), entrepreneurs (Engelberg et al., 2024), and mutual fund managers (Cassidy and Vorsatz, 2024). This study, like many of those listed above, highlights beliefs as a key channel for these partisan differences.

This paper also relates to the longstanding literature on regional variations in healthcare expenditure (Wennberg, 2010). Recent developments on this topic attribute much of the variation to physicians (Chandra et al., 2011), and in particular, Badinski et al. (2024) find that physician practice style is the most important supply-side factor. What goes into physician practice style, however, is less clear. Molitor (2018), for example, detects a large role of environmental factors, and Cutler et al. (2019) find a strong relationship with beliefs about medical treatments. This paper suggests that political alignment has now become an important dimension of these beliefs.

2 Data

2.1 Medicare Carrier File

Our source of medical data is a representative 20% sample of beneficiaries in the Medicare Carrier File from 1999 to 2019. For each beneficiary in the sample, the Carrier File records all the fee-for-service claims submitted for Medicare reimbursement by professional healthcare providers. Since some providers are not physicians (e.g., nurse practitioners and chiropractors), we restrict the sample to physician providers who based on their specialty have a Doctor of Medicine (MD) or a Doctor of Osteopathic Medicine (OD) degree. Following the previous literature, we keep beneficiaries who are between 65 and 99 years of age, have Parts A and B coverage throughout the year, and are not enrolled in Medicare Advantage (Finkelstein et al., 2016; Badinski et al., 2024).[1]

We adopt the procedure in Badinski et al. (2024) to assign medical claims to the physician most responsible for determining the treatment. Each claim records the performing physician, and in the most cases, a referring physician. Claims for office visits, which are under the "Evaluation and Management" group in the Berenson-Eggers Type of Service (BETOS) codes, are assigned to the performing physician. All other claims, which include procedures, imaging, and tests, are assigned to the referring physician.[2] For example, suppose a patient sees a primary care physician (PCP) for an ankle sprain. If the PCP refers the patient to a radiologist for an MRI, then the MRI claim is assigned back to the referring PCP. But if the PCP refers the patient to an orthopedic surgeon for an evaluation and then the orthopedic surgeon orders an MRI, the MRI claim is assigned to the orthopedic surgeon.[3]

[1] As in Finkelstein et al. (2016) and Badinski et al. (2024), we define each "year" from April to March of the following year. For example, 1999 refers to April 1999 to March 2020. This is done to match the data on the residence of the patients, which are recorded once each year in March.

[2] Claims without a referring physician are assigned to the performing physician.

[3] One of the robustness checks in Section 4.2.2 assigns all claims to the performing physician.

The main outcome is the physicians' annual healthcare utilization per patient. The sum of all the utilization that a physician allocates to a patient during the year is defined as a single physician-patient "encounter". The per-encounter utilization is calculated by adjusting the expenditure from each claim for regional price variation and then aggregating all the expenditures assigned to the physician for treating the patient over the year. We also disaggregate utilization into three-digit BETOS codes, which captures the different types of medical services that the patient received. There are around 100 BETOS codes at the most granular level, for example, "Major Procedure, Cardiovascular - Thromboendarterectomy" and "Chemotherapy".

We then categorize each annual physician-patient encounter according to the patient's primary medical diagnosis for seeing that physician. For reimbursement purposes, each claim records a diagnosis code to justify the medical services that were provided. We assign each encounter to the Clinical Classifications Software (CCS) diagnosis code that accounts for the largest share of the utilization provided by the physician for the patient in that year. The single-level CCS codes include over 200 diagnoses, such as "Cancer of bronchus; lung" and "Cataract".

These steps produce a dataset with observations at the physician-patient-year level, which record the total Medicare utilization, the utilization within each BETOS category, the number of claims within each BETOS category, and the patient's primary CCS medical condition. We also observe the patient's age and location as well as the physician's Unique Physician Identification Number (UPIN) or National Provider Identifier (NPI). We link these identification numbers to other data sources (described in Appendix C) to merge the physician's training background (i.e., medical school and graduation year), practice characteristics (e.g., working as a solo practitioner or at a medical school facility), and importantly, their names. We use their names and locations to match them to their political campaign contributions.

2.2 Matching physicians to campaign contributions

We classify a physician's party alignment according to their political donations recorded in the Database on Ideology, Money in Politics, and Donations (DIME) (Bonica, 2023). DIME has collected campaign contributions data for U.S. elections since 1980. This dataset tracks individuals' donations to political candidates, campaigns, and committees across the country and over time. The dataset also records the party of the recipients, which allows us to calculate whether a contributor has donated more to Republican or Democratic recipients. DIME has been used to study the political alignment of physicians and other professions,

as well as in prior economics research (Bonica et al., 2014, 2016; e.g., Autor et al., 2020). Compared to voter registration data, it also offers a major advantage for this study by recording the self-reported occupation of the donors, which is instrumental for finding unique matches.

We match physicians to their campaign contributions up to the 2018 election cycle using their full names and locations, building on the procedure in Bonica et al. (2014). We summarize the procedure here with further details in Appendix C.2. For each physician in the medical data, we search for a self-identified physician in the DIME data who has the exact same first and last names, middle name initial, state, and hospital referral region (HRR).[4] We match 24% of the physicians under this "exact" criteria, and an additional 4% from a wider set criteria that looks for physicians, for example, who live and work across state borders in neighboring cities. Overall, we match 28%, or 308,749 out of 1,093,790 physicians. This match rate is similar to that achieved in Bonica et al. (2014). The matched physicians account for close to half (47%) of the total utilization in the sample.[5]

Table 1: Sample characteristics

	Matched	**Unmatched**	
	Mean [SD]	Mean [SD]	Diff (SE)
Annual utilization per patient	425.88	344.95	80.93
	[771.58]	[558.93]	(1.53)
No. patients per year	46.06	29.28	16.78
	[55.37]	[39.99]	(0.11)
Female	0.23	0.37	-0.14
	[0.42]	[0.48]	(0.00)
Med school grad year	1987.37	1997.14	-9.77
	[12.30]	[13.36]	(0.03)
PCP	0.23	0.34	-0.11
	[0.42]	[0.47]	(0.00)
N	308749	785041	

This table shows the differences in characteristics between physicians who are matched to campaign contribution records and the remaining unmatched physicians. Averages are shown with standard deviations in brackets. Robust standard errors are in parentheses.

Matched physicians are more advanced in their careers, relative to those who are not found in the campaign contributions records, which characterizes political donations as a normal good. Table 1 shows that the matched physicians have higher utilization, see more

[4]A hospital referral region is a collection of zip codes based on referral patterns such that the patients in those zip codes typically receive their medical care within that area. Some of the 306 HRRs in the U.S. traverse state and county boundaries.

[5]Figures A.1a-A.1b show the match rate over the sample period.

patients, have graduated from medical school earlier, are more likely to be specialists than primary care physicians (PCPs), and are less likely to be female.[6] Given these large differences between contributors and non-contributors, all the following analyses is conditional on having donated. Physicians who begin contributing during the study period (1999-2019) are included in the sample from the year of their first contribution.

3 Party Realignment of Physicians 1999-2019

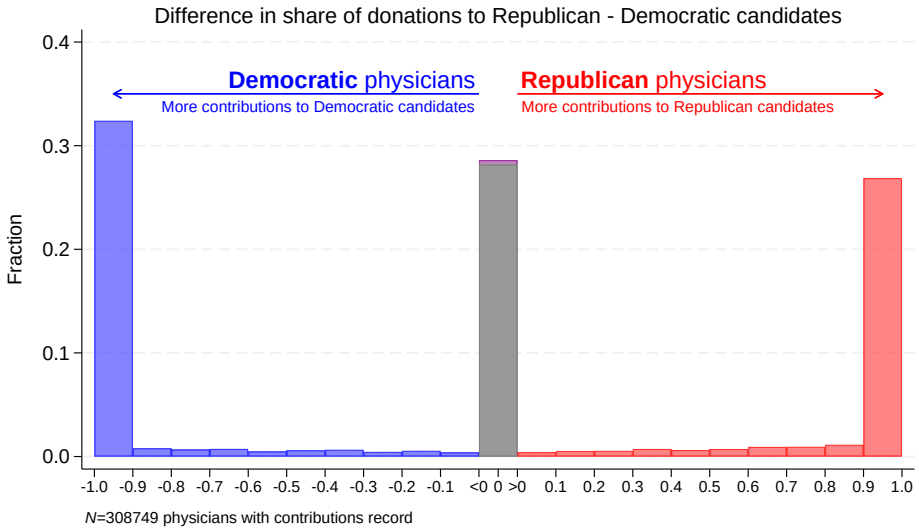
Defining party alignment Physicians are assigned to the political party to which they have donated a larger share of their total contributions up until that year. In practice, most physicians donate to one party or to neither. Figure 2 shows the distribution of each physician's difference in the share of donations to Republican candidates versus Democratic candidates by the end of the study period in 2019. The distribution has three modes each accounting for roughly 30% of the sample. From left to right, there is one group of physicians who donate (almost) entirely to Democratic candidates, a second who donate only to nonpartisan organizations such as the American Podiatric Medical Association PAC (gray bar) plus a slim fraction (purple bar) who contribute the same amount to both parties, and a third who donate (almost) entirely to Republican candidates. Over the 21-year study period, the median physician donates around $1000 in total over two separate biennial election cycles, and only 5% of physicians ever switch their party alignment as defined by the share of their donations.[7]

Realignment of physicians to the left At the start of the study period in 1999, a majority 63% of physicians were Republican. Yet as shown in Figure 3, the majority has tipped toward the Democratic Party after two decades. This trend to the left, which is also documented by Bonica et al. (2014), appears for other high-skilled occupations in the campaign contributions data, such as in finance and executive corporate roles (Figures A.4a-A.4b). Historically left-leaning professions such as attorneys and academics have become even more Democratic (Figures A.4c-A.4d). These patterns mirror the growing "diploma divide" in the overall U.S. population, or the increasing left-right gap between those with and without a college education (Kitschelt and Rehm, 2019; Gethin et al., 2022).

[6]Table A.1 provides additional comparisons between the matched and unmatched physicians in specialty, geographic location, and practice characteristics. Figures A.2a-A.2h show the comparison between the matched and unmatched samples in observable characteristics over time.

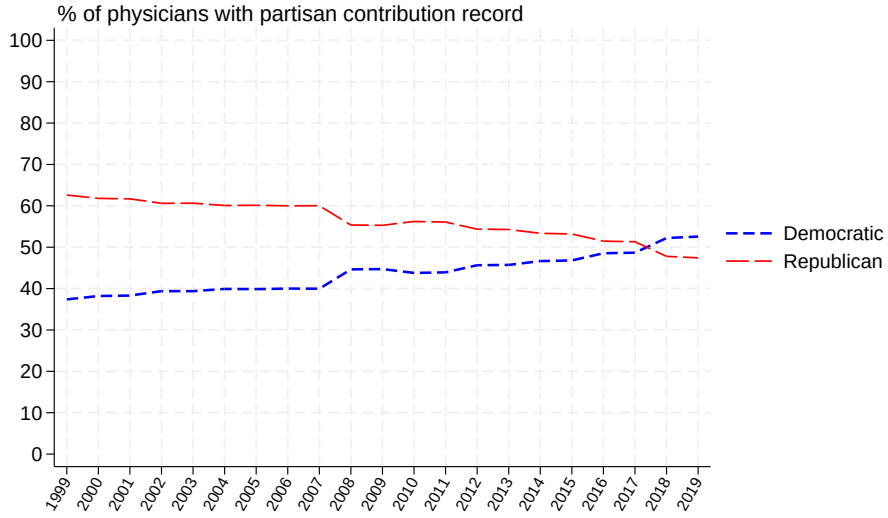
[7]Figure A.3 shows the distribution of the donated amounts, the common-space DIME ideology scores from Bonica (2023), the party share of physicians who contributed at least $1000, and the party share of physicians who contributed in at least two separate biennial election cycles. Tables A.2a-A.2d report summary statistics on the amount, frequency, and election category of the contributions.

Figure 2: Distribution of physicians by share donated to each party



This figure shows the distribution of physicians in the share donated to Republican candidates minus the share donated to Democratic candidates. For each physician, we calculate the share of total contributions up to 2019 that were donated to each party, and then take the difference between the Republican share minus the Democratic share. A difference of 1 (-1) means all the donations went to Republican (Democratic) candidates. Physicians who donated only to non-partisan organizations are shown at 0 in gray. The slim purple mass at 0 represents the fraction of physicians who donated in equal amounts to candidates from both the Republican and Democratic party.

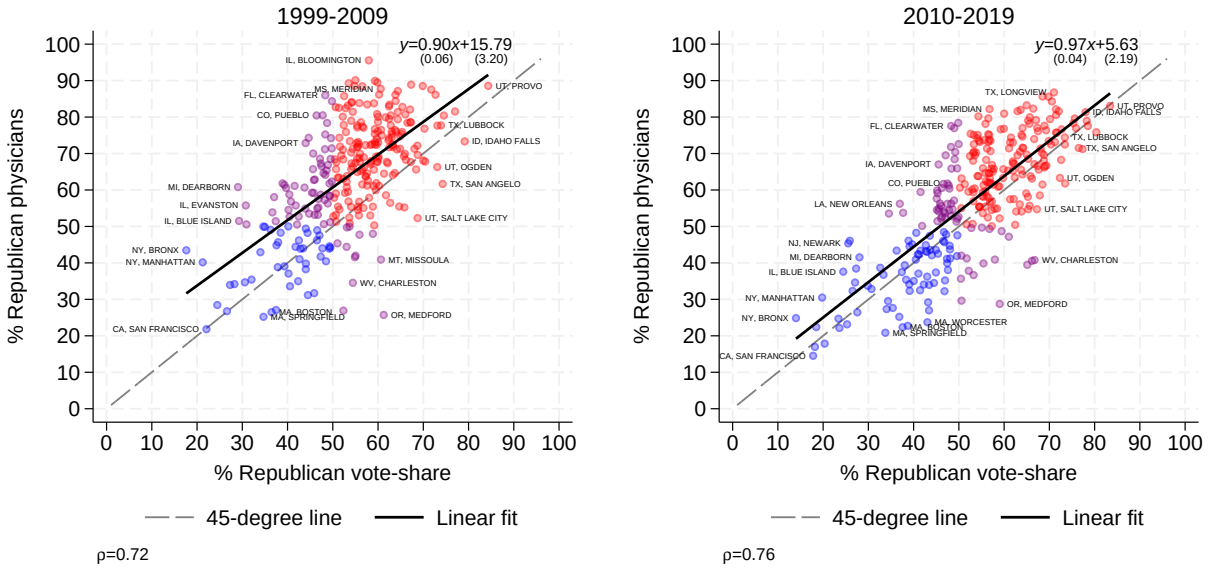
Figure 3: Party alignment of physicians 1999-2019



This figure shows the percent of practicing physicians in the Medicare data who are Republicans or Democrats in each year. The party alignment of each physician is defined starting from the year of their first political contribution. Those who have donated more to candidates of the Republican party are defined as Republican, and vice versa. Nonpartisan contributors who have donated to only nonpartisan organizations or in equal amounts to both parties are not included in this figure.

Figure 4: Party alignment of physicians and local presidential voteshare by HRR

(a) 1999-2009 **(b)** 2010-2019



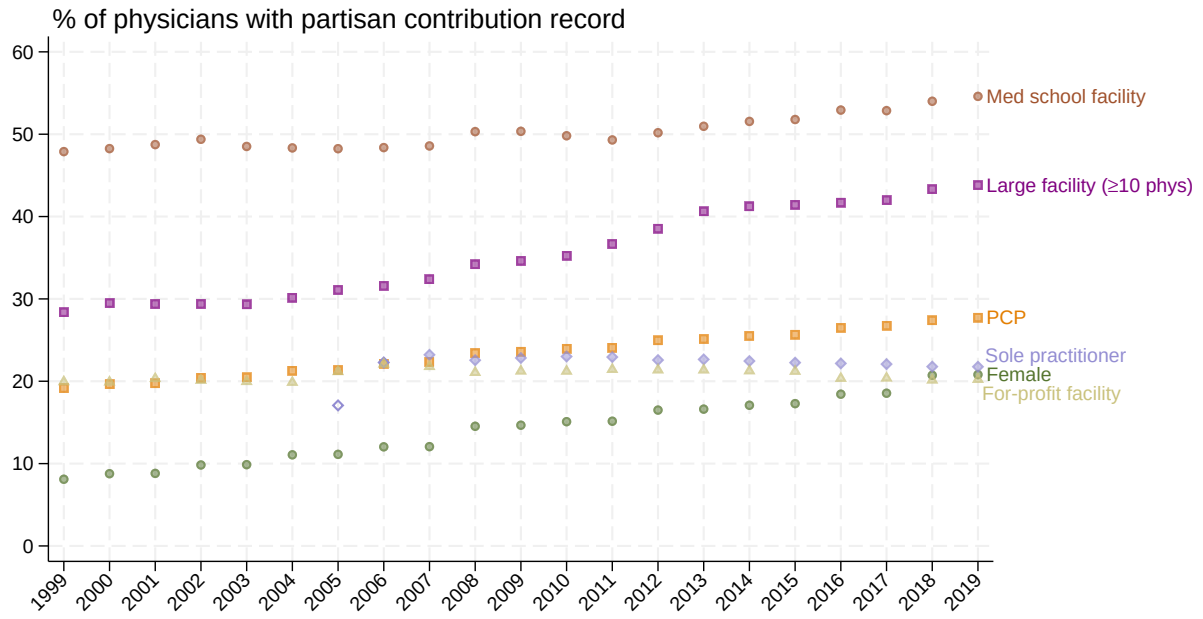
This figure shows the relationship between the share of Republican physicians in a hospital referral region and the local average voteshare in presidential elections over each decade.

Physicians have also moved closer to the average voter from their local area in their political affiliation. Figure 4a shows that during over 1999-2009, the average voteshare in a HRR strongly predicts the party alignment of the physicians in that region, but physicians across the country were more right-leaning relative to their local populations by 15.8 pp. (s.e.=3.2) on average. During the 2010s, however, Figure 4b shows that the gap between the physicians and the average local voter has diminished to 5.6 pp. (s.e.=2.2). The shift among physicians toward the Democratic party has been a nationwide phenomenon.[8]

Decomposing the party realignment How much of the party realignment of physicians can be explained by changes in the observable characteristics of the physicians? Bonica et al. (2014) reports that the increasing share of female physicians and the decline of sole practitioners may be key drivers behind the realignment. In our sample as well, Figure 5 depicts a marked rise of physicians who are female or work in larger facilities (i.e., with at least 10 physicians), both by more than 10 percentage points (pp.) over the two decades. This trend reflects the shift in the modal physician becoming less like an entrepreneur running a private practice and more like an employee embedded in a larger organization (Kane, 2023).

[8]Figure A.5 shows the geographic distribution of physicians by party, where each physician has been assigned to the HRR that accounts for most of their patients.

Figure 5: Physician characteristics 1999-2019



This figure shows the percent of Republican and Democratic physicians in each category over 1999-2019.

We apply a Oaxaca-Blinder style decomposition on Republican and Democratic physicians to separate the contribution of these observable characteristics. Specifically, we estimate the following model:

$$\text{Republican}_{dt} = \kappa_t X_d + \theta_t W_{dt} + \alpha_d + \gamma_t + \rho_{r(dt)} + \varepsilon_{dt} \tag{1}$$

$$\alpha_d = \beta X_d + \text{GradYr}_{g(d)} + \epsilon_d \tag{2}$$

where d indexes physicians and t years. The main outcome Republican_{dt} is an indicator for whether physician d has contributed more to the Republican party in year t. We estimate time-varying coefficients κ_t on fixed physician characteristics X_d, as well as coefficients θ_t on dynamic characteristics W_{dt}. The fixed characteristics include gender and an indicator for specializing in primary care. The time-varying characteristics include indicators for practicing: as a sole practitioner, in a for-profit facility, in a medical school facility, or in a large facility with at least 10 physicians. We also include a fixed physician ideology component α_d, year fixed effects γ_t, and fixed effects for hospital referral regions indexed by r.[9] We first estimate Equation 1 and then plug in the estimated $\hat{\alpha}_d$ into Equation 2 to obtain

[9] $r(dt)$ denotes the hospital referral region r for physician d in year t, which is determined by the HRR from which the physician saw the most patients, as in Badinski et al. (2024).

the coefficient on X_d in the base year. Equation 2 also includes five-year bins for medical school graduation year.

The share of Republican physicians in year t is:

$$\overline{\text{Republican}}_t = (\beta + \kappa_t)\overline{X}_t + \theta_t \overline{W}_t + \overline{\text{GradYr}}_t + \overline{\epsilon}_t + \gamma_t + \overline{\rho}_t \tag{3}$$

where $\overline{y}$ denotes the average of a variable y, and $\overline{X}_t$, $\overline{\text{GradYr}}_t$, and $\overline{\epsilon}_t$ are time-varying due to changes in the composition of physicians.[10] From Equation 3, the change in from 1999 to 2019 (notated as Δ) can then be expressed as:

$$\begin{aligned}\Delta\overline{\text{Republican}} = (\beta + \kappa_{1999})\Delta\overline{X} + \theta_{1999}\Delta\overline{W} + \Delta\overline{\text{GradYr}} + \Delta\overline{\rho} \\ + (\Delta\kappa)\overline{X}_{2019} + (\Delta\theta)\overline{W}_{2019} + \Delta\overline{\epsilon} + \Delta\gamma\end{aligned} \tag{4}$$

This decomposition contains four components. The first term $(\beta + \kappa_{1999})\Delta\overline{X} + \theta_{1999}\Delta\overline{W} + \Delta\overline{\text{GradYr}} + \Delta\overline{\rho}$ represents the change in the Republican share due to the changes in the averages of the observable characteristics, for example, the increase in female physicians. The second term $(\Delta\kappa)\overline{X}_{2019} + (\Delta\theta)\overline{W}_{2019}$ accounts for changes in the coefficients on the characteristics, for instance, if working as a sole practitioner has become more indicative of being Republican. The third term $\Delta\overline{\epsilon}$ captures the compositional change in the fixed ideology component from physicians leaving and entering the sample over time, and the last term $\Delta\gamma$ adjusts for the average shift within physicians remaining in the sample from year to year.

Table 2 reports the decomposition results. From 1999 to 2019, there has been a significant increase among politically contributing physicians who are female (8.1% to 20.8%), specializing in primary care (19.2% to 27.8%), and working in teaching hospitals (47.9% to 54.6%) or large facilities with at least 10 physicians (28.4% to 43.8%). As expected, the average medical school graduation year has also risen over time (1976 to 1988). The estimated coefficients reveal that female or primary care physicians have always been far less likely to be Republican. Meanwhile, working at teaching hospitals or large facilities began as right-leaning indicators, but have since become more associated with the left.

These observable changes constitute approximately one-half (48.5%) of the party realignment of physicians, or 7.4 of the 15.2 pp. total decline in the Republican share. The three main sources are (i) the higher share of female physicians (contributing 3.0 pp.) and PCPs (0.9 pp.), (ii) more recent graduates (1.0 pp.), and (iii) the realignment among

[10] $\overline{\text{GradYr}}_t$ and $\overline{\rho}_t$ represent the weighted average of the coefficients on the graduation year bins and HRR indicators respectively, where the weights are the proportion of physicians in each group.

Table 2: Decomposition of party realignment among physicians 1999-2019

	Change in Average		Change in Coefficient		Impact on $\Delta\overline{\text{Rep}}$ (pp.)	
	(1) 1999	(2) Δ	(3) 1999	(4) Δ	(5) Avg.	(6) Coef.
Physician observables						
Female	8.1	12.7 (0.2)	-19.7 (0.6)	-2.0 (0.5)	-2.6 (0.1)	-0.4 (0.1)
PCP	19.2	8.6 (0.2)	-9.4 (0.5)	-0.3 (0.5)	-0.8 (0.0)	-0.1 (0.1)
Sole practitioner	23.2†	-1.4 (0.2)	-0.2† (0.2)	0.3 (0.3)	0.0 (0.2)	0.1 (0.1)
For-profit facility	19.9	0.3 (0.2)	-0.8 (0.4)	1.0 (0.4)	0.1 (0.1)	-0.1 (0.2)
Med school facility	47.9	6.7 (0.3)	1.3 (0.3)	-2.0 (0.3)	0.2 (0.1)	-1.2 (0.2)
Large facility ($\geq$ 10 phys)	28.4	15.4 (0.3)	2.2 (0.3)	-2.5 (0.3)	0.1 (0.1)	-0.9 (0.1)
Med school grad year	1976.1	11.6 (0.0)	-	-	-1.8 (0.1)	-
HRR	-	-	-	-	-0.0 (0.0)	-
Year fixed effects (γ_t)	-	-	0.0 (0.0)	1.8 (0.3)	-	1.8 (0.3)
Unobserved composition (ϵ_j)	-	-	10.3 (0.3)	-9.6 (0.2)	-9.6 (0.2)	-
Total change (1999-2019)					-15.2 (0.3)	

This table reports the estimates of the decomposition in Equation 4 for the change in the share of Republican physicians from 1999 to 2019. Column 1 shows the percent of physicians that fall under each characteristic in 1999, and Column 2 shows the percentage-point change in the characteristic by 2019. For med school grad year, the number reported is the average medical school graduation year. Column 3 shows the coefficient on each characteristic in 1999; Column 4 shows the change in the coefficient by 2019. Column 5 shows the impact on the share of Republican physicians from the change in the average of each characteristic, and Column 6 shows the impact from the change in the coefficient on each characteristic. Standard errors from 50 bootstrap samples are shown in parentheses.
†Adequate data coverage on sole practitioners starts in 2007.

physicians in teaching hospitals and large facilities (1.8 pp.).[11] The remaining half is due to the unobserved changes in the composition; physicians entering the sample are increasingly more Democratic, beyond what is captured by these characteristics.

4 Partisan Differences in Medical Practice

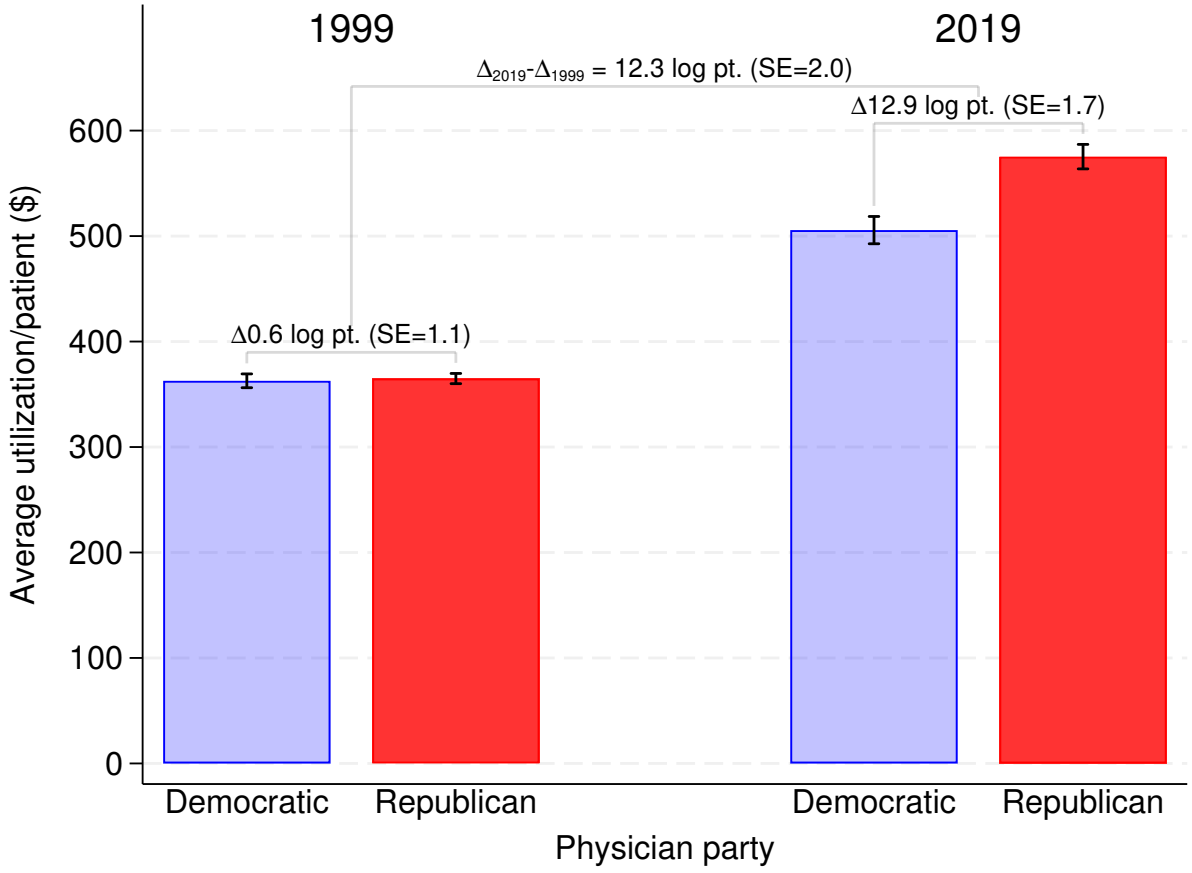
As we turn to the partisan differences in medical practice, we begin with the key finding of this paper: Republican and Democratic physicians, who practiced medicine similarly in the past, have now drastically diverged. Figure 6 shows that in 1999, there was no discernible difference between Republican and Democratic physicians in their medical utilization per patient. Two decades later, there is now a 12.9 (s.e.=1.7) log point difference, amounting to $70 annually per physician-patient encounter. This difference, multiplied over millions of encounters each year, carries substantial consequences for U.S. medical spending.

How does the partisan divergence compare to differences along other dimensions? Figures 7a-7c show that over 1999-2019, there has been little divergence between other groups of physicians, categorized by gender, graduation year, affiliation with medical schools, and

[11] Figure A.6 shows the contribution of each observable characteristic to the share of Republican physicians over time.

geography. For example, Figure 7a finds there has always been a large gender gap in per-patient utilization, likely due to differences in specialization (AAMC, 2012). Over the two decades, however, the relative difference has diminished rather than grown. Divergence in medical practice has not been a general phenomenon during this time.

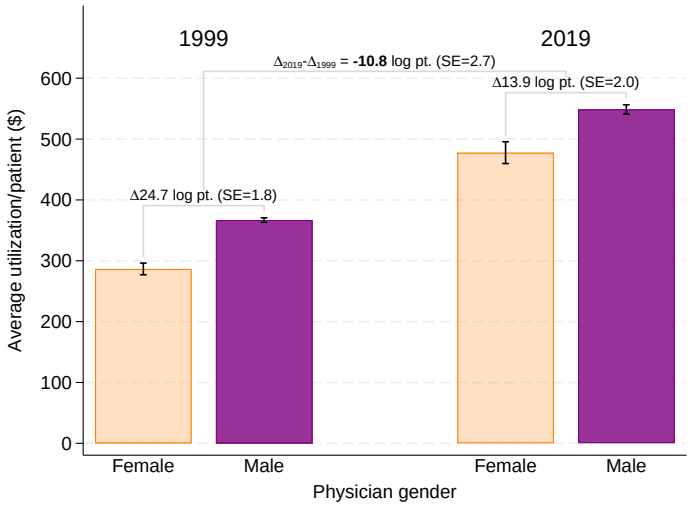
Figure 6: Partisan differences in medical utilization: 1999 versus 2019



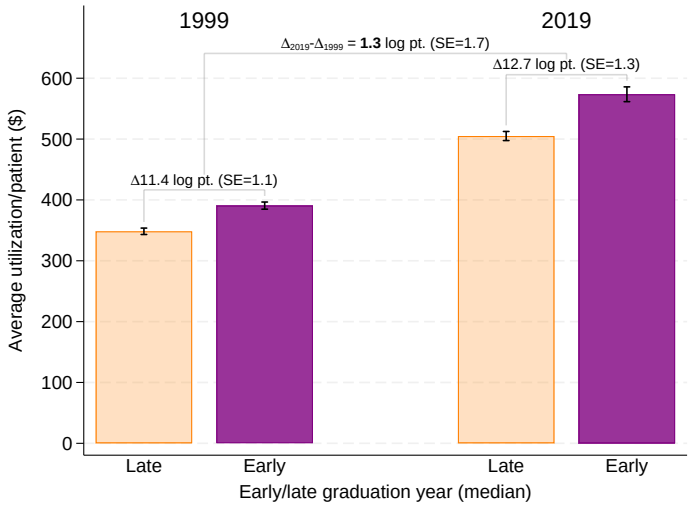
This figure shows the difference between Republican and Democratic physicians in their average per-patient annual utilization in 1999 and 2019. Utilization is a measure of healthcare expenditure after standardizing for regional price variation. The annual per-patient utilization for a physician is calculated by taking all the patients the physician treated, summing the utilization for each patient over the year, and then averaging across the patients.

Figure 7: Difference in medical practice along other dimensions 1999-2019

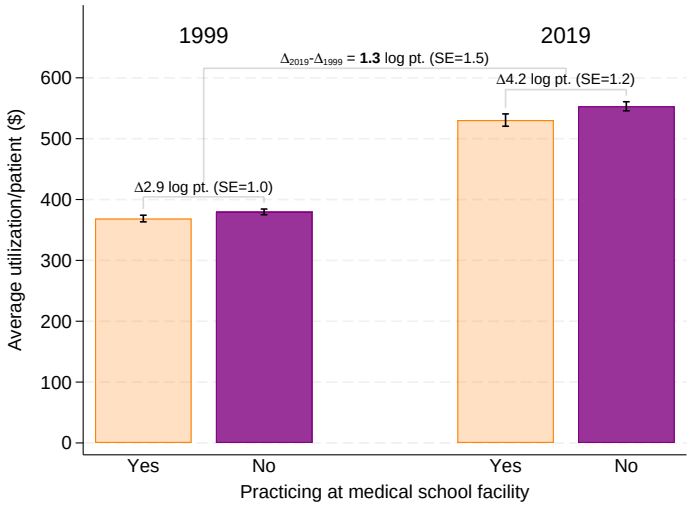
(a) Physician gender



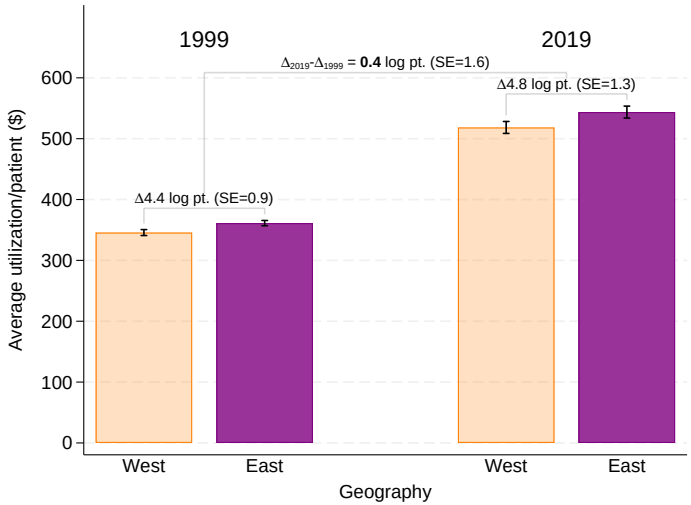
(b) Medical school graduation year



(c) Medical school affiliation



(d) Geography (West and Midwest vs. South and Northeast census regions)



4.1 Model and empirical strategy

Why do Republican and Democratic physicians differ in their medical utilization? We aim to understand the source of the partisan differences, starting with a simple model of physician decision-making based on Chandra and Skinner (2012), Finkelstein et al. (2016), Cutler et al. (2019), and Badinski et al. (2024). In this model, physicians aim to maximize the utility of their patients, but differ in their beliefs on the optimal treatment for the patient's health. Physicians also face financial incentives, patient preferences, and local factors that influence their decision.

The model starts on the demand side with patient i who has health status h_i and preference α_i for medical treatment $x_i \in \mathbb{R}^+$. A higher level of h_i denotes a more severe health condition requiring more medical care. The patient's utility function has a health component $s(x_i; h_i)$ measuring, for example, quality-adjusted life years, as well as a preference component captured by parameter α_i for more or less aggressive treatment. This preference reflects, for instance, how different patients value extending life versus avoiding painful treatments.

As in Finkelstein et al. (2016), the patient's utility function takes the form:

$$v(x_i; h_i, \alpha_i) = \overbrace{-\frac{1}{2}(x_i - h_i)^2}^{s(x_i;h_i)} + \alpha_i x_i$$

which, at the optimizing level of treatment, results in a patient demand of $x_i^D = h_i + \alpha_i$.

On the supply side, the physician's utility function is:

$$u(x_i) = \overbrace{\hat{s}(x_i; h_i) + \alpha_i x_i}^{\text{patient}} + \overbrace{\Omega(\pi x_i + I)}^{\text{financial}} + \overbrace{\phi(x_i)}^{\text{external}}$$

where the first term $\hat{s}(x_i; h_i)$ is the physician's *perceived* impact of treatment on the patient's health, which depends on the physician's beliefs. The physician also considers the patient's preferences for treatment $\alpha_i x_i$. Beyond patient outcomes, the physician faces financial incentives from the marginal profit for administering a unit of treatment π starting from a net fixed income I. The function $\Omega(\cdot)$ dictates how much the physician weighs these financial incentives relative to the patient's utility. The last term $\phi(\cdot)$ includes external non-financial factors, such as pressure from colleagues or hospital capacity constraints.

We adopt the following functional form assumptions from the literature:

$$u(x_i) = \overbrace{-\frac{1}{2}(x_i - h_i)^2 + \gamma x_i}^{\hat{s}(x_i;h_i)} + \alpha_i x_i + \overbrace{\omega(\pi x_i + I)}^{\Omega(\pi x_i + I)} + \overbrace{\phi x_i}^{\phi(x_i)} \tag{5}$$

The physician expects that the effect of the treatment on the patient's health utility will consist of the standard effect $s(x_i; h_i)$ plus a subjective component γx_i, where γ captures the physician's belief. This belief can be right or wrong. If the physician is correct, $s(x_i; h_i)$ may represent the impact of treatment when performed by a typical physician, whereas $\hat{s}(x_i; h_i)$ reflects the impact when performed by that particular physician, reflecting differences in skill (Chan et al., 2022). If the physician is incorrect, then the physician will provide too much or too little treatment, depending on the sign of γ. In addition to their beliefs, the physician places weight ω on the financial incentives and faces a constant marginal force ϕ from the external factors.

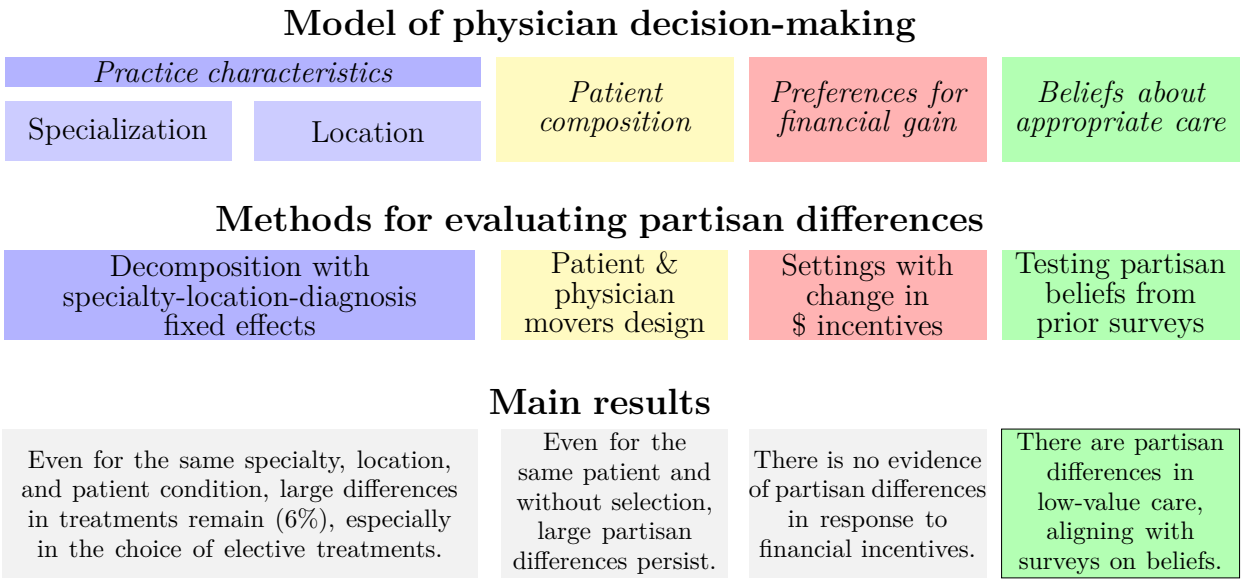
Then at the optimum of Equation 5, the medical care that physician d provides patient i in region r is:

$$x^*_{idr} = h_i + \gamma_d + \alpha_i + \omega_d \pi_{dr} + \phi_r$$

This expression illustrates the four main potential sources of differences between Republican and Democratic physicians, summarized in the top panel of Figure 8: (i) practice characteristics, (ii) patient composition, (iii) preferences for financial gain, and (iv) beliefs about appropriate care. First, physicians vary in their *practice characteristics*, which include specialization and location. Those who specialize in the treatment may have better patient outcomes and consequently more positive beliefs γ_d, as well as higher marginal profits π_{dr} from requiring fewer resources (e.g., less time) or facing lower liability risk. Figure A.7 shows that there are in fact large political differences between specialties, with more lucrative specialties attracting more Republican physicians (Bonica et al., 2014). Physicians practicing in different locations encounter diverse resources and liability environments, which can affect marginal profits π_{dr}, as well as non-financial external factors (ϕ_r), such as constraints, organizational cultures, and peer pressure (Molitor, 2018). Second, the *composition of patients* also varies for physicians, with some patients in better or worse health h_i or favoring more or less treatment α_i than others. Third, physicians may have dissimilar *preferences for financial gain* ω_d relative to patient utility, otherwise called their "professionalism" (Campbell, 2010). Lastly, physicians may hold different subjective *beliefs* γ_d on what type of treatment is appropriate (Cutler et al., 2019), especially in "gray zone" medical cases (Skinner, 2011).

We examine the evidence for each of these four potential differences in four corre-

Figure 8: Overview of model, methods, and main results



sponding analyses, described in the middle panel of Figure 8. First, we decompose partisan differences *within* hospital referral region, physician specialty, and patient diagnosis, which corrects for imbalances in practice characteristics. Second, we consider the role of patient composition by focusing on patients who move. We analyze whether there are partisan differences for the *same* patient, effectively holding constant patient preferences and unobserved health conditions. We also incorporate physician movers, following Badinski et al. (2024), to account for any selection between physicians and patients. Third, to investigate preferences for financial gain, we re-examine research designs from the medical literature that show physicians provide different treatments in response to changes in financial incentives. Finally, motivated by prior surveys that find partisan differences among physician in their beliefs regarding clinical guidelines, we look for parallel differences in the provision of low-value care.

4.2 Practice characteristics: Evidence from decomposition

In this first analysis, we investigate whether the partisan differences in medical utilization can be explained by differences in practice characteristics. We build a decomposition framework that separates the partisan differences into three main components. The first component accounts for differences due to Republican and Democratic physicians living in different areas, specializing in different fields, and seeing patients with different conditions. Then conditional on location, specialty, and diagnosis, the second component captures the extensive margin differences in treatment choice. For example, are Republican physicians more likely to choose

a knee replacement over physical therapy for osteoarthritis? The last component contains the remaining differences in the intensive margin, or the number of times a treatment is performed conditional on it being done.

4.2.1 Decomposition framework

The decomposition begins with the following formula derived in Appendix D.1 for the logarithm of the average utilization that physicians spend on each patient in a given year:

$$\log\left(\overline{\text{utilization}}\right) = \log\left(\sum_b \sum_{rsc} \overline{p}_{brsc}\overline{e}_{brsc}\overline{q}^{+}_{brsc}w_{rsc}\right) \tag{6}$$

where b indexes BETOS treatment codes, r hospital referral regions, s physician specialty, and c CCS diagnosis codes (with the year index omitted for clarity). The variable $\overline{p}_{brsc}$ is the average price per claim for the treatment within the region-specialty-diagnosis, $\overline{e}_{brsc}$ is the share of patients within the region-specialty-diagnosis who receive the treatment (extensive margin), $\overline{q}^{+}_{brsc}$ is the average number of times the treatment is given conditional on it being provided (intensive margin), and w_{rsc} is the weight for the number of physicians in the region-specialty-diagnosis cell. All physicians receive equal weight, regardless of how many patients they see, to avoid the results being skewed by any particularly high-volume physicians.

We then take the averages and the weights for Republican (R) and Democratic (D) physicians separately and express the partisan difference as:

$$\Delta\log\left(\overline{\text{utilization}}\right) = \log\left(\sum_b \sum_{rsc} \overline{p}^{R}_{brsc}\overline{e}^{R}_{brsc}\overline{q}^{+R}_{brsc}w^{R}_{rsc}\right) - \log\left(\sum_b \sum_{rsc} \overline{p}^{D}_{brsc}\overline{e}^{D}_{brsc}\overline{q}^{+D}_{brsc}w^{D}_{rsc}\right) \tag{7}$$

Within each region-specialty-diagnosis cell, Republican and Democratic physicians may still differ in other characteristics, such as their medical school graduation year, gender, and the age of their patients. We control for these observables by regressing for each BETOS code b:

$$e_{idb} = \text{Rep}_d\delta^{R}_{brsc} + \text{Dem}_d\delta^{D}_{brsc} + \text{Neu}_d\delta^{N}_{brsc} + \Gamma^{e}_{b}W_{id} + \varepsilon^{e}_{idb} \tag{8}$$

$$q^{+}_{idb} = \text{Rep}_d\theta^{R}_{brsc} + \text{Dem}_d\theta^{D}_{brsc} + \text{Neu}_d\theta^{N}_{brsc} + \Gamma^{q^+}_{b}W_{id} + \varepsilon^{q^+}_{idb} \tag{9}$$

where e_{idb} is an indicator for whether physician d treated patient i with treatment b, and if so, q^{+}_{idb} is the number of times. Each regression includes separate fixed effects for each party-region-specialty-diagnosis; Rep_d, Dem_d, and Neu_d are indicators for physician d's party affiliation, with Neu_d representing neutral physicians with nonpartisan contributions. The vector W_d contains dummies for medical school graduation five-year bins and for physician

gender, as well as for beneficiary age in five-year bins. Equation 8 is estimated on all physician-patient encounters, whereas Equation 9 is estimated only on those with $e_{idb} = 1$. In both regressions, each encounter is given weight $1/\mathcal{I}_d|$, where $\mathcal{I}_d$ is the set of patients seen by physician d, to maintain equal weight for each physician as in Equation 6.

The estimates from Equations 8 and 9 are then averaged within each party-region-specialty-diagnosis-treatment to decompose the extensive and intensive margins each into two terms: the first explained by the physician- and patient-characteristics $\overline{W}$, and the other for the remaining unexplained component: δ for the extensive margin and θ for the intensive margin. For the Republican averages, the extensive and intensive margin averages can then be expressed as:

$$\begin{aligned}\overline{e}^R_{brsc} &= \Gamma^e_b \overline{W}^R + \delta^R_{brsc} \\ \overline{q}^{+R}_{brsc} &= \Gamma^{q^+}_b \overline{W}^{+R} + \theta^R_{brsc}\end{aligned}$$

These terms, along with their counterparts for the Democratic physicians, are plugged into Equation 7 to rewrite the difference as:

$$\begin{aligned}\Delta \log\left(\overline{\text{utilization}}\right) = &\log\left(\sum_b \sum_{rsc} \overline{p}^R_{brsc}\left(\Gamma^e_b \overline{W}^R + \delta^R_{brsc}\right)\left(\Gamma^{q^+}_b \overline{W}^{+R} + \theta^R_{brsc}\right) w^R_{rsc}\right) \\ &- \log\left(\sum_b \sum_{rsc} \overline{p}^D_{brsc}\left(\Gamma^e_b \overline{W}^D + \delta^D_{brsc}\right)\left(\Gamma^{q^+}_b \overline{W}^{+D} + \theta^D_{brsc}\right) w^D_{rsc}\right)\end{aligned} \tag{10}$$

Equation 10 decomposes the differences into five parameters: (i) price per claim $\overline{p}_{brsc}$, (ii) observable characteristics $\overline{W}$, (iii) the extensive margin of treatment choice δ_{brsc}, (iv) the intensive margin of treatment quantity θ_{brsc}, and (v) weights for the distribution of physicians across region-specialty-diagnosis w_{rsc}.

We start by equalizing prices and observable characteristics. We fix prices to $\overline{p}_{brsc} = (\overline{p}^R_{brsc} + \overline{p}^D_{brsc})/2$ for all claims. This is likely to produce only a small adjustment, since our measure of utilization already standardizes prices and the variation in prices for services within a BETOS category is limited. We do likewise for the observable characteristics, setting them on both sides to $\overline{W} = (\overline{W}^R + \overline{W}^D)/2$ and $\overline{W}^+ = (\overline{W}^{+R} + \overline{W}^{+D})/2$. Then by defining the function $\Delta_{brsc}(\delta, \theta, w) = \overline{p}_{brsc}\left(\Gamma^e_b \overline{W} + \delta\right)\left(\Gamma^{q^+}_b \overline{W}^+ + \theta\right) w$, we can express the remaining difference within each BETOS-region-specialty-diagnosis ($brsc$) as:

$$\begin{aligned}&\overline{p}_{brsc}\left(\Gamma^e_b \overline{W} + \delta^R_{brsc}\right)\left(\Gamma^{q^+}_b \overline{W}^+ + \theta^R_{brsc}\right) w^R_{rsc} - \overline{p}_{brsc}\left(\Gamma^e_b \overline{W} + \delta^D_{brsc}\right)\left(\Gamma^{q^+}_b \overline{W}^+ + \theta^D_{brsc}\right) w^D_{rsc} \\ =&\Delta_{brsc}(\delta^R_{brsc}, \theta^R_{brsc}, w^R_{rsc}) - \Delta_{brsc}(\delta^D_{brsc}, \theta^D_{brsc}, w^D_{rsc})\end{aligned}$$

Next, we decompose the remaining difference into the last three parameters. As with prices and observables, we normalize the weight, the extensive margin, and the intensive margin by averaging over the Republican and Democratic physicians and setting $w_{rsc} = (w^R_{rsc} + w^D_{rsc})/2$, $\delta_{brsc} = (\delta^R_{brsc} + \delta^D_{brsc})/2$, and $\theta_{brsc} = (\theta^R_{brsc} + \theta^D_{brsc})/2$. Appendix D.2 shows that we can express the total difference as the sum of the differences from normalizing the weights, extensive margin, and intensive margin separately for each $brsc$:

$$\Delta_{brsc}(\delta^R_{brsc}, \theta^R_{brsc}, w^R_{rsc}) - \Delta_{brsc}(\delta^D_{brsc}, \theta^D_{brsc}, w^D_{rsc}) \tag{11}$$

$$= \overbrace{\Big[\Delta_{brsc}(\delta^R_{brsc}, \theta^R_{brsc}, w^R_{rsc}) - \Delta_{brsc}(\delta^D_{brsc}, \theta^D_{brsc}, w^D_{rsc})\Big] - \Big[\Delta_{brsc}(\delta^R_{brsc}, \theta^R_{brsc}, w_{rsc}) - \Delta_{brsc}(\delta^D_{brsc}, \theta^D_{brsc}, w_{rsc})\Big]}^{\text{difference due to weights}}$$

$$+ \overbrace{\Big[\Delta_{brsc}(\delta^R_{brsc}, \theta^R_{brsc}, w_{rsc}) - \Delta_{brsc}(\delta^D_{brsc}, \theta^D_{brsc}, w_{rsc})\Big] - \Big[\Delta_{brsc}(\delta_{brsc}, \theta^R_{brsc}, w_{rsc}) - \Delta_{brsc}(\delta_{brsc}, \theta^D_{brsc}, w_{rsc})\Big]}^{\text{difference due to extensive margin}}$$

$$+ \overbrace{\Big[\Delta_{brsc}(\delta^R_{brsc}, \theta^R_{brsc}, w_{rsc}) - \Delta_{brsc}(\delta^D_{brsc}, \theta^D_{brsc}, w_{rsc})\Big] - \Big[\Delta_{brsc}(\delta^R_{brsc}, \theta_{brsc}, w_{rsc}) - \Delta_{brsc}(\delta^R_{brsc}, \theta_{brsc}, w_{rsc})\Big]}^{\text{difference due to intensive margin}}$$

In $brsc$ groups where there are only Republican or only Democratic physicians, we assign the entire difference to the weights. That is, we assume that if there had been physicians from both parties in that $brsc$, they would have provided their patients with the exact same selection and intensity of medical services. Therefore, the results from this decomposition likely overstate the partisan imbalances due to the weights (i.e., location, specialty, and patient diagnosis), and provide a conservative estimate of the partisan differences in treatment choice and quantity.

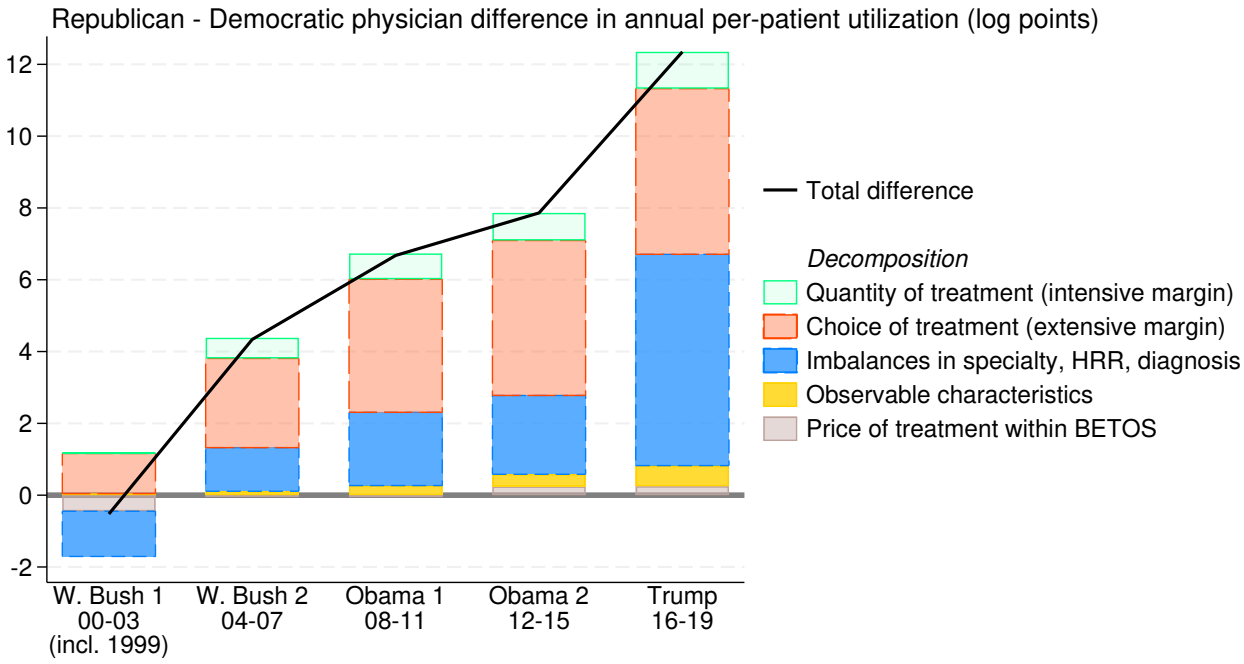
We sum over all $brsc$ to calculate the proportion of the overall difference due to the weights, the extensive margin, and the intensive margin.[12] To translate into log units, we multiply each component's proportion with the total log difference from Equation 7. For example, if the extensive margin accounts for 50% and the log difference in the average utilization between Republican and Democratic physicians is 10 log points in that year, then the extensive margin accounts for 5 of the 10 log points. To aggregate across years, we average each component's portion of the log difference.

4.2.2 Decomposition results

In Figure 9, we find that one-third (33%, s.e.=3) of the total partisan difference in utilization over 1999-2019 can be explained by differences in practice characteristics, by correcting the imbalances in the distribution of physicians across location, specialty, and patient diagnoses.

[12] We can also normalize the extensive and intensive margins first, and then assign the remaining difference to the weights. We do both methods and take the average.

Figure 9: Decomposition of partisan differences in medical utilization 1999-2019



This figure shows the estimates of the decomposition in Section 4.2.1. The outcome is the difference between Republican and Democratic physicians in log(utilization per patient) over each presidential term, shown by the trend line. The decomposition separates the difference into: (i) price per claim in each three-digit BETOS category; (ii) observable characteristics (physician gender, five-year bins for medical school graduation year, and five-year bins for beneficiary age); (iii) specialty, location, and patient diagnosis (CCS codes); (iv) the extensive margin in treatment choice, as categorized by three-digit BETOS codes (e.g., knee replacement vs. minor procedure for osteoarthritis); and (v) the intensive margin in treatment quantity (e.g., the number of office visits).

The figure shows the decomposition of the partisan difference across presidential terms.[13] Prices and observables explain very little of the difference in utilization between Republican and Democratic physicians.[14]

The remaining 67% of the partisan gap in utilization over 1999-2019 is due to different choices of treatment within specialty, location, and diagnosis. In other words, patients with the same condition, from the same hospital referral region, and seen by physicians trained in the same specialty are systematically receiving different treatments, depending on whether their physician is a Republican or a Democrat. The large majority, 84% (s.e.=1), comes from differences in the extensive margin. Compared to their Democratic counterparts, Republican physicians are performing distinct and costlier medical treatments, not just more of the same treatment.

By the Trump administration, the partisan difference in average utilization due to

[13]Figure A.8 and Table A.3 show the decomposition estimates by year.

[14]Standard errors are calculated from 50 bootstrap samples each year resampled at the physician level.

treatment choice and quantity has reached 5.64 log points (s.e.=0.56). Compared to other administrations, the imbalances in specialty, location, and patient diagnosis are more pronounced, contributing 5.88 log points (s.e.=0.66). An analysis of the imbalances (described in Appendix D.3) finds that during the Trump administration, 12% of the differences in utilization from the weights is due to Republican and Democratic physicians selecting into different specialties, 42% due to geographic separation, and the remaining 46% due to differential diagnoses of patients. The differential diagnoses may reflect either Republican physicians specializing in more resource-intensive diseases even within their own specialty field, or Republican physicians being more likely to detect such diseases in their patients.[15] All the partisan differences in specialty-location-diagnosis groups that have no overlap between Republican and Democratic physicians are also allocated to the weights, rather then treatment choice or quantity. Without this conservative assumption, the partisan difference due to treatment choice and quantity rises to 6.90 log points, whereas the role of the weights falls to 4.36 log points (Figure A.9).

For comparison, Figure A.10 implements the decomposition for physician gender, instead of party alignment. For male and female physicians, the bulk of the differences in medical practice comes from the weights, which reflects the large gender imbalances across specialties (AAMC, 2012). In contrast to partisan differences, the role of treatment choice in gender differences is relatively small.

Robustness and heterogeneity We incorporate several robustness checks in Figure A.11a. These robustness checks confirm that Republican and Democratic physicians have diverged in which treatments they provide their patients, as opposed to other confounding factors. We assign physicians to the hospital that accounts for the greatest share of their Inpatient and Outpatient Claims and let r index *hospitals* instead of hospital referral *regions* in the decomposition. Figure A.11a shows the partisan differences *within* facilities, focusing on the facility-specialty-diagnosis groups that have both Republican and Democratic physicians. We also only keep the physicians who can be linked to campaign contribution records under a "strict" match as defined in Section 2.2. We expand the set of controls W_{id} to include the number of physicians who have the same specialty as d that patient i sees for condition c, as well as indicators for physician d's practice characteristics (sole practitioner, for-profit, medical school facility, and large facility with at least 10 physicians). Democratic physicians, for instance, may work at larger practices and share patients among a greater number of physicians, which may drive down their individual per-patient utilization. Yet even with

[15]The decomposition with more granular specialty codes in Figure A.11c and the event study analysis in Figure 11c provide evidence for the latter explanation.

these additional checks, we still see a divergence between Republican and Democratic physicians practicing at the same facility. The point estimate of the partisan differences is similar to the baseline, at 5.54 log points from treatment choice and quantity during the Trump administration. This result aksi provides evidence that the partisan gap is not from differences in specialization, specifically those from productivity spillovers (Chandra and Staiger, 2007).

As explained in Section 2.1, our main sample links all non-office-visit claims to the referring physician (whenever the referring physician is recorded), in the attempt to assign claims to the physician most responsible for the treatment decision (Badinski et al., 2024). Nevertheless, there may be cases when the performing physician rather than the referring physician has a greater role in determining the treatment. To address this concern, in Figure A.11b we assign all claims to the performing physician. The partisan divergence widens even further, with a 17% difference by 2019. The amount due to the weights increases, which reflects a greater number of claims being assigned to specialists who are more likely to be Republican. The partisan differences in treatment choice and quantity become even larger than the baseline, at 6.69 log points during the Trump administration.

Another concern is that the specialty codes in the Medicare data are too broad to capture physicians who are trained to treat the same medical conditions. In Figure A.11c, we instead categorize the physicians' specialties using the National Uniform Claim Committee (NUCC) taxonomy codes from the National Plan and Provider Enumeration System (NPPES) database.[16] These taxonomy codes increase the number of physician specialty categories from 63 in the Medicare data to 407. For example, the specialty codes in the Medicare data identify "Orthopedic Surgeons" as one category, but the NUCC codes further distinguish between "Orthopedic Surgeons – Hand Surgery" and "Orthopedic Surgeons – Foot and Ankle Surgery". These more granular specialty codes have little impact on the decomposition estimates, still finding a 5.76 log point partisan difference due to treatment choice and quantity during the Trump administration.

We also consider other definitions of partisan physicians. First, Figure A.11d instead categorizes physicians based on the sign of the common-space ideological score provided in the DIME dataset (Bonica, 2023). Second, Figure A.11e uses only donations to presidential candidates to determine the physicians' party alignment. Third, Figure A.11f includes physicians only between their first and last donations, dropping them after their final donation, to isolate the partisan physicians who are current contributors. Fourth, Figure A.11g keeps in each year only the top 11% of physicians, to match the rate of coverage in 1999 (see Figure

[16] We find the more granular NUCC taxonomy codes for 89% of the physicians in the sample. For physicians without a match, we assign them to the NUCC code that is most prevalent among physicians of the same specialty.

A.1a), ranked first by who contributed most recently and then by who has contributed the highest amount cumulatively. This design aims to compare the partisan differences within the same "tails" of the ideological distribution throughout the study period. Across these four alternate definitions, the partisan differences by the Trump administration due to treatment choice and quantity range from 5.84 to 6.84 log points, consistent with the baseline estimates.

Are the partisan differences more or less extreme among larger contributors? Physicians with large contributions could be more ideologically extreme, or simply richer. Figures A.11h-A.11i aggregate the decomposition estimates from Figure 9 separately for physicians who have donated less than $1000 (roughly the median) versus $1000 or more. The partisan differences in treatment choice and quantity are in fact greater among smaller contributors, standing at 6.30 log points (s.e.=0.52) during the Trump administration. The corresponding difference for larger contributors is 3.88 log points (s.e.=0.58), or 2.41 log points (s.e.=0.72) lower.

4.2.3 Decomposition by treatment categories and specialty

Table 3 lists the top five most "polarized" specialty-diagnoses, as measured by the contribution to average difference in utilization per patient (reported in Column 1). These estimates come from the previous decomposition framework, after controlling for location and observable characteristics. Column 2 describes the two BETOS treatment categories that carry the largest partisan differences, and Column 5 reports the relative risk. The relative risk is defined as the percent of patients in the specialty-diagnosis cell who see a Republican physician and receive the treatment, divided by the percent of those who see a Democratic physician and receive the treatment. For example, Republican physicians are 11% more likely to perform a knee replacement for a patient with knee arthritis. The last column calculates the percent of the partisan difference in that treatment due to the extensive margin, which (besides office visits and lab testing) typically accounts for the large majority.

Table 3: Top five most polarized speciality-diagnoses

		Top 2 BETOS				
Specialty - Diagnosis	(1) Total Δ%	(2) Description	(3) Weight	(4) $\overline{\text{Util.}}$	(5) Rel Risk.	(6) Ext. %
PCP - Essential hypertension	3.2 (0.20)	Office - est	0.39	264	1.02 (0.002)	32 (3.0)
		Lab - other (non-Med)	0.19	86	1.10 (0.003)	59 (2.9)
PCP - Spondylosis/IVD/back	3.2 (0.32)	Office - est	0.21	313	1.03 (0.004)	30 (3.6)
		Major proc - excisdic	0.13	2045	1.23 (0.036)	103 (8.4)
Orthopedic Surgery - Osteoarthritis	2.9 (0.32)	Major proc - knee repl	0.51	1848	1.11 (0.014)	82 (3.3)
		Major proc - hip repl	0.24	1757	1.14 (0.025)	92 (4.0)
Ophthalmology - Cataract	2.4 (0.36)	Eye proc - cataract rem	0.83	1450	1.02 (0.006)	10 (6.7)
		Eye proc - other	0.16	432	1.06 (0.009)	59 (3.7)
PCP - Diabetes mellitus	2.2 (0.16)	Office - est	0.41	292	1.05 (0.003)	41 (2.5)
		Lab - other (non-Med)	0.19	100	1.07 (0.004)	45 (2.2)

This table shows the five specialty-diagnoses with the largest aggregate partisan difference in medical utilization. Column 2 reports the share of the total partisan difference over 1999-2019 that is due to the specialty-diagnosis. Within each specialty-diagnosis, Columns 3-6 provide details on the two most polarized BETOS services. Column 3 is the proportion of the partisan difference due to the BETOS; Column 4 is the average utilization for this BETOS treatment on patients who receive it; Column 5 is the partisan relative risk, or the proportion of patients seeing a Republican physician who receive the service divided by the proportion of those seeing a Democratic physician who receive the service; and Column 6 is the percent of the partisan difference in this BETOS due to the extensive margin. Standard errors from 50 bootstrap samples are shown in parentheses.

Figure 10a aggregates the partisan differences into broader first-digit BETOS categories. In general, Republican physicians are particularly providing more procedures, drugs, and chemotherapy, relative to office visits, testing, or imaging. The categories are Evaluation and Management; Procedures; Imaging; Tests; Durable Medical Equipment; and Other, which includes drugs and chemotherapy. The category with the most partisan difference is Procedures, which accounts for 34% of all partisan differences over 1999-2019. The Procedures category includes several of the polarized treatments in Table 3, such as disc surgery, knee and hip replacements, and cataract removal surgery. The Other category contains 24% of all partisan differences, of which 68% is from administering drugs, such as corticosteroid injections, and 28% is from chemotherapy.

The partisan differences are concentrated in medical areas with greater scope for discretion, which indicates that these differences are due to the preferences or beliefs of either the physicians or the patients. Within the Procedures category, Clemens and Gottlieb (2014) classify a subset of treatments as either elective or non-elective. Elective procedures are more discretionary services, such as knee replacements or cataract removal surgeries, in contrast to non-elective procedures like hip fracture repair, which are applicable only to clear defined cases. The differences for the elective and non-elective procedures labeled in Figure 10a are far greater for the elective ones.

Figure 10b shows the top five specialties that contribute the most to the total partisan differences over 1999-2019. These five specialties (PCP, Hematology/Oncology, Medical Oncology, Orthopedic Surgery, and Dermatology) face many "gray-zone" cases, for instance, whether to administer chemotherapy for late-stage cancer or provide a knee replacement for arthritis. Meanwhile, there are other specialties such as Radiology or Anesthesiology have less discretion in the types of medical services they perform. Although Radiology and Anesthesiology are both among the top five specialties in terms of the number of physicians in the sample (Table A.1), they exhibit minimal partisan differences.[17]

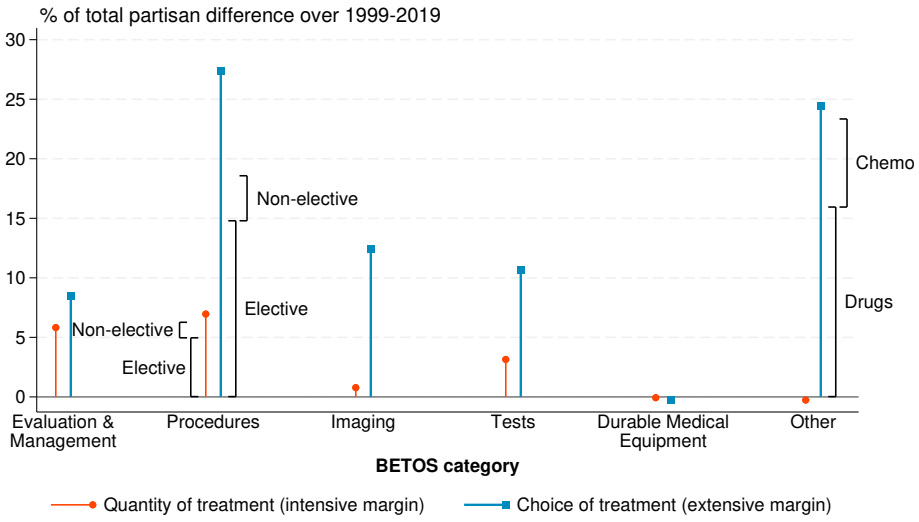
4.2.4 Practice characteristics: Summary of results

From this decomposition, we find that even after controlling for imbalances in practice characteristics, there still remains a large partisan difference of around 6% in annual utilization per patient. Republican and Democratic physicians, who otherwise look similar on paper in terms of specialty, location, and the diagnosis of their patients, are systematically providing different medical services. Republican physicians tend to provide more aggressive treatments, especially in elective procedures where there is more room for discretion. In the next analysis, we examine the role of patient composition.

[17]Figure A.12 decomposes the partisan differences by hospital referral region.

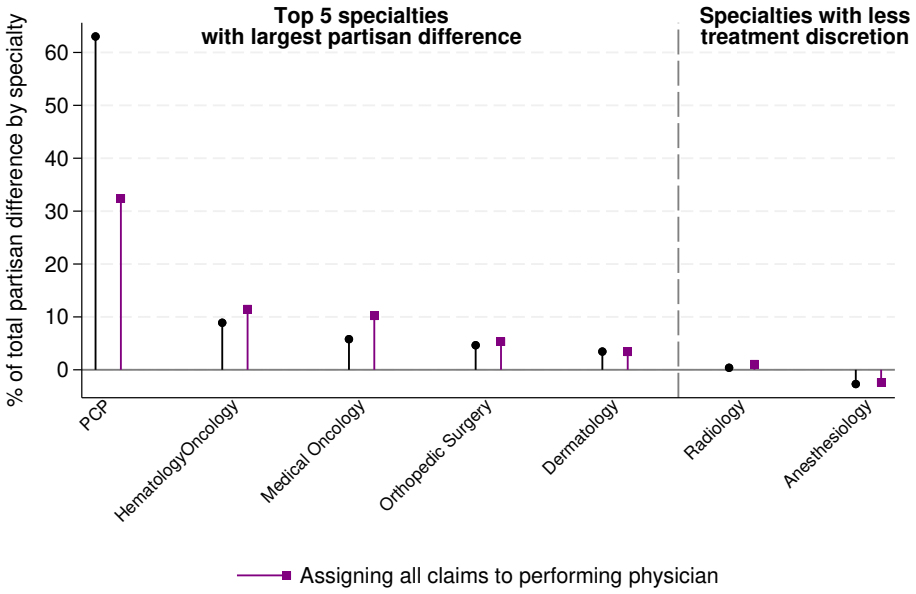
Figure 10: Partisan differences by BETOS and specialty

(a) By first-digit BETOS category



This figure shows the share of the partisan differences in medical practice over 1999-2019 within each first-digit BETOS category. The difference between Republican and Democratic physicians in the average per-patient utilization for each medical service is aggregated within BETOS categories and then expressed as a share of all partisan differences in utilization. The figure labels the share due to a subset of medical services in the "Procedures" category that have been defined as either elective or non-elective services by Clemens and Gottlieb (2014).

(b) By specialty



This figure shows the five specialties with the highest shares of the partisan differences in medical practice over 1999-2019, as well as Radiology and Anesthesiology, which are two specialties with a large number of physicians (Table A.1) but with less discretion in the types of medical services they perform. The partisan differences marked by the circles are calculated from the baseline decomposition, whereas those marked by the squares are calculated from assigning all claims to the performing physician, instead of the referring physician for non-office-visit claims (Figure A.11b).

4.3 Patient composition: Evidence from movers

The previous decomposition reveals large partisan differences due to treatment choice — but whose choice? The physician or the patient? A key factor may be that Republican physicians are simply seeing patients who need more intensive treatments or prefer more aggressive care.

We address patient composition using movers. We first study patients who move across hospital referral regions and compare the utilization of those who switch from seeing Democratic to Republican physicians and vice versa. Next, we add physicians movers, and estimate a model of utilization with patient, physician, and location fixed effects, following Badinski et al. (2024). This model allows us to correct for endogenous matching between patients and physicians, as well as to estimate each physician's "practice style" via their fixed effects.

4.3.1 Event study with patient movers

For each patient who moves to a different hospital referral region, we categorize the change in their physicians' party alignment before and after the move. To identify patient movers, we follow Finkelstein et al. (2016) and select the patients whose HRR of residence changes just once during the study period and whose location of claims after the move match their destination HRR.[18] For each patient mover i, we then calculate the share of i's physicians who are Republicans or Democrats in each year t:

$$s_{it}^R = \frac{1}{|\mathcal{D}_{it}|} \sum_{d_t \in \mathcal{D}_{it}} \mathbf{1}\{d_t \text{ is Republican}\}$$
$$s_{it}^D = \frac{1}{|\mathcal{D}_{it}|} \sum_{d_t \in \mathcal{D}_{it}} \mathbf{1}\{d_t \text{ is Democrat}\}$$

where $\mathcal{D}_{it}$ is the set of physicians whom patient i sees in year t. We then take the average of the shares over the pre-move years $(\overline{s}_{i,\text{pre}}^R, \overline{s}_{i,\text{pre}}^D)$ and over post-move years $(\overline{s}_{i,\text{post}}^R, \overline{s}_{i,\text{post}}^D)$.[19]

[18] Specifically, we require that the proportion of claims in their destination HRR, out of the total number of claims in the origin and destination HRR, increases by 0.75 after the move, as in Finkelstein et al. (2016). Among this sample of patient movers, Figure A.13a shows the average share of claims in the origin vs. destination HRR around the move, and Figure A.13b shows the distribution of the years relative to the move year. Table A.4a compares characteristics of patient movers versus non-movers. As in Finkelstein et al. (2016), movers are more likely to be female, white, aged 75-84, and from the South and West census regions. Table A.4b reports the top 10 origin-destination hospital referral region pairs with the highest number of patient movers in the sample. Twenty-seven percent of moves are between HRRs within the same state, and the median distance between the origin and destination HRRs is 459 miles.

[19] In particular, we calculate $\overline{s}_{i,\text{pre}}^R = \sum_{t<m_i} s_{it}^R / \sum_{t<m_i} 1$ for the pre-move Republican average and $\overline{s}_{i,\text{post}}^R = \sum_{t>m_i} s_{it}^R / \sum_{t>m_i} 1$ for the post-move Republican average, where m_i is the move year for patient i; the Democratic averages are calculated analogously.

We examine the utilization for patients movers whose physicians "switch" party alignments after the move. That is, we compare patients who go from seeing majority Democratic physicians before the move ($\overline{s}^D_{i,\text{pre}} > 0.5$) to majority Republican physicians after the move ($\overline{s}^R_{i,\text{post}} > 0.5$), versus other movers who experience the opposite ($\overline{s}^R_{i,\text{pre}} > 0.5, \overline{s}^D_{i,\text{post}} > 0.5$). We also compare movers whose pre-move physicians were not aligned to one party in particular ($\overline{s}^R_{i,\text{pre}} < 0.5, \overline{s}^D_{i,\text{pre}} < 0.5$), but then after the move, saw physicians who were aligned with one of the parties ($\overline{s}^R_{i,\text{post}} > 0.5$ vs. $\overline{s}^D_{i,\text{post}} > 0.5$). These are the patients whose physicians switch from "Neutral" alignment to either Republican or Democratic.[20]

Consider two patients of the same age who move to the same destination, except one goes to see majority Republican physicians and the other majority Democratic physicians. How does the amount of healthcare they receive change, relative to their previous utilization? This is the premise of the following event study on this sample of patient movers around the year of their move:

$$y_{it} = \sum_g \mathbf{1}\{\Delta\text{PhysParty}_i = g\} \left(\sum_{k=-6}^{6} \beta^{gk} e^k_{it} \right) + \alpha_i + \tau_t + \rho^{\text{orig}}_{r(it)} + \rho^{\text{dest}}_{r(it)} + \gamma_{\text{age}(it)} + \varepsilon_{it} \quad (12)$$

Here g represents the change in the party alignment of the physicians who treated patient i before versus after the move: Democratic to Republican; Republican to Democratic; Neutral to Republican; Neutral to Democratic; Republican to Neutral; Democratic to Neutral; or No Change. The dummies $e^k_{it} = \mathbf{1}\{t - m_i = k\}$ stand for the year relative to the move year m_i with e^{-1}_{it} normalized to 0, $\rho^{\text{orig}}_{r(it)}$ and $\rho^{\text{dest}}_{r(it)}$ are fixed effects for HRR r, which are allowed to differ depending on whether the patient is moving to or from the HRR, and $\gamma_{\text{age}(it)}$ are year-of-age fixed effects. This specification isolates the within-patient changes, controlling for their location and age in each year. The outcome y_{it} is the log annual utilization for patient i, aggregating over all the physicians whom the patient sees in that year.

Figure 11a shows that patients who switch from seeing mostly Democratic to mostly Republican physicians experience a significantly higher rise in their utilization, relative to patients who switch from seeing mostly Republican to Democratic physicians. The figure plots the relative differences of interest, $\beta^{\text{Dem to Rep},k} - \beta^{\text{Rep to Dem},k}$ and $\beta^{\text{Neutral to Rep},k} - \beta^{\text{Neutral to Dem},k}$. The differences in the pre-trends are flat relative to the year right before the move and show no indication of the divergence that follows. Patients who switch from seeing majority Democratic to majority Republican physicians incur an average increase of 23% (s.e.=2) utilization relative to those who switch the other direction. Among patients

[20]Figure A.13c shows the distribution of $(\overline{s}^R_{i,\text{post}} - \overline{s}^D_{i,\text{post}}) - (\overline{s}^R_{i,\text{pre}} - \overline{s}^D_{i,\text{pre}})$, where values greater than 0 represent patients who see relatively more Republican than Democratic physicians after their move, and the opposite for values less than 0.

who start from Neutral, those who switch to majority Republican experience an average increase of 14% (s.e.=1%) relative to those who switch to majority Democratic.

Figure 11b plots the levels, where the trend is typically flat before the move, spikes right after the move likely from finding new physicians at the destination, before falling back toward pre-move levels. The figure shows the β^{gk} coefficients for each group, or the levels relative to year $m_i - 1$. Those who switch to seeing a majority of Republican physicians have a sharper initial post-move spike and converge to a higher level of utilization afterwards.

Figures 11c-11f show that patients who switch to seeing mostly Republican physicians after moving are also diagnosed with more conditions and receive more procedures — especially elective procedures. The figures plot the event-study estimates for the following outcomes: the number of unique CCS codes that the patient is diagnosed with (Figure 11c), the probability of receiving any procedure (Figure 11d), and the utilization for elective versus non-elective procedures (Figures 11e-11f). The patients seeing mostly Republican physicians after moving are diagnosed with 0.26 more conditions (s.e.=0.02, mean=2.43), are 9 pp. more likely to receive a procedure (s.e.=1, mean=50%), and have 41% more utilization on elective procedures (s.e.=3). The concurrent rise in elective procedures mirrors the results from the decomposition in Figure 9. The increase in diagnoses suggests that Republican physicians are finding more reasons to treat their patients, especially for conditions where treatment is more discretionary, leading to higher utilization and procedure rates.[21]

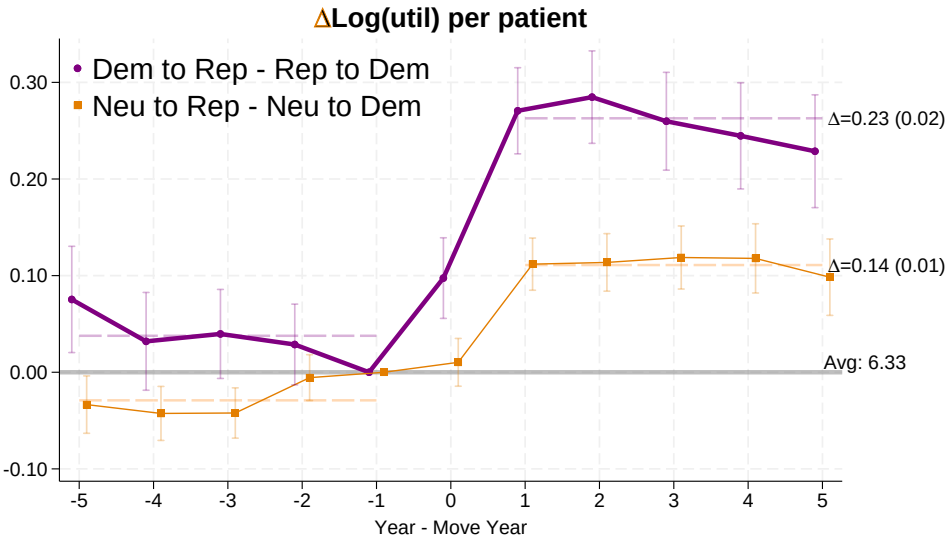
Robustness One concern is that the geographic unit of the HRR is too coarse to capture patients moving to and from comparable areas. For example, the "Boston, MA" HRR encompasses the city of Boston and all the way down to Cape Cod. Instead of HRRs, Figures A.15a-A.15d repeat the event study using origin and destination fixed effects at the Hospital Service Area (HSA) level. The boundaries of HSAs are drawn such that most residents from the HSA who are hospitalized end up at a hospital within the HSA. There are over 3,400 HSAs in the U.S., more than the number of counties. Even within this finer level of geography, the event study results show similar partisan differences after the move.

To isolate the variation from "swing" HRRs, Figures A.15e-A.15h repeat the event study on only the HRRs with an average two-party Republican voteshare over 1999-2019 between 40-60%. Out of the 304 HRRs, 183 fit this criteria. The results remain very similar.

[21] Tables A.5a-A.5e reports the event-year estimates for all groups and outcomes. Figure A.14 show the levels for other outcomes.

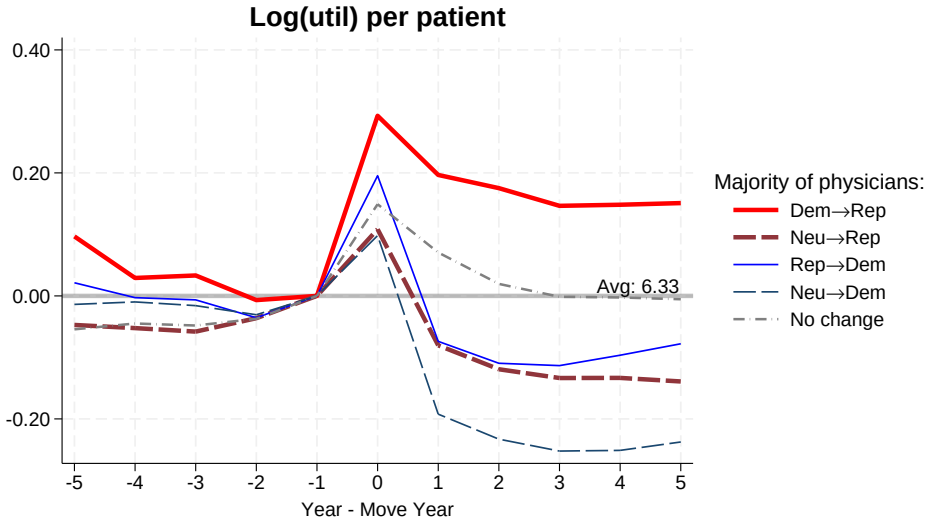
Figure 11: Event study from patient movers

(a) Relative trends in utilization



This event study figure estimated from Equation 12 compares the relative trends in log utilization for patient movers. The purple thicker line shows the trend for patients who move HRRs and switch from seeing majority Democratic to majority Republican physicians, relative to the trend for patient movers who switch from seeing majority Republican to majority Democratic physicians. The other line shows the trend for patient movers who go from seeing majority neutral (i.e., nonpartisan) to majority Republican physicians, relative to the trend for patient movers who go from seeing majority neutral to majority Democratic physicians. The difference-in-differences estimates are reported on the right. Standard errors are clustered by patient.

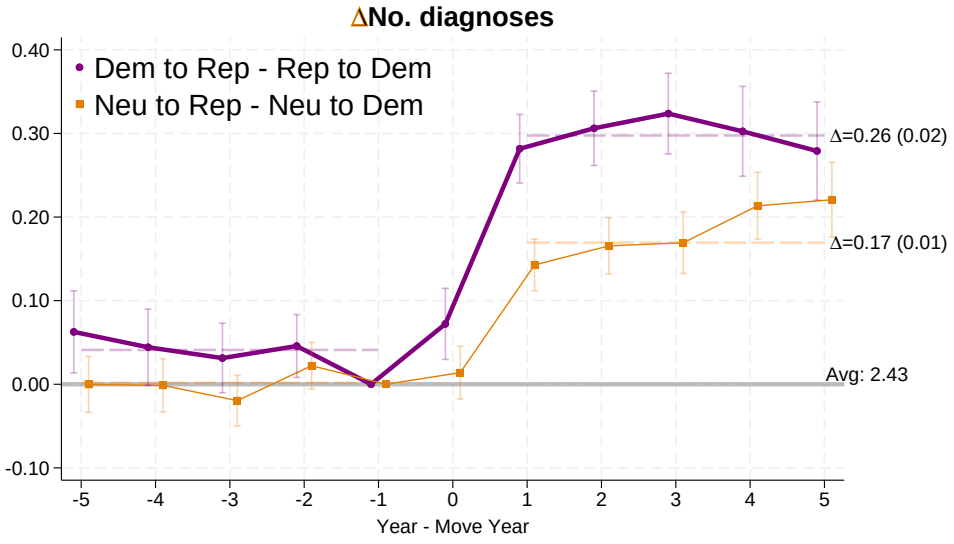
(b) Levels in utilization



This figure shows the levels in log utilization for each patient group relative to the year before the move. The estimates are from Equation 12.

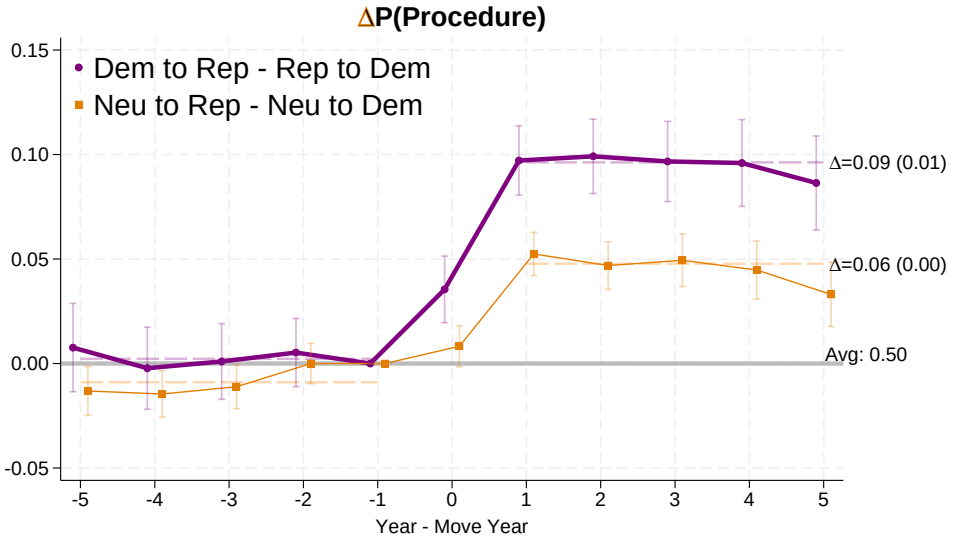
Figure 11: Event study from patient movers

(c) Relative trends in no. diagnoses



This event study figure shows the same relative trends as in Figure 11a, but for the outcome of the number of unique CCS codes that the patient is diagnosed with in each year.

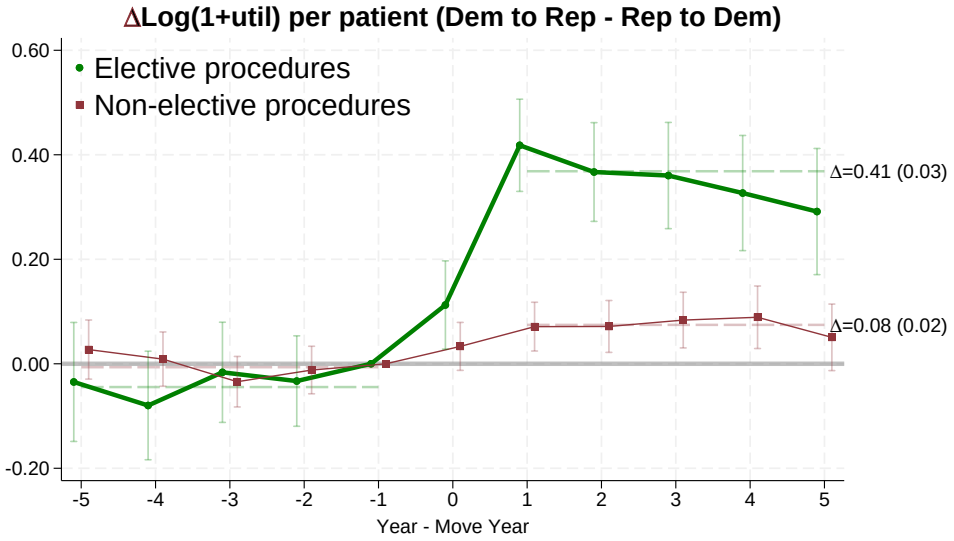
(d) Relative trends in procedure rate



This event study figure shows the same relative trends as in Figure 11a, but for the outcome of receiving a procedure (i.e., a medical service that falls under the "Procedure" first-digit BETOS category) in that year.

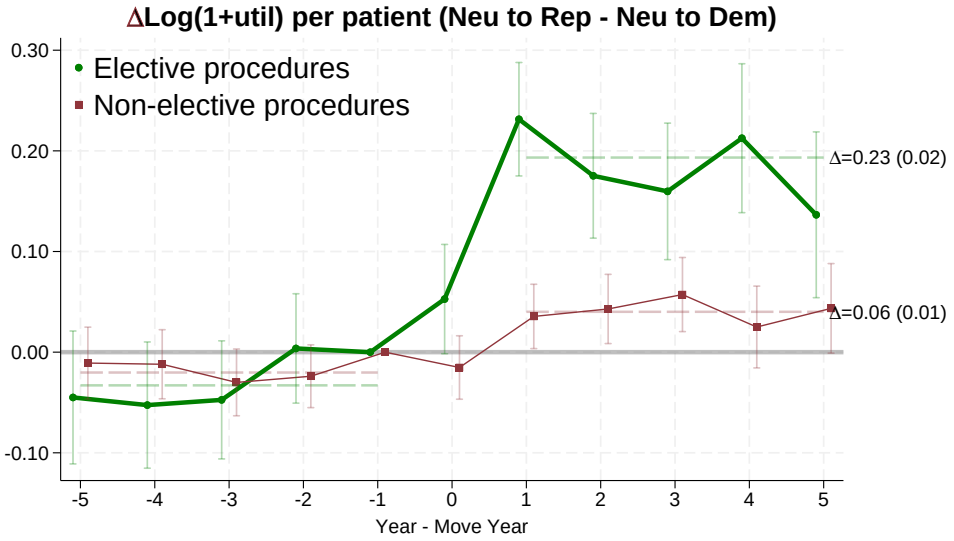
Figure 11: Event study from patient movers

(e) Elective vs. non-elective procedures (switch)



This event study figure shows the trends in log(1+utilization) expended on elective procedures (thicker green line) versus non-elective procedures (thinner maroon line) for patients who move HRRs and switch from seeing majority Democratic to majority Republican physicians, relative to the trends for patient movers who switch from seeing majority Republican to majority Democratic physicians. Elective and non-elective procedures are defined by Clemens and Gottlieb (2014).

(f) Elective vs. non-elective procedures (from Neutral)



This event study figure shows the same relative trends as in Figure 11e, except comparing patient movers who go from seeing majority neutral (i.e., nonpartisan) to majority Republican physicians, relative to the trend for patient movers who go from seeing neutral Republican to majority Democratic physicians.

Another potential concern is that patients who see more Republican physicians at their destination do so because they become sicker after the move and consequently see more specialists, who are more likely to be Republican. For this to explain the results, the onset of sickness would have to coincide exactly the timing of the move. Differences in gradual health deterioration would manifest as pre-trends, which we do not see. As discussed in previous papers using patient mover designs (e.g., Finkelstein et al., 2016), sudden health shocks immediately after the move would likely appear as a post-move spike in utilization for acute care, which then diminishes in the subsequent years. Instead, we see a sustained higher level of post-move utilization, especially in elective services.

Furthermore, we can directly control for the type of specialists whom the patient sees, by including indicators in each for year for whether the patient sees a cardiologist, an orthopedic surgeon, and so on. However, these specialty indicators are likely to be "bad controls" if the partisan difference arises from Republican physicians performing more tests, finding more conditions, and referring patients to more specialists. With this caveat in mind, Figures A.15i-A.15l show the results with these specialty controls. The differences in the number of diagnoses become insignificant, which simply demonstrates that seeing a specialist requires a qualifying diagnosis. Yet even after controlling for the composition of specialists seen by the patient, there are still significant partisan differences in utilization and the likelihood of receiving a procedure. The magnitudes of the effect do become smaller, which is consistent with the partisan difference operating through a greater propensity to diagnose conditions and consequently deliver more specialized care.

4.3.2 Three-way fixed effects with patient and physician movers

Patients who move, however, can still choose which physicians to see at their destination. To account for this non-random selection between patients and physicians, we follow the empirical strategy in Badinski et al. (2024) that uses both patient and physician movers to estimate patient, physician, and HRR fixed effects. We take the estimates from this model to compute counterfactuals where physicians see a locally representative patient.

We identify physician movers analogously to Badinski et al. (2024), where a physician's hospital referral region is based on the location of the patients they treat. Intuitively, we look for physicians who consistently treat the majority of their patients in one HRR, and then starting from a certain year, consistently treat the majority of their patients in a different HRR.[22] We then analyze the connected set of physicians and patients across time

[22]Specifically, we look for physicians who have two principal HRRs, where a principal HRR is one that contains 75% or more of the physician's patients in at least one year. We then check that the last year for which the first principal HRR accounted for 75% or more of the physician's patients is strictly before the first

and location.[23]

We estimate the same three-way fixed effect specification from Badinski et al. (2024):

$$y_{idt} = \alpha_i + \beta X_{it} + \rho_{r(it)} + \delta_d + \Phi W_{dt} + \tau_t + \varepsilon_{idt} \tag{13}$$

where y_{idt} is log annual utilization per encounter between patient i and physician d, X_{it} includes five-year age bins and event-time dummies for patient movers, W_{dt} contains event-time dummies for physician movers, and τ_t is an indicator for each year t. The three sets of fixed effects are for patients (α_i), physicians (δ_d), and hospital referral regions ($\rho_{r(it)}$).

In Figure 12, we first confirm partisan differences in the predicted values of the model. Using the estimated coefficients in Equation 13, we calculate:

$$\hat{y}_{idt} = \hat{\alpha}_i + \hat{\beta} X_{it} + \hat{\rho}_{r(it)} + \hat{\delta}_d + \hat{\Phi} W_{dt} + \hat{\tau}_t$$

where $\hat{y}_{idt}$ denotes the predicted values of y_{idt}. We then regress $\hat{y}_{idt}$ on indicators for Republican and Democratic physicians, again weighting each idt observation by $1/|\mathcal{I}_{dt}|$, where $\mathcal{I}_{dt}$ is the set of patients seen by physician d in year t. We confirm that the average difference between Republican and Democratic physicians has steadily risen since 1999. We then control for the physician's gender, graduation year, and specialty, which somewhat attenuates the slope of the trend, but still leaves a large difference that has tripled over the two decades.

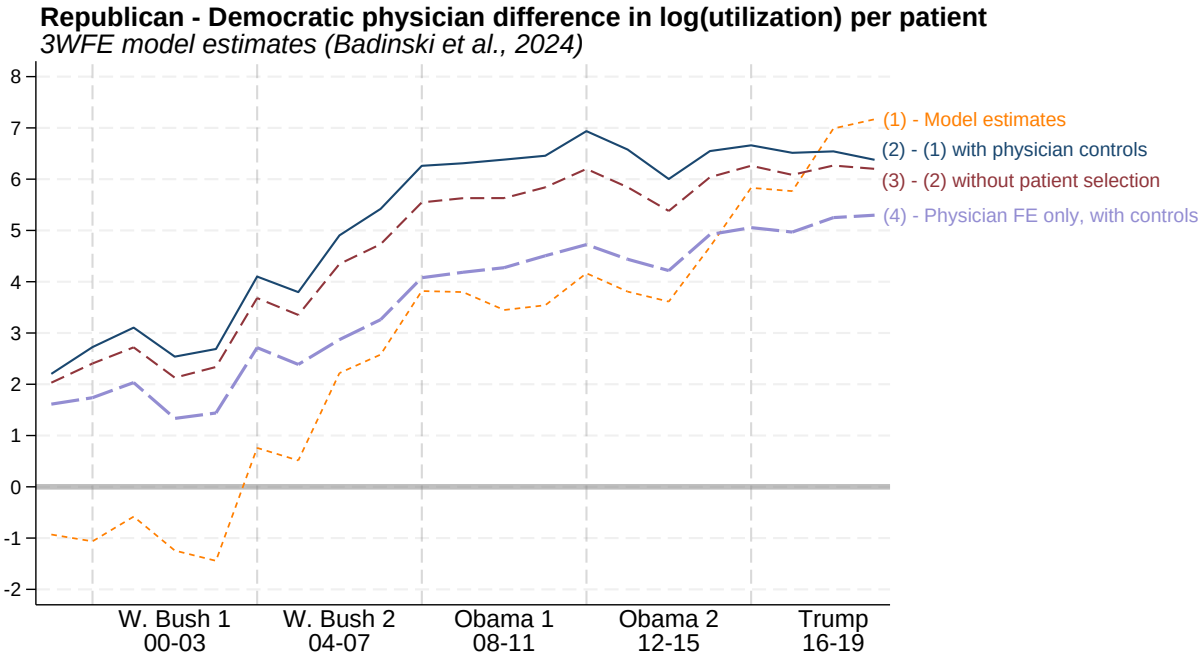
We now account for the selection between patients and physicians. For patient i in year t, let $\mathcal{I}_{r(it)}$ be the set of all the patients in the same hospital referral region r. We replace the patient component in $\hat{y}_{idt}$ with the average in $\mathcal{I}_{r(it)}$:

$$\begin{aligned} \hat{y}_{\bar{i}dt} &= \overline{\varrho}_{r(it)} + \hat{\delta}_d + \hat{\Phi} W_{dt} + \hat{\tau}_t \\ \overline{\varrho}_{r(it)} &= \frac{1}{|\mathcal{I}_{r(it)}|} \sum_{i \in \mathcal{I}_{r(it)}} \hat{\alpha}_i + \hat{\beta} X_{it} + \hat{\rho}_{r(it)} \end{aligned}$$

year for which the second principal HRR accounted for 75% of more of the physician's patients — that is, we check that the two principal HRRs do not overlap. We assign the move year as the year in which the share of patients in the origin and destination principal HRRs is the closest to 50% in absolute value. Finally, we ensure that the physician mover is "settled" in that the average share of patients from their origin HRR is at least 50% in the four years before their move, and the average share of patients from their destination HRR is at least 50% in the four years after their move. For physician movers who pass these criteria, Figure A.16 shows the average share of their patients from the destination HRR, out of patients from either the origin or destination HRR, in the years around the move. Table A.6 compares the characteristics of mover versus non-mover physicians.

[23]The connected set covers almost the entire sample and contains 99.99% of the total utilization.

Figure 12: Partisan differences from Badinski et al. (2024) model estimates



This figure shows the estimated difference between Republican and Democratic physicians in the three-way fixed effects model of Equation 13 from Badinski et al. (2024). For each year, we regress the predicted values for log utilization per physician-patient encounter on indicators for Republican and Democratic physicians, with each physician receiving equal weight. Line 1 plots the difference in the predicted values between the Republican and Democratic indicators. Lines 2-4 control for physician specialty, gender, and medical school graduation year (5-year bins). That is, we regress $\hat{y}_{idt} = \beta_t^R \text{Rep}_{dt} + \beta_t^D \text{Dem}_{dt} + \xi_t \text{Female}_d + \text{GradYr}_{gt(d)} + \text{Specialty}_{st(d)} + \varepsilon_{idt}$ where g indexes five-year bins for medical school graduation year and s specialties. The figure shows $\hat{\beta}_t^R - \hat{\beta}_t^D$ over time. Line 3 replaces the patient component in the predicted values with the local average of the patient component within the HRR. Line 4 removes all other components besides the physician fixed effect.

The predicted $\hat{y}_{\bar{i}dt}$ captures the counterfactual in which all physicians in a HRR see the same locally representative patient, effectively undoing any endogenous matching between physicians and patients. As Figure 12 shows, however, this adjustment does little to explain the partisan difference.[24]

Stripping all else away besides the physician fixed effect $\hat{\delta}_d$, we find that by 2019, over 5 of the overall 7 percent difference between Republican and Democratic physicians is due to the differences in "practice style" measured by these fixed effects.[25] Practice style

[24]Badinski et al. (2024) also find that doctor-patient selection explains only a small component of the variation in utilization.

[25]We regress the physician fixed effects $\hat{\delta}_j$ on the partisan indicators, as well as the controls for physician gender, specialty, and medical school graduation year. Technically, Badinski et al. (2024) estimate a separate physician-HRR fixed effect for each physician who sees patients from different HRRs, except for the physician movers seeing patients in their origin and destination HRRs, which are assigned the same physician fixed effect. We follow their estimation procedure and then calculate the physician fixed effect $\hat{\delta}_j$ as the average

refers to the tendency of a physician to treat more or less aggressively. In our model, this tendency originates from either the physician's preferences for financial gain or their beliefs about which treatments are appropriate. The magnitude of the differences in practice style is also consistent with the partisan differences in treatment choice and quantity from the decomposition in Section 4.2.2.

Since practice style is estimated by physician fixed effects, the practice style of a physician is constant over time in this model. The partisan divergence in practice style is then driven by compositional changes over the two decades in the type of physicians who are joining the Republican and the Democratic parties. But which side is driving the separation? Is the divergence due to the entry of increasingly more aggressive Republican physicians, less aggressive Democratic physicians, or both?

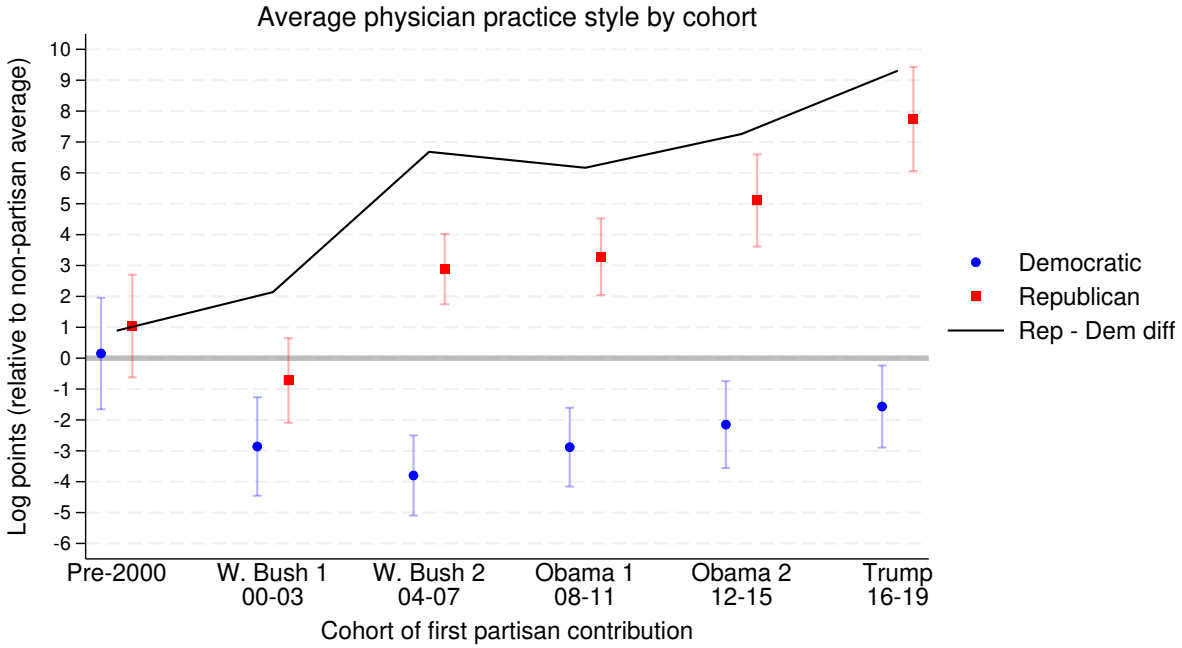
Figure 13 shows that this polarization in practice style is driven by the entry of Republican physicians who made their first political contributions after 2004. The figure plots the average physician practice style across cohorts defined by when they began donating to their party. The Republican and Democratic averages are shown relative to the neutral physicians who made their first donation to nonpartisan organizations during the same presidential term. Compared to the reference group of nonpartisan contributors, Democratic physicians have always been similar or slightly less aggressive in their practice style. Republican physicians were also similar in practice style — until 2004. Since the second W. Bush term, Republicans entering the sample have exhibited increasingly more aggressive practice styles. In the earliest cohort of pre-2000 contributors, the partisan gap stood at just 0.04 standard deviations of the physician fixed effects. In the latest cohort who began donating during the Trump administration, the difference now explains 0.26 standard deviations.

The majority of physicians in both parties are now consist from the "polarized" cohorts that started contributing during or after the second W. Bush term. Figures A.17a-A.17b shows the composition of physicians across the cohorts. Most physicians have been practicing medicine before they first donate (Figures A.17c-A.17d); the majority (64%) of all the physicians in the sample have been seeing Medicare patients since 1999. On the Democratic side, the modal physician joining the party has remained fairly consistent in practice style (relative to nonpartisan physicians) over the two decades. Meanwhile, the Republican party has shifted in the type of physicians it attracts, appealing more recently to physicians who practice medicine more aggressively.[26]

of the physician-HRR fixed effects within each year, weighted by the number of patients seen in each HRR, and then averaged across years.

[26]Figure A.18 shows that if we assign physicians to their "final" party alignment even before they begin contributing to that party, the difference in practice style remains high around 5-6% throughout the study period.

Figure 13: Practice style by party and first contribution cycle



This figure shows the average physician fixed effects within cohorts categorized by the presidential term during which the physicians made their first political contributions. We regress the estimated physician fixed effects $\hat{\delta}_d$ from Equation 13 on dummies for each cohort, as well as the cohort dummies interacted with indicators for Republican and Democratic physicians, controlling for physician gender, specialty, and medical school graduation year (5-year bins). The figure plots the coefficients on the interacted cohort dummies for each party, which represents the average fixed effect relative to the non-partisan physicians.

4.3.3 Patient composition: Summary of results

Using patient and physicians movers, we find that patient composition does not explain the differences in utilization between Republican and Democratic physicians. Even for the same patient, we observe large partisan differences in an event study analysis around geographic moves. With a three-way fixed effects design, we then correct for endogenous patient selection, which has little impact. The fixed-effects estimates also reveal that the partisan difference emerged during the second W. Bush term from 2004, with the Republican physicians in the more recent cohorts exhibiting increasingly aggressive practice styles. In our model, this divergence in practice style reflects differences in either preferences for financial gain or beliefs about which treatments are appropriate. We explore preferences for financial gain next.

4.4 Preferences for financial gain: Evidence from two studies

Thus far, we have seen a growing disparity between Republican and Democratic physicians in the treatment choices for their patients, much of which is not explained by practice characteristics or patient composition. Under the model in Section 4.1, these differences may be rooted in either their preferences for financial gain or their beliefs about which treatments are appropriate for a patient's condition. This section examines the evidence for the former using two research designs from the medical literature: a change in the chemotherapy drug reimbursement schedule in 2005, and referrals for MRIs following the acquisition of a machine.

4.4.1 Chemotherapy drug reimbursement cuts

The Medicare Prescription Drug, Improvement, and Modernization Act of 2003 drastically reduced the payments to physicians for administering certain chemotherapy drugs. Starting January 1, 2005, Medicare set the reimbursement rate of a drug to be 106% of the nationwide average sale price in the prior two quarters. Under the previous reimbursement scheme, which was tied to the wholesale price, physicians were able to procure certain drugs at a third under the wholesale price, thus earning a high profit margin on those drugs. The new pricing rule made these drugs much less profitable. In particular, Figure A.19 shows that the reimbursement rate for Paclitaxel dropped steeply in January 2005, but stayed near constant for the other drugs, Docetaxel, Etoposide, and Gemcitabine HCl. Each of these chemotherapy drugs has its own specific uses, but none has clear clinical advantages over the rest.

Jacobson et al. (2010) find that oncologists switched away from the drugs that became less profitable for treating their lung cancer patients. They study the change in the share of the chemotherapy patients who received Paclitaxel, as opposed to Docetaxel, Etoposide, or Gemcitabine HCl.[27] After January 2005, they detect a decrease in the share treated with Paclitaxel with a corresponding increase in those treated with Docetaxel, which became relatively more lucrative.

Motivated by Jacobson et al. (2010), we compare which chemotherapy drugs Republican and Democratic oncologists administer to their lung cancer patients after the new reimbursement rule.[28] For each oncologist in a given month, we identify all the lung cancer

[27] Jacobson et al. (2010) include Carboplatin, which also incurred a drop in reimbursement rates. They note, however, that the drug went off patent in October 2004 and may have consequently maintained its high profit margin even after the new reimbursement rule took effect in January 2005. Including Carboplatin in our analysis gives similar results, shown in Table A.7a.

[28] Specifically, we include as "oncologists" the physicians whose specialty is either Hematology-Oncology, Medical Oncology, Internal Medicine, Hematology, Radiation Oncology, or Gynecological Oncology. We

patients who received either Paclitaxel, Docetaxel, Etoposide, or Gemcitabine HCl. We examine the partisan difference in the response to financial incentives by estimating the linear probability model:

$$\text{Paclitaxel}_{idt} = \text{Rep}_d + \delta \mathbf{1}\{t \geq \text{Jan 2005}\} + \beta \text{Rep}_d \times \mathbf{1}\{t \geq \text{Jan 2005}\} + \Gamma X_{idt} + \varepsilon_{idt} \quad (14)$$

The outcome is whether lung-cancer patient i is treated with Paclitaxel, as opposed to Docetaxel, Etoposide, or Gemcitabine HCl. Our coefficient of interest is β, or the partisan difference in the change in the share of patients receiving Paclitaxel, pre- versus post-January 2005. Oncologists are indexed by d, months by t, and X_{idt} includes specialty, five-year bins for medical graduation year, and gender on the physician side, and five-year age bins and HRR on the patient side. Standard errors are clustered by physician and by patient. We keep only the oncologists who treated lung-cancer patients with one of these chemotherapy drugs both before and after January 2005. We assign oncologists to their "final" party alignment, which is clear in most cases given that only a small fraction ever switch parties, and include them in the sample regardless of when they made their first political contribution.[29] Under the assumption that practice style is stable within physician over time, this specification analyzes whether the partisan divergence in practice style reflects differences in preferences for financial gain, at least within this sample of oncologists.

The oncologists do respond to financial incentives and become less likely to administer Paclitaxel after January 2005 — but there are no significant partisan differences. Table 4a reports the regression results for Equation 14 in Column 1. In the year after January 2005, Democratic oncologists become 5.23 pp. (s.e.=1.69) less likely to administer Paclitaxel from a baseline of 42.09% in the year before; Republican oncologists become 2.96 pp. (s.e.=1.53) less likely from a baseline of 40.29%. The change in percentages is -12.43% (s.e.=3.78) for the Democrats and -7.34% (s.e.=3.67) for the Republicans (diff.=5.09 pp., s.e.=5.06). Column 2 adds physicians fixed effects, and Columns 3 and 4 separate the interaction term based on whether the oncologist made their first political contribution before or after 2004, when the divergence in practice styles first appears (Figure 13). Table A.7b repeats the analysis, but with a longer two-year window around January 2005. In all these specifications — and even among the "polarized" cohorts who first contributed after 2004 — Republican oncologists

assign chemotherapy claims to the physician recorded as the performing physician, not the referring physician. Like Jacobson et al. (2010), we keep only the claims in which the chemotherapy drug was administered in the physician's office (99% of the claims), where the physician likely has discretion over the choice of chemotherapy drug, rather than physicians in an institutional hospital setting.

[29]For the 5% of physicians who do switch party alignment during the study period, we set their final party alignment to the party to which they were aligned for the greater number of years. If the number of aligned years is equal for both parties, we assign them to their most recent party.

Table 4a: Partisan differences in response to January 2005 chemotherapy drug reimbursement rate changes

Administered Paclitaxel (pp.)	(1)	(2)	(3)	(4)
Post-January 2005	-5.23	-5.34		
	(1.69)	(1.73)		
Interactions with Post-January 2005				
Republican physician	2.27	2.14		
	(2.20)	(2.24)		
Pre-2004 contributor			-6.36	-5.77
			(2.68)	(2.79)
Pre-2004 contributor × Rep			5.51	5.39
			(3.43)	(3.54)
Post-2004 contributor			-4.52	-5.06
			(2.12)	(2.16)
Post-2004 contributor × Rep			-0.32	-0.76
			(2.89)	(2.89)
Republican physician	-1.80		-1.39	
	(1.79)		(2.69)	
Post-2004 contributor			0.09	
			(2.74)	
Post-2004 contributor × Rep			-0.90	
			(3.55)	
Constant	42.09	41.17	42.07	41.19
	(1.31)	(0.64)	(2.08)	(0.64)
Physicians controls	✓		✓	
Physician fixed effects		✓		✓
Physician N	1829	1829	1829	1829
Patient N	7400	7400	7400	7400
N(Phys-Patient-Month)	26683	26683	26683	26683
R^2	0.07	0.34	0.07	0.34

Coefficients are in percentage points. All regressions include controls for hospital referral regions and five-year bins for patient age. Physician controls include specialty, gender, and five-year bins for medical school graduation year. Standard errors are clustered by physician and patient.

do not seem any more sensitive to financial incentives than Democratic oncologists.

4.4.2 MRI referrals after machine acquisition

Prior research in health economics has found that physicians refer more patients for magnetic resonance imaging (MRI) once they acquire a machine (Baker, 2010). Rather than convenience, the literature points to financial incentives as the main driver of these self-referrals, given that MRIs bring in additional revenue for little marginal cost (Sunshine and Bhargavan, 2010).

We compare the increase in the rate of MRI referrals between Republican and Democratic physicians after they acquire an MRI machine.[30] Following Baker (2010), we locate non-radiologist physicians who see at least ten patients for office visits and begin billing for taking MRI scans, not just interpreting them, during 1999-2019.[31] We assign the quarter they begin billing for MRIs as the quarter they acquired an MRI machine as in Clemens and Gottlieb (2014), and in similar spirit to Baker (2010), we record the outcome as the number of patients they refer for an MRI divided by the total number of patients they see for an Evaluation and Management claim (an office visit) in each quarter.

Mirroring the analysis on the chemotherapy drugs, we conduct a "difference-in-differences" on the MRI referral rate:

$$\text{MRI referral rate}_{dt} = \text{Rep}_d + \delta \mathbf{1}\{t \geq e_d\} + \beta \text{Rep}_d \times \mathbf{1}\{t \geq e_d\} + \Gamma W_{dt} + \varepsilon_{dt}$$

where now the observations are at the physician-quarter level, e_d is the quarter in which physician d acquires the MRI, and W_{dt} contains HRR, specialty, five-year bins for medical graduation year, and gender. Standard errors are clustered by physician.

The MRI referral rate does increase following the acquisition of a machine, but yet again, no differently for Republican physicians. Table 4b shows in Column 1 that the referral rate increases by 3.33 pp. (s.e.=0.32) from a baseline of 5.18% for Democratic physicians (+64%), and by 3.36 pp. (s.e.=0.20) from a baseline of 5.01% for Republican physicians (+67%). The partisan gap stays small and insignificant with physician fixed effects (Column 2) and shows no meaningful difference after partitioning by pre- or post-2004 contributors (Columns 3-4). The results remain similar limiting to only orthopedic surgeons and neurol-

[30] The decision to acquire an MRI machine in the first place, which we do not consider here, may be based on financial incentives as well (Clemens and Gottlieb, 2014). Yet investing in an MRI machine also requires substantial capital and depends on a plethora of external factors, such as the practice characteristics, which makes it difficult to determine the denominator of physicians who plausibly could acquire an MRI.

[31] Specifically, we look for physicians who (i) are not radiologists, (ii) have at least ten claims under the Evaluation and Management BETOS category, and (iii) billed for at least three MRI claims under BETOS categories I2C or I2D with either the technical or global component.

Table 4b: Partisan differences in response to MRI acquisition

MRI referral rate (%)	(1)	(2)	(3)	(4)
Post-MRI acquisition	3.33	3.37		
	(0.32)	(0.31)		
Interactions with Post-MRI acquisition				
Republican physician	0.03	-0.06		
	(0.37)	(0.37)		
Pre-2004 contributor			2.93	2.95
			(0.79)	(0.76)
Pre-2004 contributor × Rep			0.31	0.20
			(0.85)	(0.82)
Post-2004 contributor			3.51	3.57
			(0.29)	(0.29)
Post-2004 contributor × Rep			-0.08	-0.16
			(0.38)	(0.38)
Republican physician	-0.17		-0.36	
	(0.31)		(0.61)	
Post-2004 contributor			-0.95	
			(0.59)	
Post-2004 contributor × Rep			0.25	
			(0.68)	
Constant	5.18	5.07	5.82	5.07
	(0.25)	(0.09)	(0.52)	(0.09)
Physicians controls	✓		✓	
Physician fixed effects		✓		✓
Physician N	5483	5483	5483	5483
N(Phys-Quarter)	47244	47244	47244	47244
R^2	0.08	0.39	0.08	0.39

The outcome is the number of MRI referrals divided by the number of patients seen for an Evaluation and Management visit. Coefficients are in percentage points. All regressions include controls for hospital referral regions. Physician controls include specialty, gender, and five-year bins for medical school graduation year. Standard errors are clustered by physician.

ogists as in Baker (2010) (Table A.8a), or broadening the time horizon to two years around the acquisition of the MRI machine (Table A.8b).

4.4.3 Preferences for financial gain: Summary of evidence

In two prominent settings from the medical literature, we find no evidence that Republican physicians have stronger preferences for financial gain. Physicians from both parties respond to financial incentives — oncologists shifted away from a chemotherapy drug after it became less profitable, and non-radiologists order more MRI scans once they acquire a machine — but the magnitude of the response is similar across the two parties. While these studies do not cover the entire sample of physicians, oncologists and orthopedic surgeons (who typically are the non-radiologist physicians acquiring MRIs) are the two specialties after PCPs that contribute the most to the overall partisan difference in utilization (Figure 10b). In the next analysis, we turn to the final potential explanation: differences in beliefs about appropriate care.

4.5 Beliefs about appropriate care: Testing prior survey evidence

Without a leading explanation thus far, we now study the potential role of beliefs. Do physicians vary in their beliefs to the extent that they systematically perform different treatments? Is there any evidence of partisan differences in beliefs? And do those beliefs predict actual differences in medical practice? While we do not have a direct measure of beliefs in our medical claims data, we draw on the existing surveys that find partisan differences in beliefs regarding clinical guidelines. We then test whether these beliefs are reflected in medical practice.

4.5.1 Prior survey evidence on physician beliefs

Is it plausible that physician beliefs can lead to consequential differences in medical practice? Cutler et al. (2019) elicit physician beliefs through vignette surveys and find that these beliefs explain a substantial amount of variation in medical utilization. They ask, for example, a sample of cardiologists whether they would recommend an implantable cardiac defibrillator for a patient with Class IV (the most severe) heart failure, which is explicitly against guidelines of the American College of Cardiology and the American Heart Association. Based on the survey responses, physicians are categorized as "cowboys" (who recommend more aggressive treatments than what is endorsed by clinical guidelines), "comforters" (who recommend less intensive palliative care), and high versus low follow-up types. These four indices explain around 60% of the end-of-life spending in a hospital referral region. Furthermore, Badinski

et al. (2024) find a significant relationship between the share of cowboy physicians and the average physician practice style in a HRR.[32] Cutler et al. (2019) consider whether these survey responses reflect organizational features or financial incentives, but conclude that they are primarily driven by what the physicians believe is the appropriate treatment.

Beliefs matter, but do beliefs differ between Republican and Democratic physicians? Patashnik et al. (2020) report that on a national 2015 survey, Republican physicians (i) are less likely to think that differences in physician beliefs drive regional variation in medical spending, (ii) place a higher priority on preserving clinical autonomy, and (iii) consider it less important to discourage the use of treatments that may have little to no benefit. In other words, Republican physicians have stronger beliefs in the ability of physicians to determine the best treatment for patients on a case-by-case basis. Naturally, they also place more value on leaving physicians to practice as they see fit, and less on ensuring physicians adhere to clinical guidelines.

The survey evidence from Patashnik et al. (2020) motivate a testable prediction: If Republican physicians are less likely to believe in the clinical relevance of the guidelines, then they should also comply less with the guidelines in practice. We examine this hypothesis next.

4.5.2 Partisan differences in low-value services, end-of-life cancer care, and preventive services

Low-value services We test whether the partisan differences in beliefs regarding clinical guidelines translate to differences in medical practice. Schwartz et al. (2014) provide a list of "low-value" services that clinical guidelines recommend against, such as back imaging for lower back pain, arthroscopy for knee osteoarthritis, and renal artery angioplasty or stenting. Although these services have found little to no benefit in clinical trials and have been discouraged by medical associations, some remain widespread (Rosenberg et al., 2015). For our analysis, we take the services that can be identified at the claim level using International Classification of Diseases (ICD) codes for the diagnosis and Healthcare Common Procedure Coding System (HCPCS) codes for the treatment.[33]

[32] On the other hand, they find that patient preferences elicited using similar vignettes are insignificant predictors of regional utilization.

[33] Specifically, we apply the base definition in Schwartz et al. (2014) to identify low-value services. We require that the low-value service can be identified solely within each claim, which excludes those that (i) require access to the Chronic Conditions Data Warehouse, (ii) are standalone procedures without qualifying a diagnosis, such as homocysteine testing, or (iii) depend on other qualifying claims, such as a claim for preoperative chest radiography before a future claim for noncardiothoracic surgery. This ensures that the denominator of patients who could have received the low-value service (even if they did not) is clearly defined for the decomposition. The low-value services we study are under the Imaging, Cardiovascular Testing and

We implement the same decomposition from Section 4.2, controlling for hospital referral region, specialty, diagnosis, regional price variation, and physician characteristics. We compare the partisan differences among those who began contributing before 2004 to those after 2004. This comparison evaluates whether the divergence in practice style among the more recent cohorts also exists in low-value care.

Table 5a finds that Republican physicians provide significantly more low-value services than Democratic physicians, and the partisan gap has widened between the pre- and post-2004 contributor cohorts. The table reports the partisan difference in utilization for post-2004 contributors in Column 1 and for pre-2004 contributors in Column 4. For example, post-2004 Republican physicians spend on average 2.70% more on back imaging for each patient they treat for lower back pain compared to their Democratic counterparts. The bulk of this difference is due to the extensive margin as shown in Columns 2 and 5. The weights in Columns 3 and 6 represent the number of physicians who see patients with the diagnosis.[34] Overall, post-2004 Republican physicians spend 3.87% (s.e.=0.39) more on low-value care per patient than Democratic physicians, whereas pre-2004 Republican physicians spend 2.24% (s.e.=0.54) more (diff.=1.62, s.e.=0.59).

This partisan difference in low-value utilization is likely to be inefficient, but another possibility is that Republican physicians are better at targeting the rare cases when these services may have clinical benefits. For example, imaging for lower back pain generally has no impact on clinical outcomes and can expose patients to unnecessary radiation, but in certain rare cases, it can detect cancers. To assess the evidence for whether Republican physicians are directing aggressive treatments on cases that warrant such care, we next study an example from the medical literature of an aggressive treatment that was retrospectively unnecessary and unambiguously burdensome for patients: chemotherapy within the last 14 days of life.

End-of-life cancer care Among specialists, oncologists drive the highest share of the partisan difference in utilization (Figure 10b). Are Republican oncologists treating cancer more aggressively, even in unwarranted cases? In previous medical studies, giving cancer patients chemotherapy during the last two weeks of life has been used as an indicator for overly aggressive cancer care (Morden et al., 2012; Wasp et al., 2020).

Procedures, and Other Surgery categories in Schwartz et al. (2014). We use the 2015 General Equivalence Mappings to create a crosswalk between the ICD-9 provided by Schwartz et al. (2014) and the associated ICD-10 codes.

[34]Even though both "Head imaging for headache" and "EEG for headache" have the same diagnosis codes, there are many HRR-specialty-headache cells with zero EEGs performed, which drops those cells.

Table 5a: Partisan differences in the provision of low-value care

	Post-2004 contributors			Pre-2004 contributors			
Diagnosis - Procedure	$\Delta\overline{\text{Util.}}$ log pt. (1)	Ext. % (2)	Weight (3)	$\Delta\overline{\text{Util.}}$ log pt. (4)	Ext. % (5)	Weight (6)	(1)-(4)
Back imaging for low back pain	2.70 (0.31)	70.74	0.42	1.39 (0.36)	65.39	0.46	1.31 (0.47)
Head imaging for syncope	3.75 (0.96)	99.49	0.15	1.33 (1.71)	-9.11	0.12	2.42 (2.01)
Carotid artery screening for syncope	12.41 (1.42)	101.99	0.15	4.65 (1.66)	94.00	0.12	7.76 (2.24)
Head imaging for headache	0.68 (0.67)	73.88	0.10	2.41 (0.90)	81.45	0.10	-1.72 (1.11)
Sinus CT for acute rhinosinusitis	-2.00 (1.13)	92.74	0.09	-1.97 (1.08)	77.16	0.10	-0.03 (1.31)
Arthroscopy for knee osteoarthritis	4.22 (3.70)	132.29	0.07	5.58 (3.68)	134.36	0.09	-1.36 (4.73)
EEG for headache	13.59 (6.52)	101.21	0.01	30.03 (6.47)	99.86	0.01	-16.45 (9.23)
Renal artery angioplasty or stenting	1.27 (2.92)	149.74	0.01	2.68 (3.19)	60.58	0.01	-1.42 (3.78)
Average	3.87 (0.39)	87.34		2.25 (0.54)	69.71		1.62 (0.59)

This table decomposes the partisan difference in utilization for a set of low-value services taken from Schwartz et al. (2014). Columns 1 and 4 show the difference in utilization between Republican and Democratic physicians. The partisan difference is calculated separately for physicians who made their first contribution before 2004 (Columns 1-3), and those that made their first contribution on or after 2004 (Columns 4-6). Columns 2 and 5 report the percent of the partisan difference due to the extensive margin, and Columns 3 and 6 show the weights from the number of physicians seeing a patient with this diagnosis. Standard errors from 50 bootstrap samples are shown in parentheses.

Table 5b: Partisan differences in end-of-life (EOL) cancer care: Chemotherapy in final 14 days

	ΔRep-Dem $\overline{\text{Util.}}$ (log pt.) (1)	Δ due to Extensive (%) (2)	EOL Chemo Rate among Dem (%) (3)	ΔRep-Dem EOL Chemo Rate (pp.) (4)	Relative Risk (5)
Post-2004 contributors	13.60 (4.88)	88	2.24	0.30 (0.08)	1.13 (0.03)
Pre-2004 contributors	2.17 (4.03)	79	2.53	0.06 (0.08)	1.02 (0.03)
Difference	11.43 (5.69)			0.11 (0.05)	0.11 (0.05)

This table decomposes the partisan difference in utilization on chemotherapy in the final 14 days before death for patients with a diagnosis for a poor-prognosis cancer within the last six months of their life. Columns 1 and 2 are analogous to Table 5a. Column 3 reports the rate of chemotherapy within the last 14 days among Democratic physicians. Column 4 shows the difference in the rate for Republican physicians. Column 5 is the Republican rate divided by the Democratic rate. Standard errors from 50 bootstrap samples are shown in parentheses.

Following Morden et al. (2012) and Wasp et al. (2020), we take all the patients who died during the study period and were diagnosed with a poor-prognosis cancer within their last six months.[35] We assign each cancer patient to the physician (most frequently an oncologist) who was responsible for the highest share of the patient's utilization on cancer treatments.[36] We control for the physician's specialty and location and decompose the partisan differences in chemotherapy within the patient's final 14 days.

Table 5b finds that in addition to low-value services, recent Republican physicians have become significantly more likely than Democratic physicians to perform chemotherapy on end-of-life cancer patients in the final two weeks of life. Among the post-2004 contributor cohorts, Republican physicians spend an average of 13.60% (s.e.=4.88) more on chemotherapy for cancer patients within the last 14 days before death (Column 1), primarily due to the extensive margin of whether to do chemotherapy at all (Column 2). Democratic physicians perform chemotherapy for 2.24% of their patients at this late stage (Column 3), whereas Republican physicians do so for 2.54%, an absolute difference of 0.30 pp. (s.e.=0.08, Column 4) and a relative increase of 13% (s.e.=3, Column 5). Meanwhile, for the pre-2004 contributor cohorts, there is no significant difference between Republican and Democratic physicians (diff. in average utilization=2.17%, s.e.=4.03).

Preventive service For both low-value services and end-of-life chemotherapy, Republican physicians are practicing more aggressively, but are they also performing more high-value care? One possibility is that Republican physicians simply do more of everything. For example, they may do more back imaging for lower back pain, which is likely wasteful for most patients, but they might also do more beneficial preventive screenings, which could balance the inefficient spending on low-value services.

We again analyze a specific group of medical services, namely preventive care, which is typically considered high-value. We select from the list of services offered in the official Medicare Preventive Services Chart[37] the ones that do not require qualifying conditions for coverage besides age and sex. This excludes, for instance, HIV screening, which is only

[35]ICD-9 codes for poor-prognosis cancers are from Morden et al. (2012), and the ICD-10 codes are from Wasp et al. (2020). We use the same HCPCS/CPT codes to identify chemotherapy treatment as in Morden et al. (2012) and Wasp et al. (2020).

[36]Specifically, we assign patients to the performing physician with the most cumulative utilization spent on cancer treatments (identified by CCS codes for various cancers) for the patient in the year of death. The assigned physician is responsible for around 80% on average of all utilization on cancer treatments for a typical patient. As a robustness check, Table A.9 shows the results assigned patients to the referring physicians with the most utilization for cancer treatments, instead of performing physicians. The results are similar.

[37]`https://web.archive.org/web/20140630154254/http://www.cms.gov/Medicare/Prevention/PrevntionGenInfo/Downloads/MPS_QuickReferenceChart_1.pdf`

covered for patients who are pregnant or have an increased risk of HIV infection. We then check the remaining eligible services for any that should be omitted based on clinical guidelines from the U.S. Preventative Services Task Force (USPSTF) and the medical literature. For example, Medicare covers prostate cancer screening, but the USPSTF cautions that the potential benefit may be small relative to the potential harms, and explicitly recommends against screening men over 70 (USPSTF, 2018).

We decompose the partisan differences in preventive services, again controlling for specialty and location. We limit the sample of physicians to PCPs and OB/GYNs, who are primarily responsible for providing these services. Unlike the low-value services, however, preventive care is not dependent on specific diagnosis codes and hence does not have a clear denominator for which patients the physician could have provided the service to, regardless of whether she did or not. For each physician, we thus define the set of patients eligible for a service in a given year as those who: (i) see the physician for either a screening, medical exam, or immunization,[38] (ii) meet the age or sex requirements, for example, only female patients for mammography screenings, (iii) see at most one PCP and at most one OB/GYN in that year, to clearly define the set of patients for whom the physician is most responsible for their preventive care, and (iv) did not receive the service elsewhere in the same year, since services such as flu shots are only covered once per annum.

Table 5c shows that in contrast to low-value care and end-of-life chemotherapy, Republican physicians provide preventive services at similar rates as Democratic physicians. Republican physicians provide some preventive services more frequently, such as flu shots, and others less frequently, such as annual wellness visits. On average, there is no significant partisan difference and no change between the pre- and post-2004 cohorts.

4.5.3 Beliefs about appropriate care: Discussion of results

We find evidence that physician beliefs are an important channel for the partisan differences in medical practice. Republican physicians perform more services that are discouraged by clinical guidelines, which aligns with their reported beliefs from prior survey evidence (Patashnik et al., 2020). This congruence between beliefs and practice is also consistent with previous studies (Cutler et al., 2019).

[38]Screening, medical exam, or immunization encounters have a single-level CCS code of either 10, 256, or 258.

Table 5c: Partisan differences in the provision of preventive care

	Post-2004 contributors			Pre-2004 contributors			
Diagnosis - Procedure	$\Delta\overline{\text{Util.}}$ log pt. (1)	Ext. % (2)	Weight (3)	$\Delta\overline{\text{Util.}}$ log pt. (4)	Ext. % (5)	Weight (6)	(1)-(4)
Influenza vaccine	4.22 (0.51)	101.37	0.24	1.04 (0.56)	102.44	0.29	3.18 (0.81)
Pneumococcal vaccine	-3.92 (1.17)	108.32	0.20	-1.10 (1.58)	84.35	0.22	-2.82 (1.95)
Cardiovascular disease blood tests	-2.99 (1.56)	125.38	0.15	-10.91 (2.19)	109.94	0.15	7.93 (2.19)
Annual wellness visit	-3.55 (0.82)	91.49	0.11	-3.58 (1.47)	103.67	0.09	0.02 (1.68)
Colorectal cancer screening until age 75	10.89 (3.89)	95.04	0.11	7.24 (5.93)	97.16	0.11	3.65 (7.47)
Mammography screening until age 75	-2.28 (0.66)	149.78	0.08	1.02 (0.84)	41.90	0.09	-3.30 (1.09)
Bone density test for women	-13.14 (4.65)	103.89	0.06	4.70 (7.08)	47.91	0.04	-17.84 (8.47)
Screening for depression	0.30 (4.15)	215.43	0.03	7.07 (6.17)	107.65	0.02	-6.77 (6.89)
Alcohol misuse screening	8.87 (6.45)	98.99	0.02	2.09 (8.57)	100.61	0.01	6.78 (9.97)
Average	-0.25 (0.63)	112.25		-0.68 (0.72)	91.90		0.43 (1.01)

This table decomposes the partisan difference in utilization for a set of preventive services covered by Medicare. Each column conveys the same information as in Table 5a. Standard errors from 50 bootstrap samples are shown in parentheses.

From their treatment choices, Republican and Democratic physicians appear to disagree on which medical services are appropriate for a given condition, which may arise from several different beliefs. Relative to their Democratic counterparts, Republican physicians may believe that aggressive treatments have greater expected benefits for patient outcomes. Alternatively, Republican and Democratic physicians may be aligned on the expected benefit of a given treatment, but Republican physicians may place less weight on the costs, either to the patient or to Medicare. In this case, the partisan differences reflect separate views on medical resource allocation. Relatedly, Republican physicians may hold different attitudes toward risk and may consider treatments such as chemotherapy for severe cancer cases still "worth trying", even if they have low chances of success and provide little benefit for the average patient. These patterns raise concerns about the inefficiency of the additional spending from these partisan differences.

The timing of the partisan divergence between physicians who began contributing pre-versus post-2004 reflects the concurrent polarization among politicians in Congress regarding evidence-based medicine. Patashnik et al. (2020) documents that before the second W. Bush term, policies for Comparative Effectiveness Research (CER), which aimed to clinically investigate which drugs and treatments are most effective, began as a bipartisan effort in 2003 with eight Republican and seven Democratic cosponsors. During the second W. Bush term starting in 2004, the bipartisan effort began to fracture, and by 2007, only one Republican cosponsor remained. When the Obama Administration adopted CER as one of its priorities for healthcare reform, Republican support all but collapsed. Republican politicians then cast CER as government overreach that would lead to "rationing" and "death panels" (Patashnik et al., 2020).

Meanwhile, we find that physicians who deviate more from clinical guidelines began donating to Republican candidates when these Republican politicians started taking more negative positions on evidence-based medicine and standardized practice. In other words, the type of physicians whom the Republican party has attracted since 2004 is consistent with the stance on medical policy that the party has adopted. Ultimately, the Republican party has increasingly appealed to physicians who practice more aggressively beyond the recommended guidelines.

What is different about the Republican and Democratic physicians who started contributing from this point in time, and why might they hold different beliefs on what is appropriate medicine? While we cannot definitively answer how physicians beliefs are formed in the first place, our final analysis explores one potential factor: their medical school training.

4.6 Partisan segregation in medical school training

We present several new facts about medical school training and physician party alignment. Prior studies have found that medical programs predict physician treatment choice and performance, with physicians from higher ranked medical institutions achieving better patient outcomes. (Doyle Jr. et al., 2010; Currie at al., 2016). This correlation could reflect the quality of training at top medical schools or the selection of higher ability students. Although there have been surveys that ask medical students about party affiliation (e.g., Frank et al., 2007), to the best of my knowledge, this is the first to study partisan differences in medical school training.

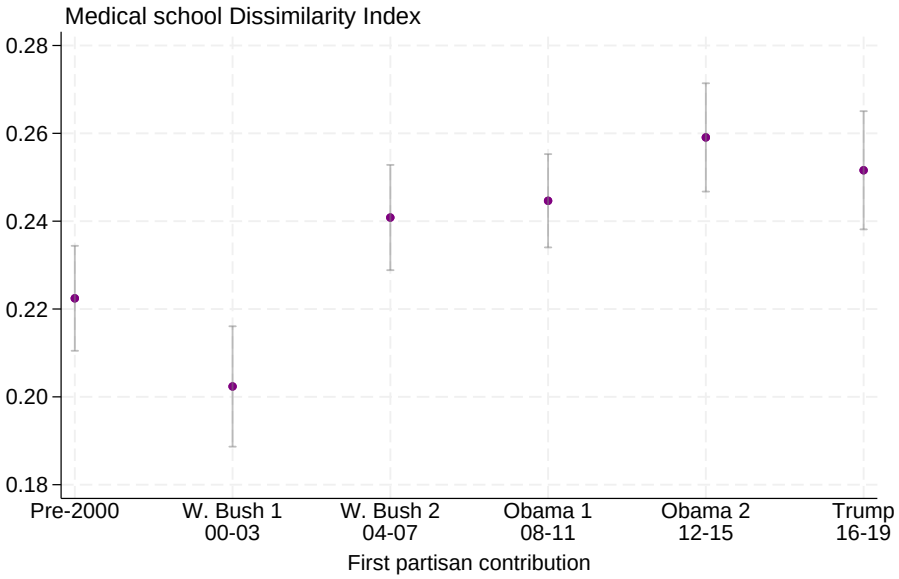
We apply a measure commonly used for residential segregation, the Dissimilarity Index (DI). From the National Downloadable File, we identify the medical school background for 62% of the partisan physicians, who are responsible for 72% of the utilization among all partisan physicians. We then calculate the DI by taking the absolute value of the difference in proportions, summed over all locations, and then divided by two. That is, $\text{DI} = \frac{1}{2}\sum_m |p_m^R - p_m^D|$, where m indexes medical schools, R, D indexes Republicans and Democrats, and p_m is the proportion of physicians who graduated from m. The measure ranges from 0 (complete integration) to 1 (complete segregation).

Figure 14a shows that the Republican and Democratic physicians who began contributing after 2004 not only differ in their practice styles, but are also more segregated in which medical schools they attended. The figure plots the Dissimilarity Index for Republican and Democratic physicians by the presidential administration when they began contributing. The DI has significantly increased among the post-2004 contributors, matching the timing of when the partisan divergence in medical practice emerged. It has risen from a low of 0.20 in the pre-2004 cohort, to 0.25 in the most recent cohort. For comparison, the DI for gender is 0.06 in the first cohort and 0.07 in the last.

Figure 14b finds that medical schools consistently produce physicians with predictable intensities in practice style. We take the physician fixed effects estimated in Section 4.3.2, standardize them by demeaning and dividing by the standard deviation within each specialty, and then average the standardized fixed effects for each medical school. We do this separately for the physicians who began donating before 2004 and those after 2004. The figure plots the binscatter demonstrating the strong correlation between the two cohorts. The pre-2004 cohort graduated on average 10 years before the pre-2004 cohort, but can explain 58% of the latter cohort's average practice style. Given this strong autocorrelation, we use the pre-2004 cohort to characterize the average practice style of a medical school program.

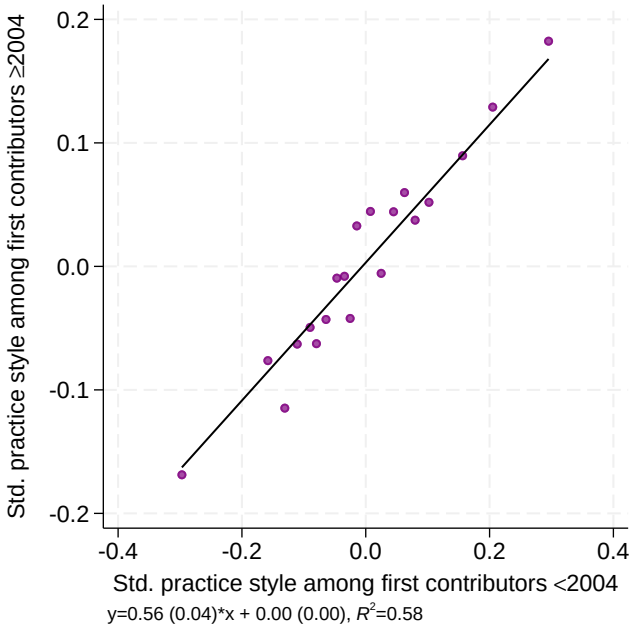
Figure 14: Partisan segregation in medical schools and autocorrelation in practice style

(a) Partisan segregation in medical school training



This figure shows the Dissimilarity Index for medical school segregation between Republican and Democratic physicians in each cohort. Physicians are grouped into cohorts based on the presidential term when they made their first political contribution. Confidence intervals are shown with standard errors from 1000 bootstrap samples.

(b) Autocorrelation in medical school practice style



This figure shows the binscatter of the average physician fixed effect among the graduates who attended the same medical school in the pre-2004 cohort and in the post-2004 cohort. Each observation is a medical school. Physician fixed effects are the estimated $\hat{\delta}_d$ from Equation 13. Fixed effects are standardized to have mean zero and unit standard deviation within each specialty.

What are the characteristics of the medical schools that have become more or less common among Republican or Democratic physicians in recent cohorts? We also link each medical school to the average MCAT score of its matriculants, as well as the average two-party Republican voteshare in the surrounding county for the presidential elections over the study period.[39] Building on the DI, we calculate the standardized dissimilarity for each medical school m, or the z-score of the difference in proportions:

$$z(\text{DI}_m) = (p_m^R - p_m^D)/\sqrt{p_m^R(1-p_m^R)/N^R + p_m^D(1-p_m^D)/N^D} \tag{15}$$

where N^R is the number of Republican physicians and N^D the number of Democratic physicians in the medical school sample. The standardized measure $z(\text{DI}_m)$ is positive if a greater proportion of Republican physicians attend medical school m, and negative if the opposite. We also standardize the explanatory variables to interpret the relationship with $z(\text{DI}_m)$ in terms of standard deviations.

Table 6: Patterns of partisan segregation in medical school training

	z-score DI (P(Rep) − P(Dem))			
	Pre-2004	Post-2004	Δz(DI)	$\mathbf{1}\{\Delta z(\text{DI}) > 0\}$
	(1)	(2)	(3)	(4)
Medical school characteristics (standardized averages)				
Pre-2004 practice style	0.00	0.06	0.06	0.05
	(0.03)	(0.05)	(0.03)	(0.04)
MCAT score	-0.06	-0.22	-0.16	-0.17
	(0.04)	(0.06)	(0.03)	(0.04)
County Republican voteshare	0.13	0.24	0.10	0.18
	(0.04)	(0.06)	(0.03)	(0.04)
Constant	0.00	0.00	0.00	0.48
	(0.03)	(0.05)	(0.02)	(0.04)
N (medical schools)	132	132	132	132
R^2	0.16	0.32	0.40	0.34

This table shows the characteristics of the medical schools that Republican physicians attend at higher rates. The outcome in Columns 1 and 2 is the Dissimilarity Index z-score from Equation 15. Higher values of z-score DI represent higher relative attendance by Republicans. Column 1 shows the results for the physicians who made their first contribution before 2004, and Column 2 for those that made their first contribution on or after 2004. In Column 3, the outcome is the change in z-score DI between the pre- and post-2004 contributor cohorts. In Column 4, the outcome is an indicator for whether z-score DI is positive. The explanatory variables have been standardized to have have a mean of zero and unit standard deviation. Robust standard errors are shown in parentheses.

Table 6 finds that relative to their Democratic counterparts, Republican physicians in

[39] We can find these medical school characteristics for 96% of the partisan physicians with a medical school record.

recent cohorts have attended medical schools that are located in more right-leaning counties, have lower MCAT scores on average, and have produced more aggressive physicians in previous cohorts. For the pre-2004 contributors, Column 1 finds no significant partisan differences in practice style and MCAT scores. There are signs of geographic sorting, in that Republican physicians are more likely to attend medical schools in counties with a higher Republican voteshare and vice versa. On the other hand in Column 2, Republican physicians among the post-2004 contributors are significantly more likely to attend medical schools with lower MCAT scores. In Column 3, the outcome is the post-2004 minus the pre-2004 cohort difference in $z(\text{DI}_m)$. The medical schools that attracted relatively more Republican physicians from the recent cohorts have significantly higher: (i) practice styles in the past, (ii) lower MCAT scores, and (iii) higher Republican voteshare in their local county. Column 4 reveals similar patterns, where the outcome is a coarser indicator measure for whether $z(\text{DI}_m)$ has increased toward more Republican matriculants.

In summary, beyond their diverging practice styles and beliefs, recent Republican and Democratic physicians are less likely to have attended the same medical school relative to Republican and Democratic physicians from previous cohorts. The partisan differences have grown, not only in practice style, but also in medical training. This relationship could be due to causal training effects or simply to selection. In either case, the current divergence in training seems likely to reinforce partisan differences in medical practice.

5 Discussion

Two decades ago, there was no difference between Republican and Democratic physicians in how much they spent per patient. Now, there is. Under our model, there are four potential sources for these differences: practice characteristics, patient composition, preferences for financial gain, and beliefs about appropriate care.

While practice characteristics (i.e., location and specialization) do play a role, they still leave the majority of the partisan differences intact. Most of the gap is concentrated in the extensive margin of treatment choice, especially in elective procedures. Republican and Democratic physicians are systematically choosing to treat patients who have the same condition with different treatments. This partisan difference is not due to patient composition, which we account for using patient and physician movers.

Between preferences for financial gain and beliefs about appropriate care, the sum of the evidence rests with the latter. Republican physicians are no different from Democratic physicians in their response to financial incentives. For example, both Republican and Democratic both switched away at similar rates from using a chemotherapy drug that became less

profitable. Republican oncologists, however, are more likely to administer chemotherapy to patients with poor-prognosis cancer in the final two weeks before death, which indicates they are more willing to try treatments with low chances of success. In general, Republican physicians provide more services that are discouraged in clinical guidelines, which is consistent with prior survey evidence on their beliefs.[40] These beliefs may differ on several margins, such as higher expected benefits from aggressive treatments or lower weight on the costs.

What are the implications for medical spending and patient outcomes? A welfare analysis of the partisan differences in all treatments is challenging, as the net benefit or harm of many elective treatments are difficult to determine in the medical claims data. Typical measures like the mortality rate are not as relevant for procedures such as knee replacements. However, we do find partisan differences in a subset of medical services identified by clinical studies as low-value care, without any compensating difference in preventive services that are typically considered high-value care. The higher rate of chemotherapy for cancer patients within their final two weeks also indicates that Republican physicians are not necessarily targeting cases that warrant more aggressive treatment. These results suggest that the additional utilization may be clinically inefficient (Abaluck et al., 2021).

While the Medicare setting has both empirical advantages and practical relevance, we may expect the partisan differences to be greater in the general population. The scale of the Medicare program is vast, covering a fifth of the U.S. population and now consuming 15% of federal spending, but it serves mostly elderly patients. The recent politicized topics in health, such abortion or gender dysphoria, primarily affect younger groups. Furthermore, our sample period ends before the heavily politicized COVID pandemic. The partisan differences discovered in this paper may then be a lower bound for what we can expect to find more recently at large.

It is concerning that physicians have followed the footsteps of political parties in the polarization of medicine. Physicians are an economically elite and politically powerful group (Landers and Sehgal, 2000; Cooper et al., 2022; Alsan and Neberai, 2024). If the medical community becomes fragmented along partisan lines, with physicians on either side holding different beliefs on what is appropriate care, then the role of scientific evidence in guiding medical practice may become further undermined by politics, putting patients at risk in our increasingly polarized society.

[40]These results also align with Wennberg (2010), who originated the research into regional variations in healthcare and, after decades of observation, still did not believe that many physicians were "cynically rubbing their hands together every time a patient walks in the door, thinking of ways to deliver more care, and thus make more money."

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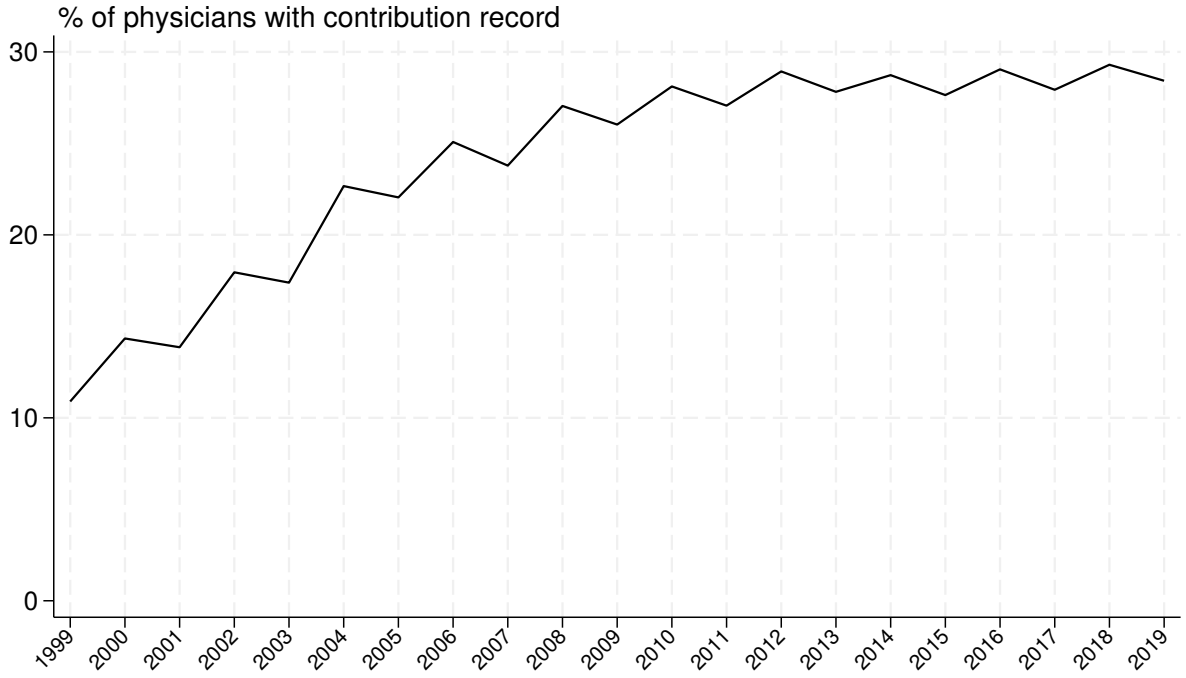
Wasp, Garrett, Shama Alam, Gabriel Brooks, Inas Khayal, Nirav Kapadia, Donald Carmichael, Andrea Austin, and Amber Barnato. (2020). "End-of-life quality metrics among medicare decedents at minority-serving cancer centers: A retrospective study." *Cancer Medicine*, 9(5), 1911-1921.

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A Appendix Figures

Figure A.1: Percent matched to campaign contributions

(a) Number of physicians



(b) Total utilization

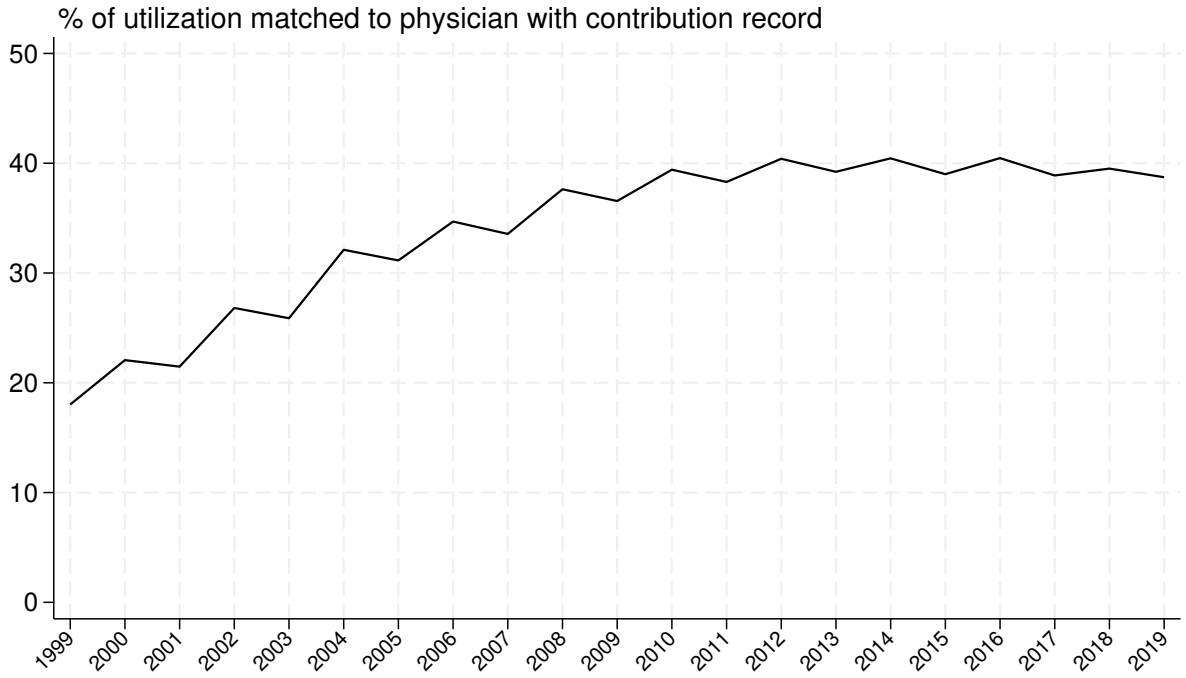
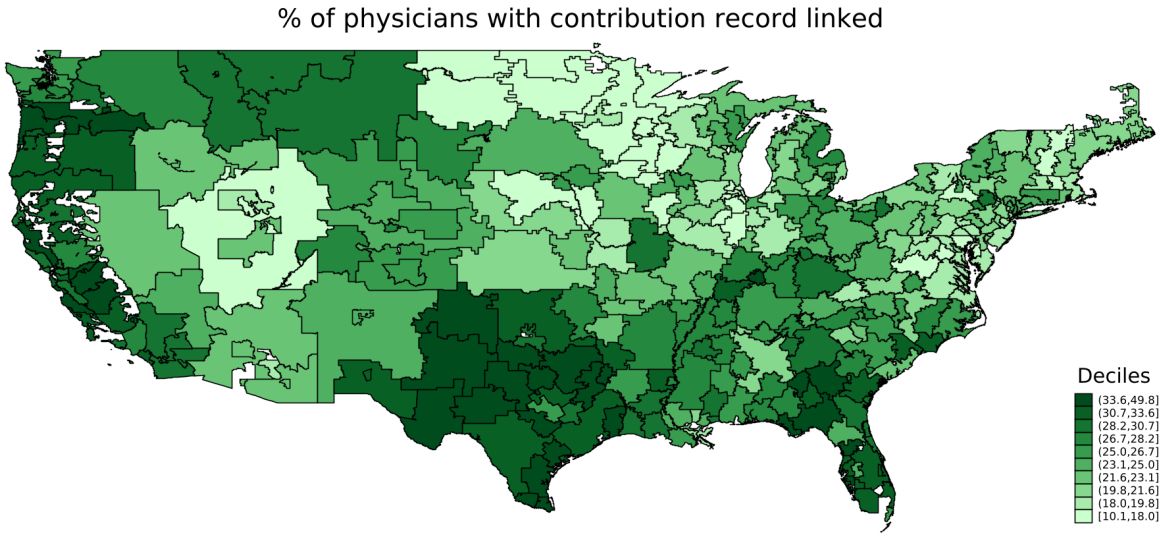
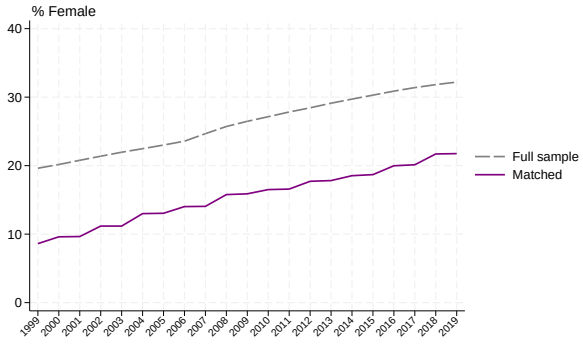


Figure A.2: Characteristics of physicians matched to campaign contributions

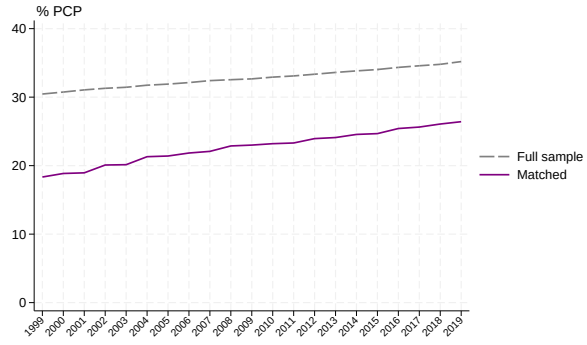
(a) Hospital referral region



(b) Gender



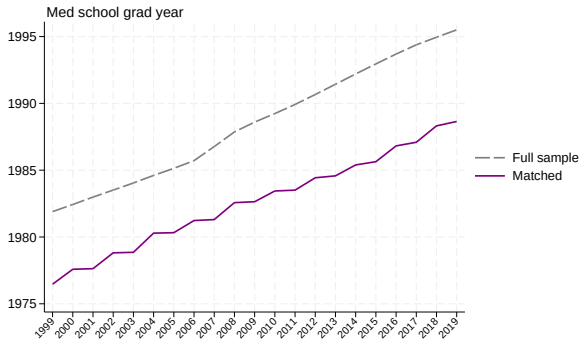
(c) Specialization in primary care



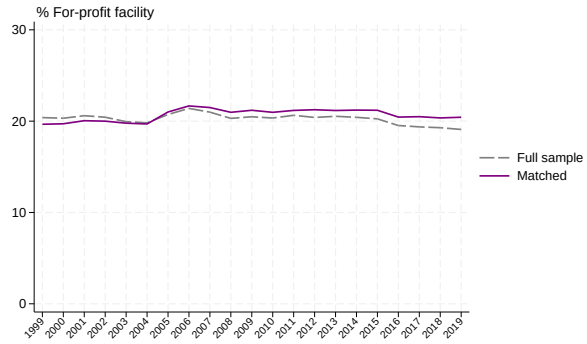
For Figure A.2a, we assign physicians in each year to the hospital referral region where most of their patients came from and average the match rate across years.

Figure A.2: Characteristics of physicians matched to campaign contributions

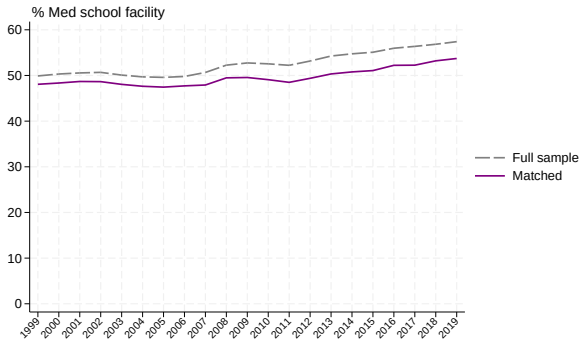
(d) Graduation year



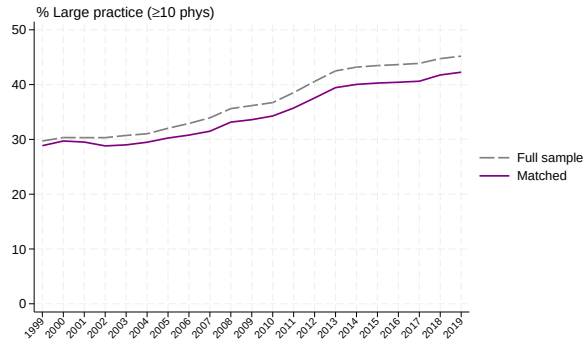
(e) For-profit practice



(f) Practicing at medical school facility



(g) Practicing at large facility



(h) Sole practitioner

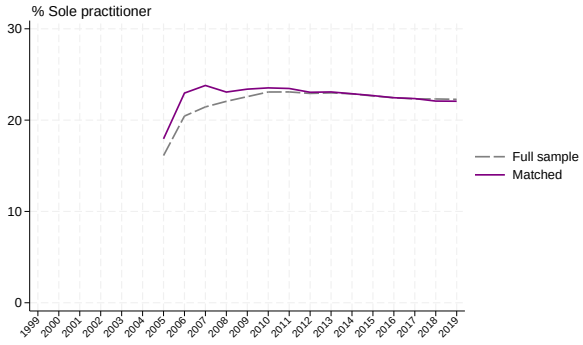
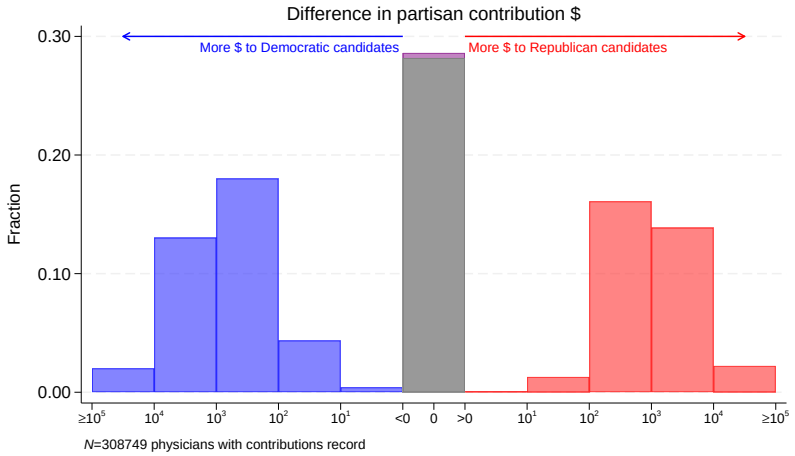
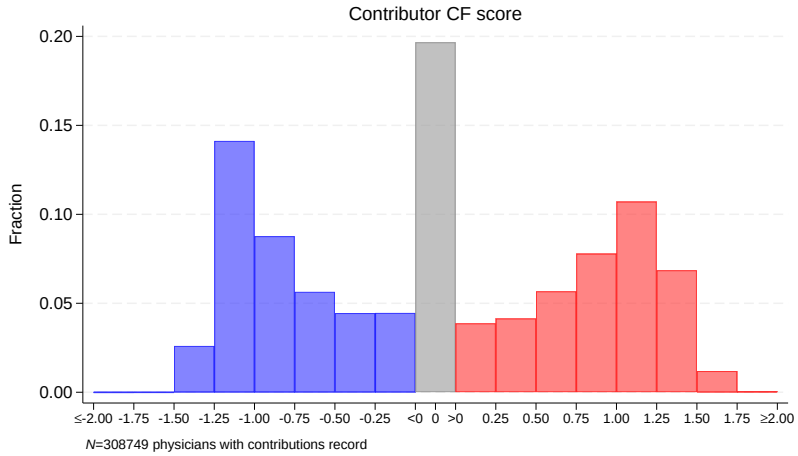


Figure A.3: Additional distributions of physician party alignment

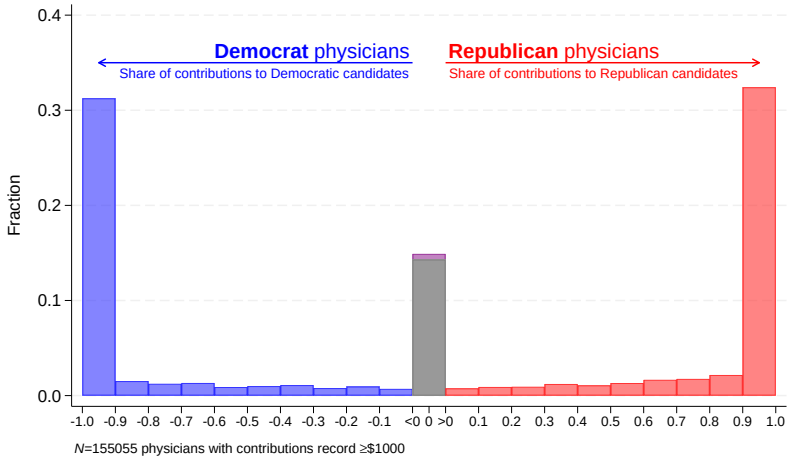
(a) Total amount donated up to 2019



(b) Common-space ideology scores from DIME



(c) Party share for $\geq$ \$1000 contributors



(d) Party share of contributors who donated in multiple election cycles

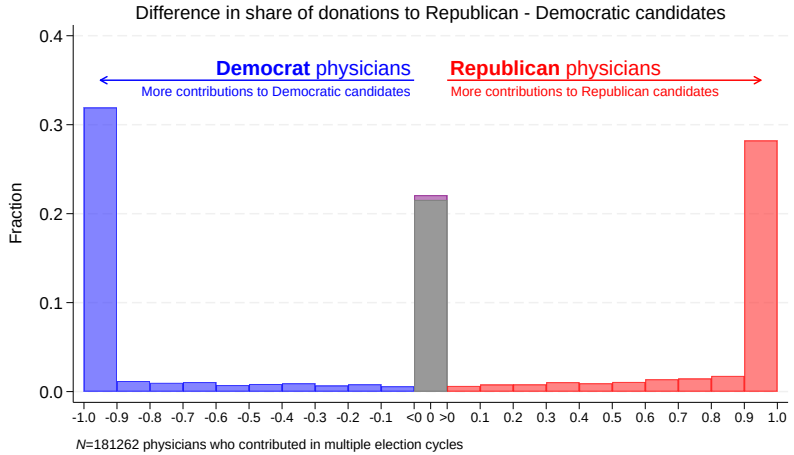
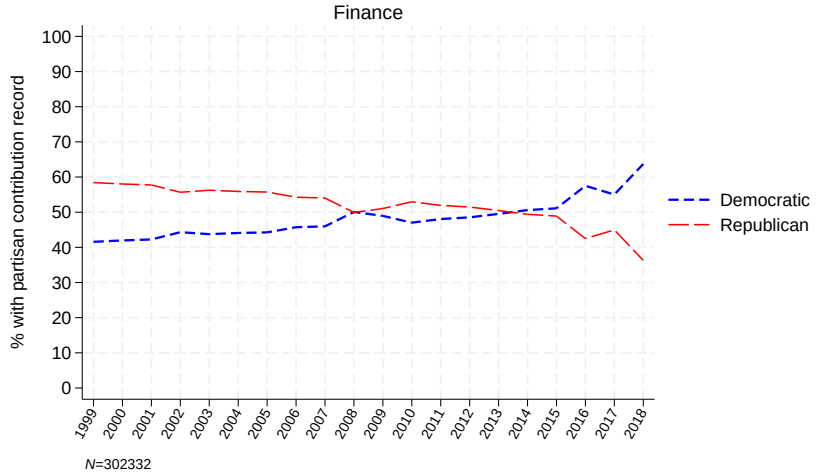


Figure A.4: Trends in party alignment of other professions 1999-2019

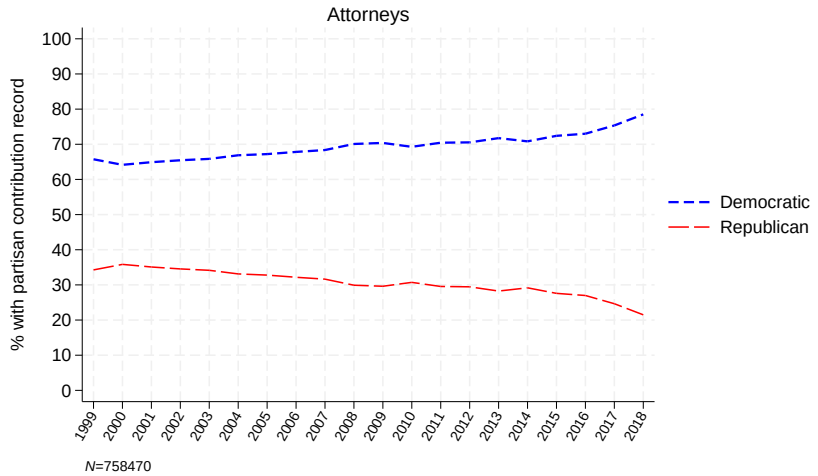
(a) Finance



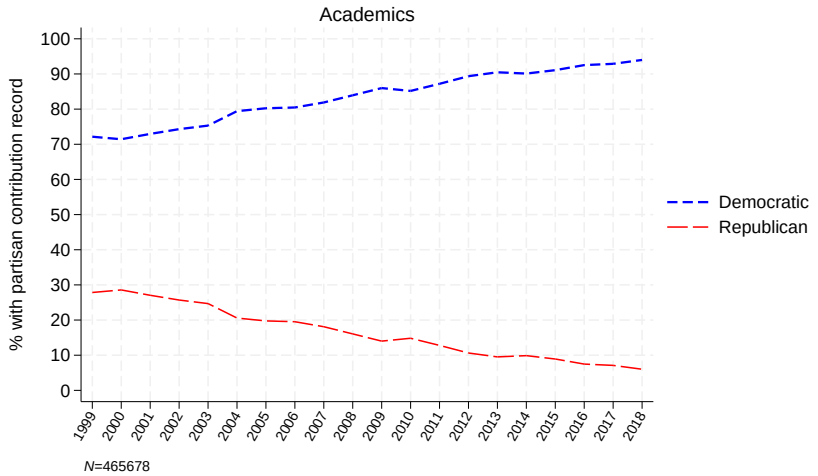
(b) Corporate executives



(c) Attorneys

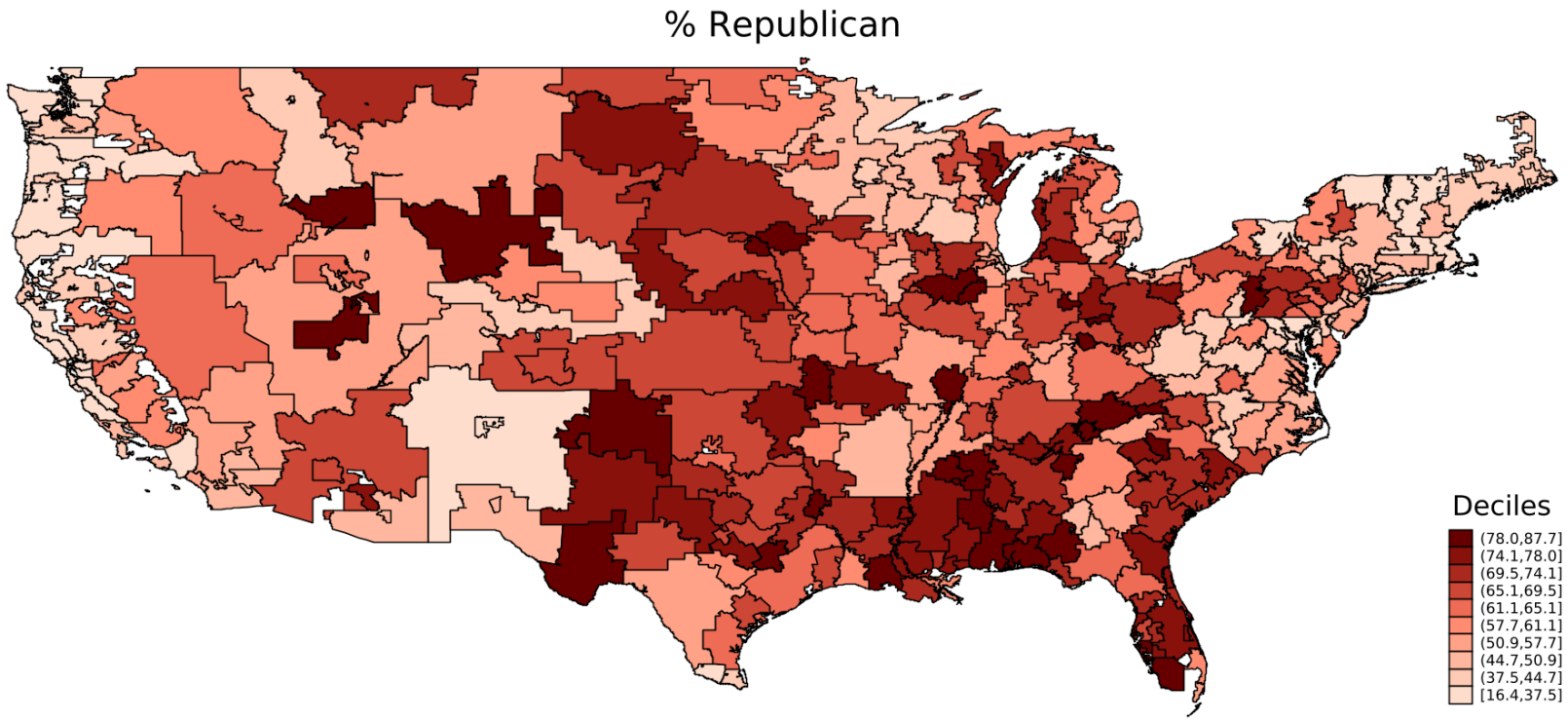


(d) Academics



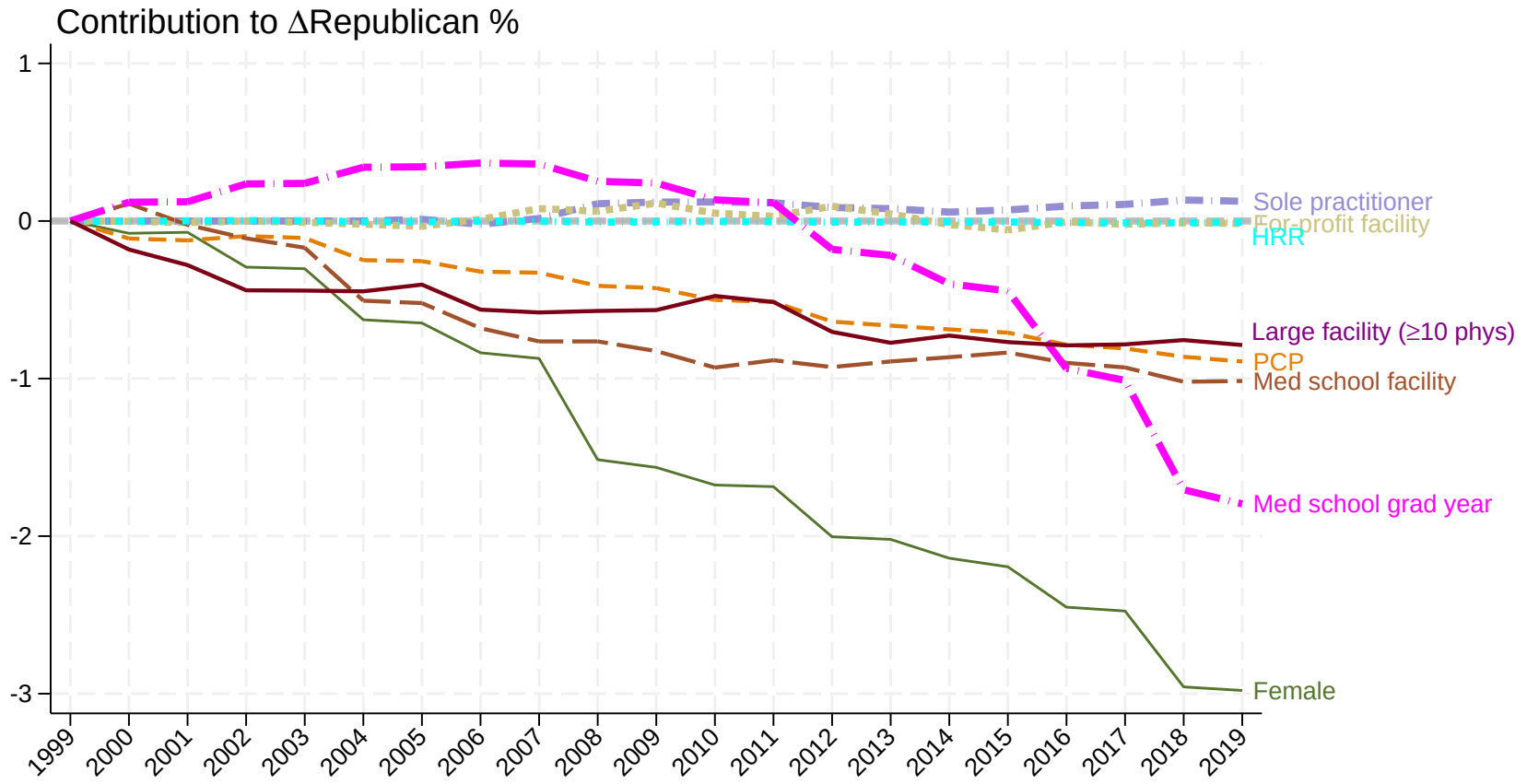
Contributors are categorized into professions based on the standardized occupation variable provided in Bonica (2023).

Figure A.5: Republican share by hospital referral region



This map shows the two-party share of Republican physicians, averaging all physician-year observations over 1999-2019.

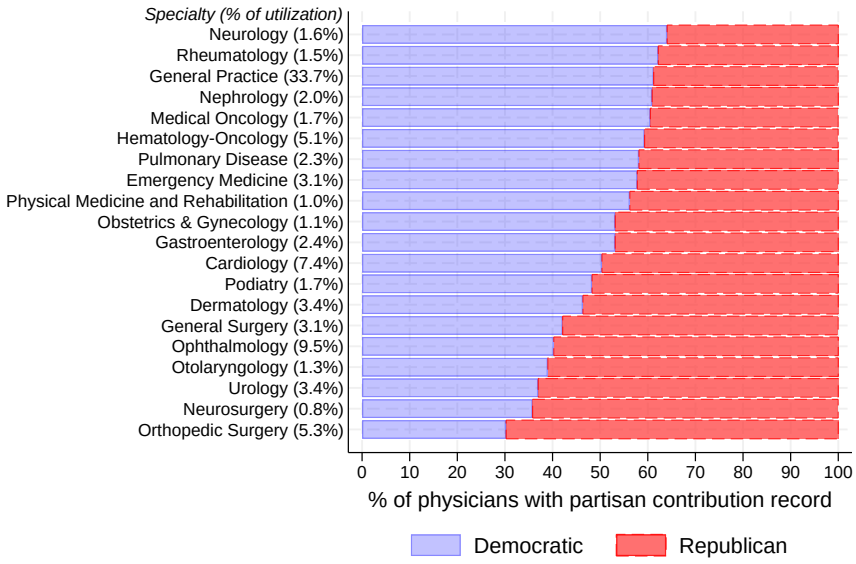
Figure A.6: Contribution of observable characteristics to party realignment of physicians 1999-2019



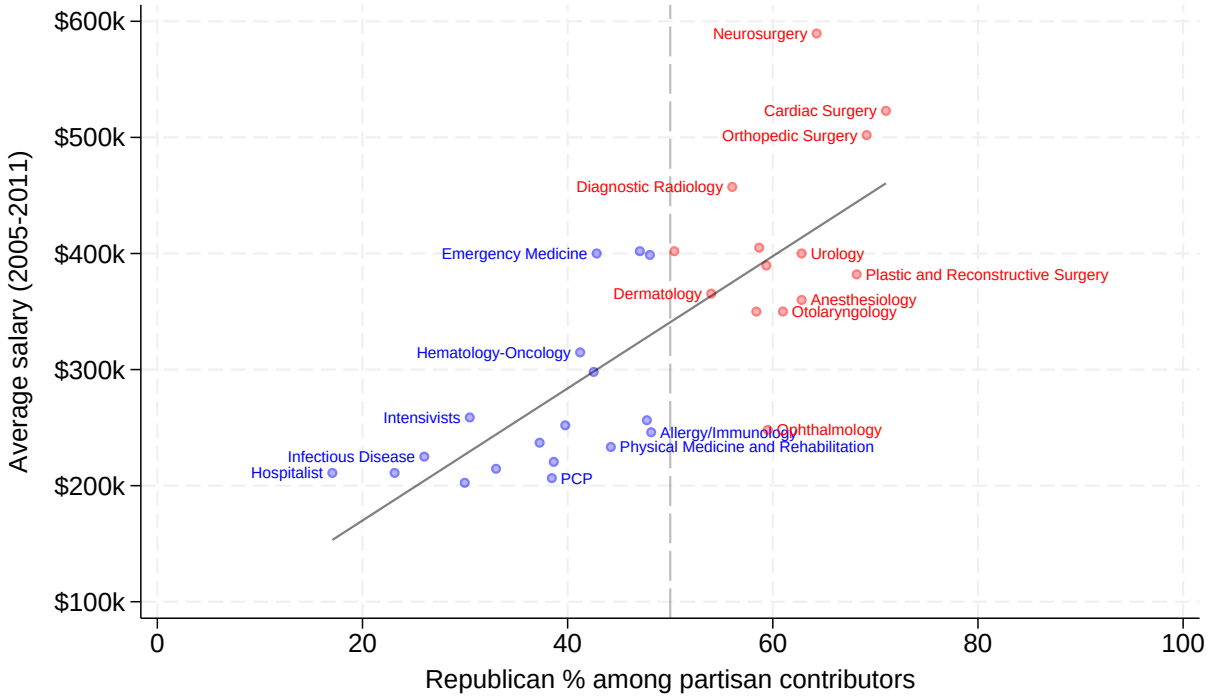
This figure shows the contribution of each observable characteristic to the change in the percent of Republican physicians from 1999 to each year, based on the Oaxaca-Blinder decomposition in Section 3.

Figure A.7: Republican share by specialty

(a) Top 20 specialties by total utilization

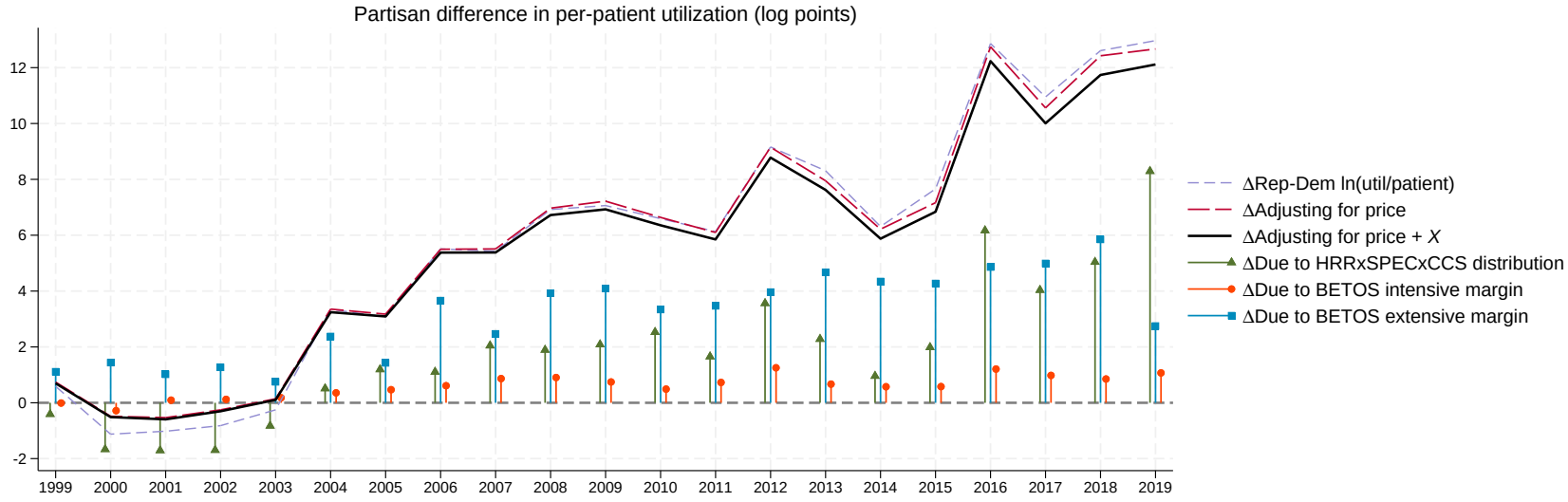


(b) By salary of specialty



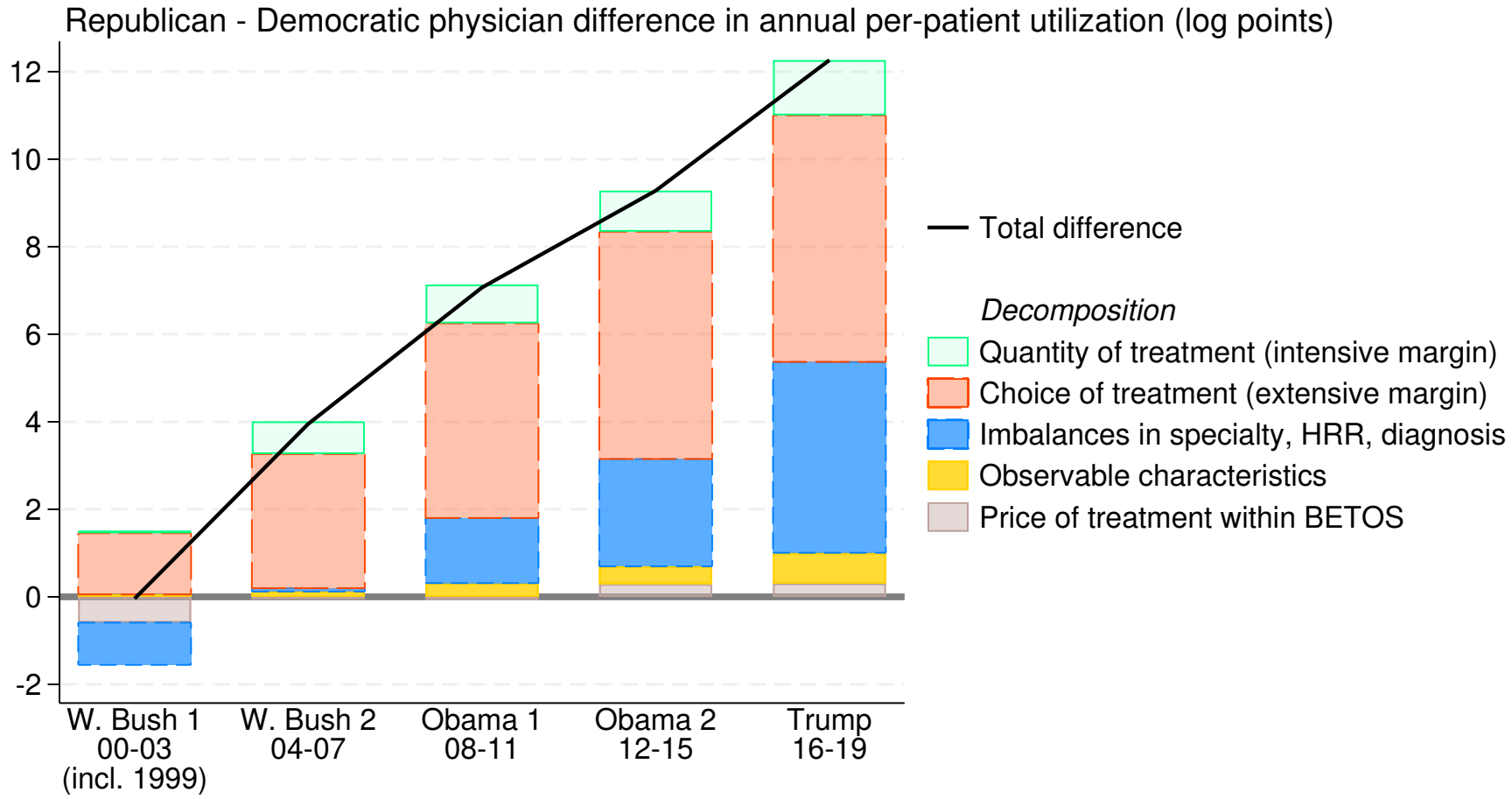
Salary data is taken from the same source used in Bonica et al. (2014), `https://web.archive.org/web/20130728191904/http://www.profilesdatabase.com/resources/2011-2012-physician-salary-survey`.

Figure A.8: Annual decomposition of partisan differences



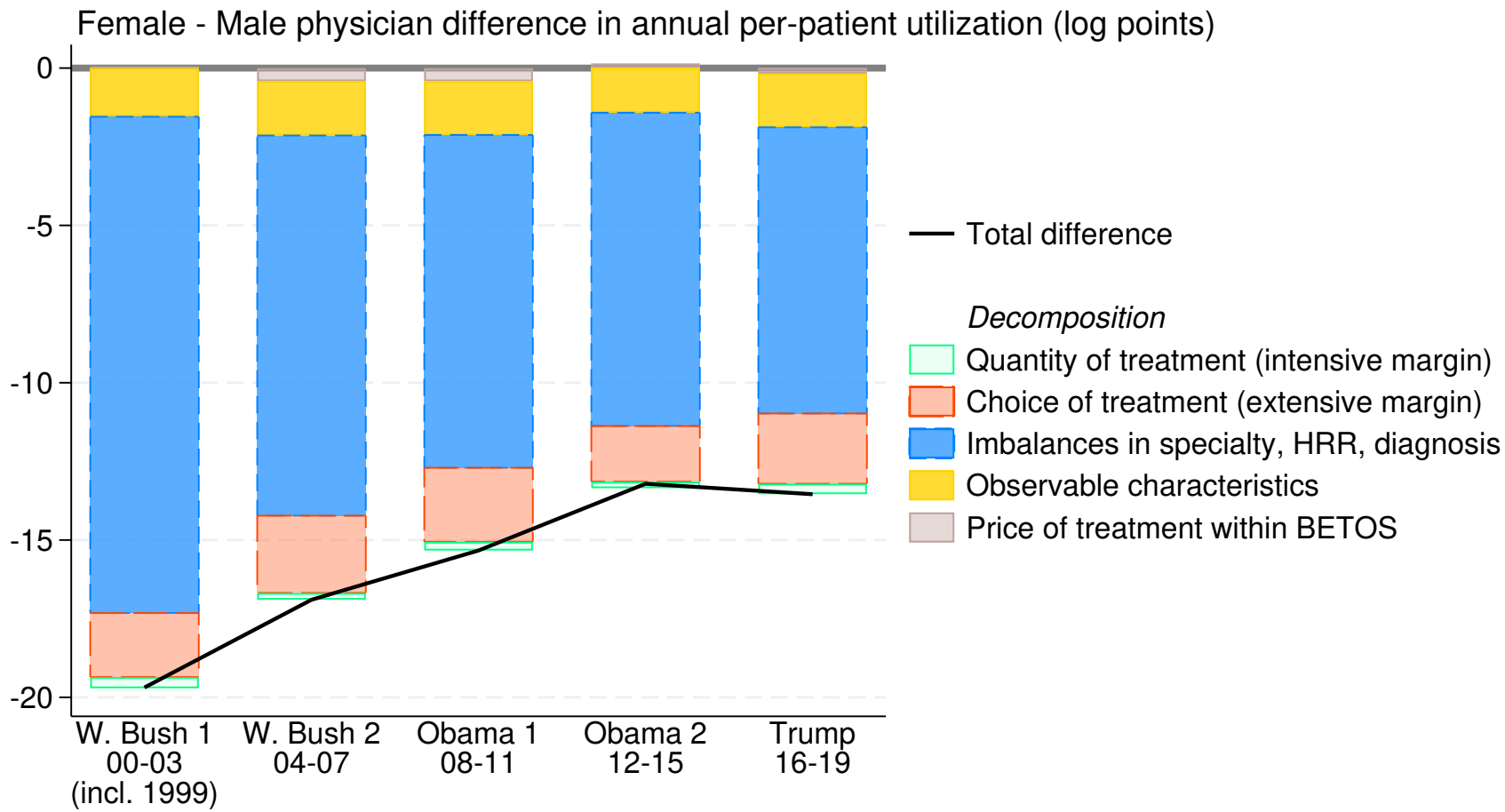
This figure shows the results of the decomposition in Section 4.2.1 at the annual level. It decomposes the annual differences between Republican and Democratic physicians in log(utilization per patient). The three trend lines show the raw differences, the differences after adjusting for prices, and the differences after adjusting for prices and observable characteristics. The remaining differences are decomposed into differences due to: specialty, location, and patient diagnosis (CCS codes); the extensive margin in treatment choice, as categorized by 3-digit BETOS codes (e.g., knee replacement vs. physical therapy for osteoarthritis); and the intensive margin (e.g., if physical therapy, the number of sessions).

Figure A.9: Decomposition of partisan differences within specialty-HRR-diagnosis



This decomposition reproduces Figure 9 but excludes specialty, HRR, and diagnosis groups where there are only Republican or only Democratic physicians.

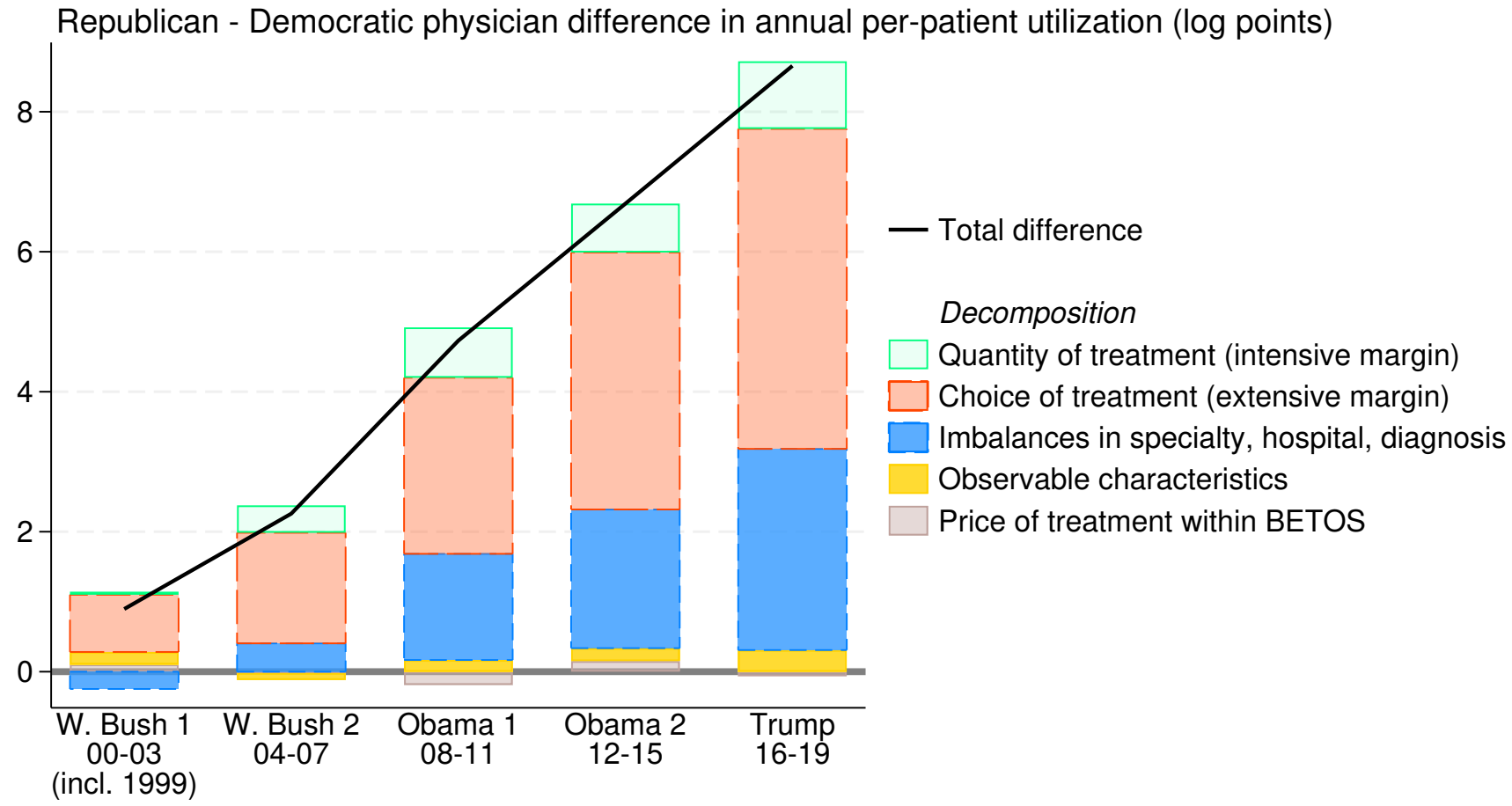
Figure A.10: Decomposition of gender differences in medical practice



This decomposition uses the estimates of the coefficient on female physicians from Section 4.2 to decompose the gender differences in medical practice.

Figure A.11: Robustness in decomposition of partisan differences

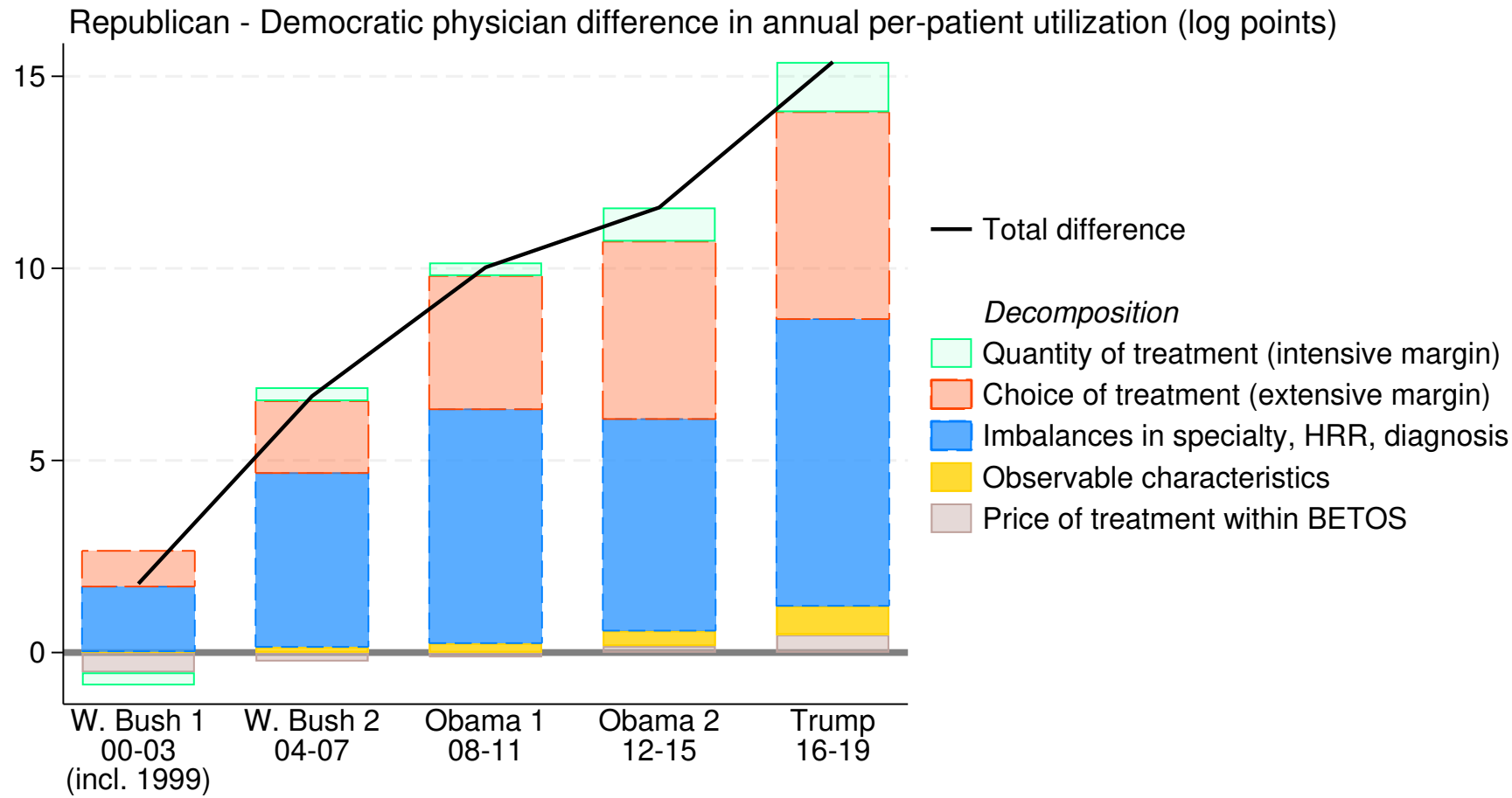
(a) Within-facility partisan differences with additional controls



This decomposition reproduces Figure 9 but with additional controls. This version: is estimated within hospital (as opposed to hospital referral region); includes only the physicians that can be linked to campaign contribution records under a "strict" match as defined in Section 2.2; includes the number of physicians who have the same specialty that patient sees for the condition, as well as indicators for physician's practice characteristics (sole practitioner, for-profit, medical school facility, and large facility with at least 10 physicians).

Figure A.11: Robustness in decomposition of partisan differences

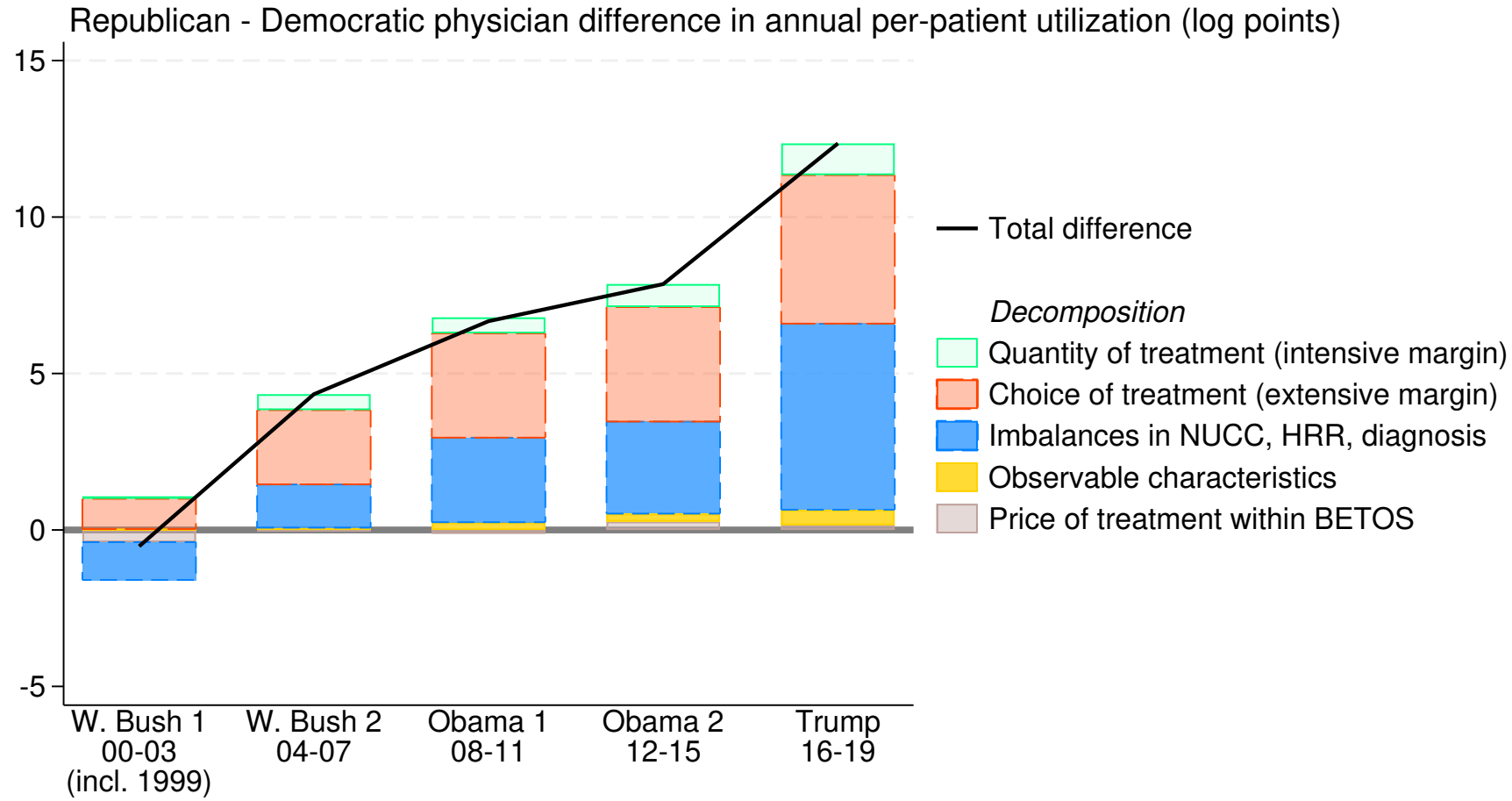
(b) Assigning claims to performing physician



This decomposition reproduces Figure 9 but assigns all claims to the performing physician, as opposed to the referring physician (when recorded) for non-office visits.

Figure A.11: Robustness in decomposition of partisan differences

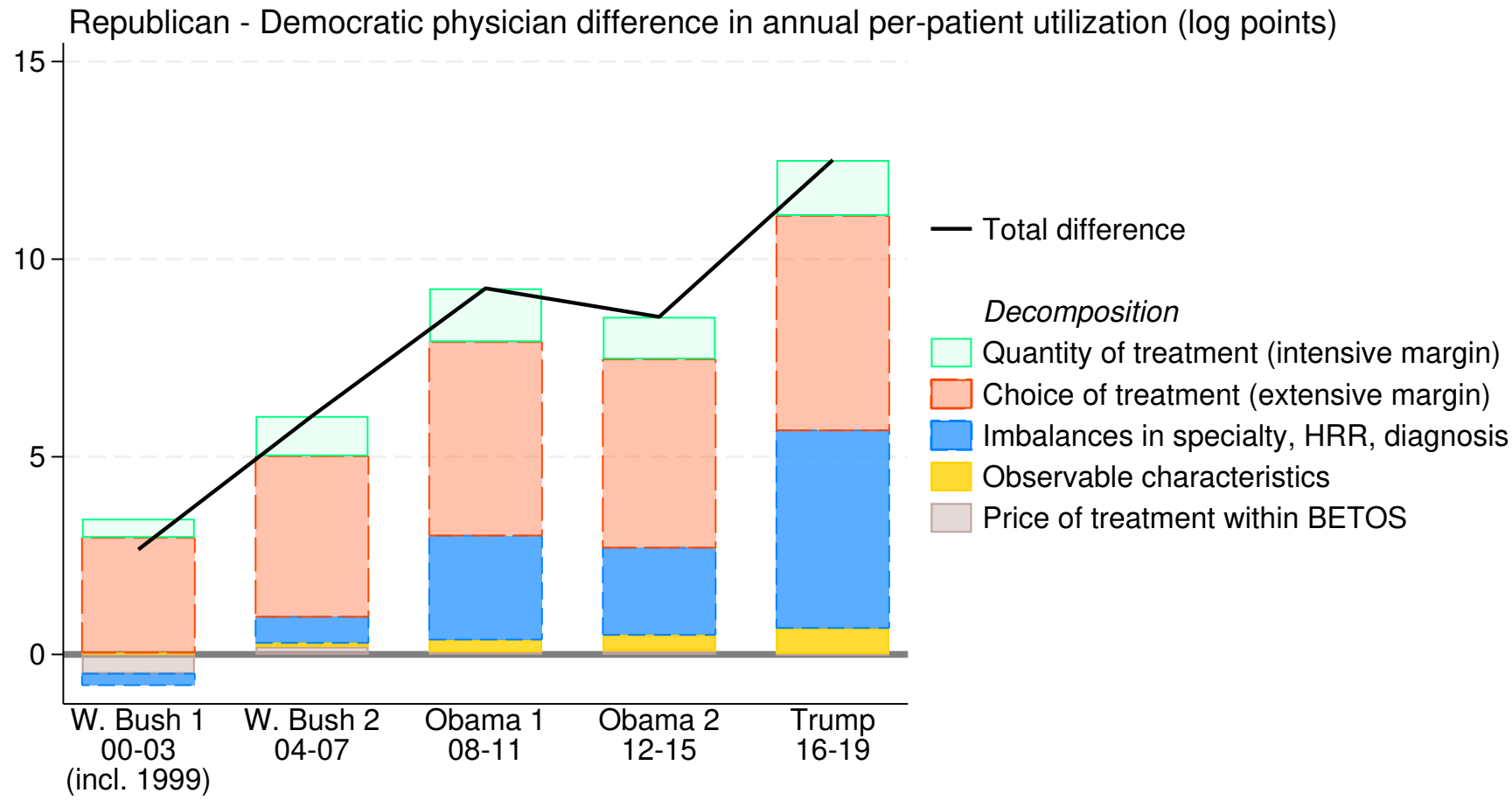
(c) Using more granular National Uniform Claim Committee (NUCC) specialty codes



This decomposition reproduces Figure 9 but uses the more granular NUCC specialty codes rather than the specialty codes in the Medicare data.

Figure A.11: Robustness in decomposition of partisan differences

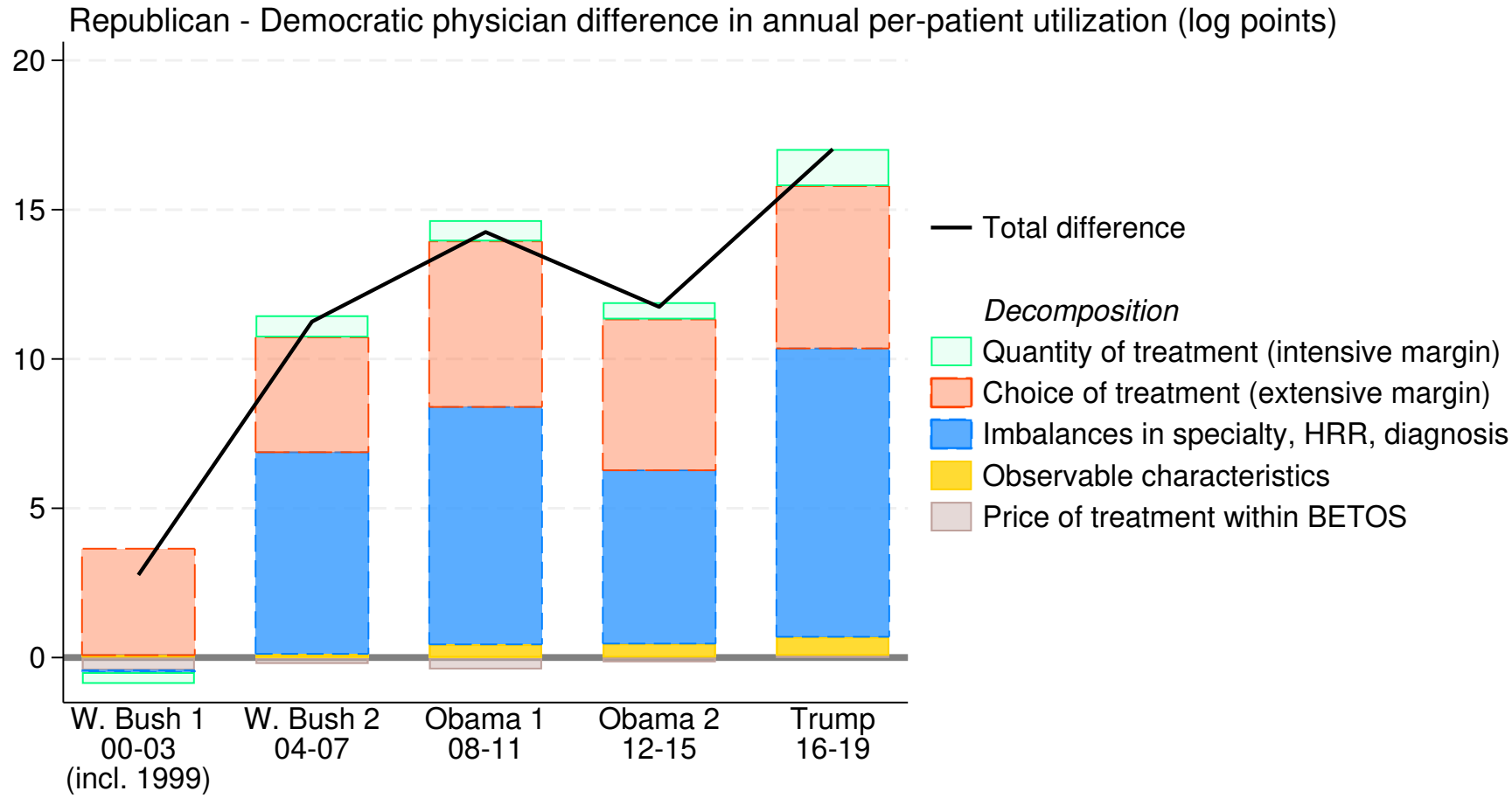
(d) Defining party by DIME ideology scores



This decomposition reproduces Figure 9 but instead categorizes physicians based on the sign of the common-space ideological score provided in the DIME dataset (Bonica, 2023).

Figure A.11: Robustness in decomposition of partisan differences

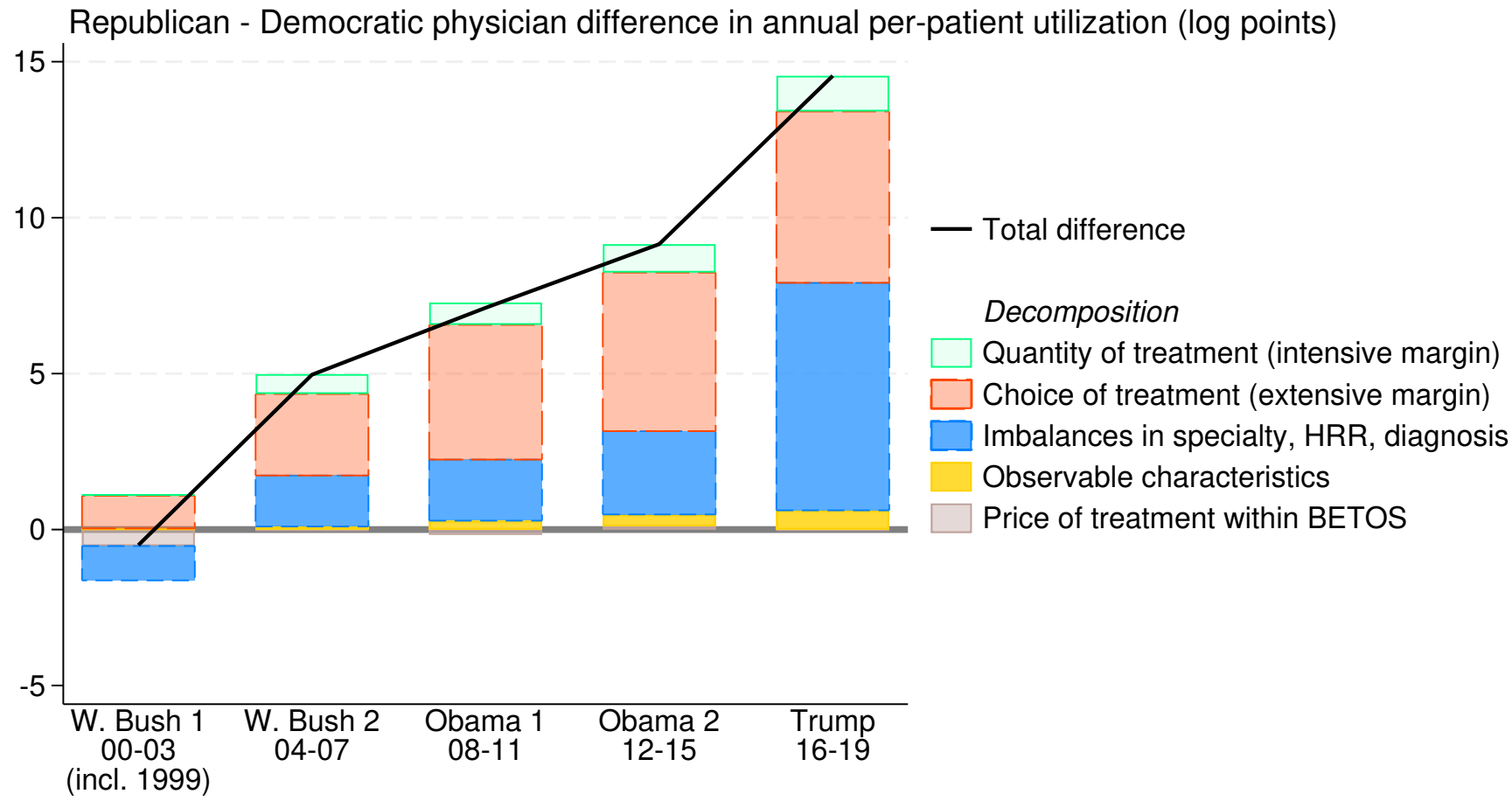
(e) Using only donations to presidential candidates



This decomposition reproduces Figure 9 but instead categorizes the party alignment of physicians using only donations to presidential candidates.

Figure A.11: Robustness in decomposition of partisan differences

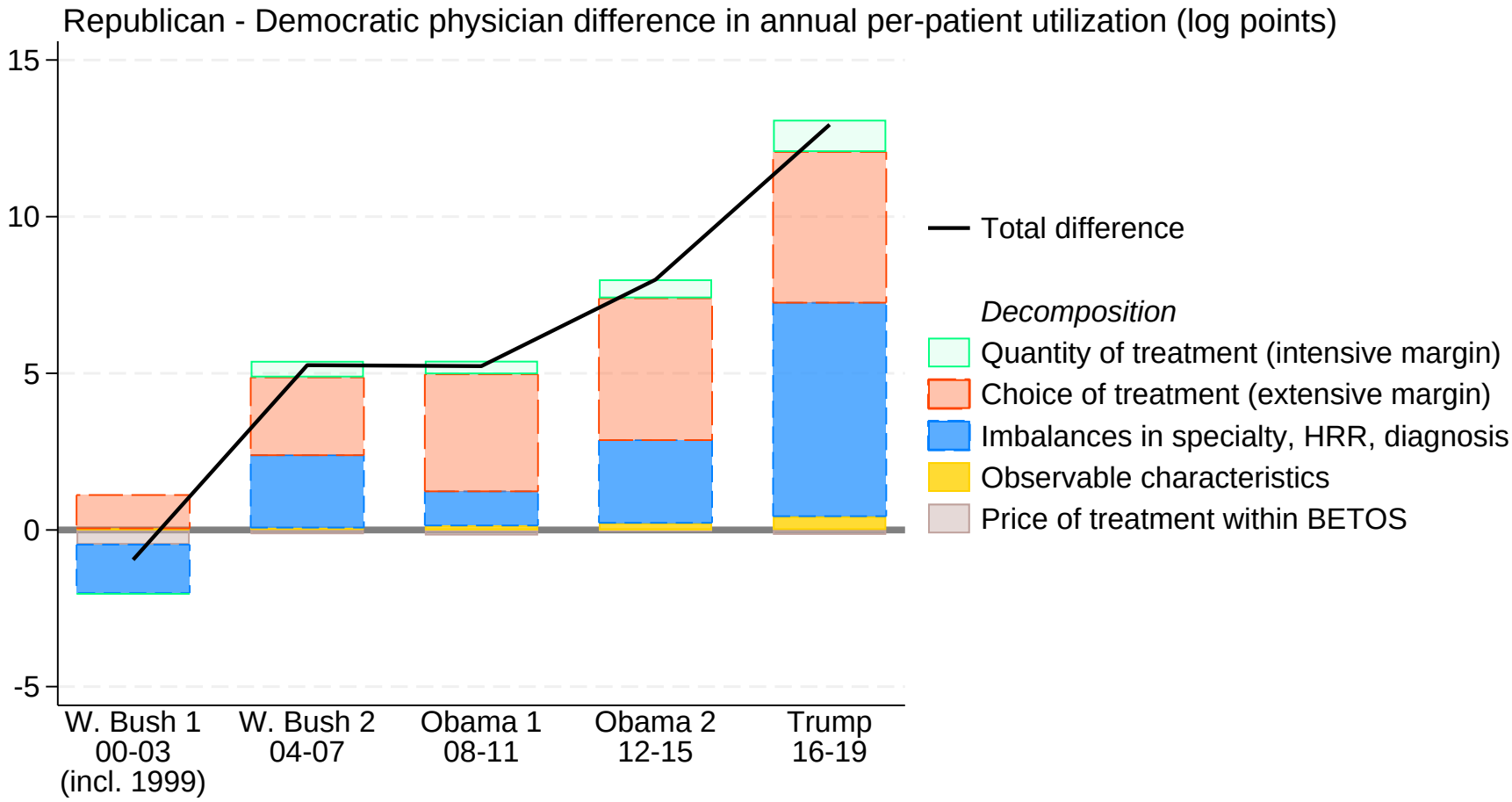
(f) Dropping physicians after their last donation



This decomposition reproduces Figure 9 but excludes physicians after they stop making political contributions (i.e., dropping physicians after the year of their last donation).

Figure A.11: Robustness in decomposition of partisan differences

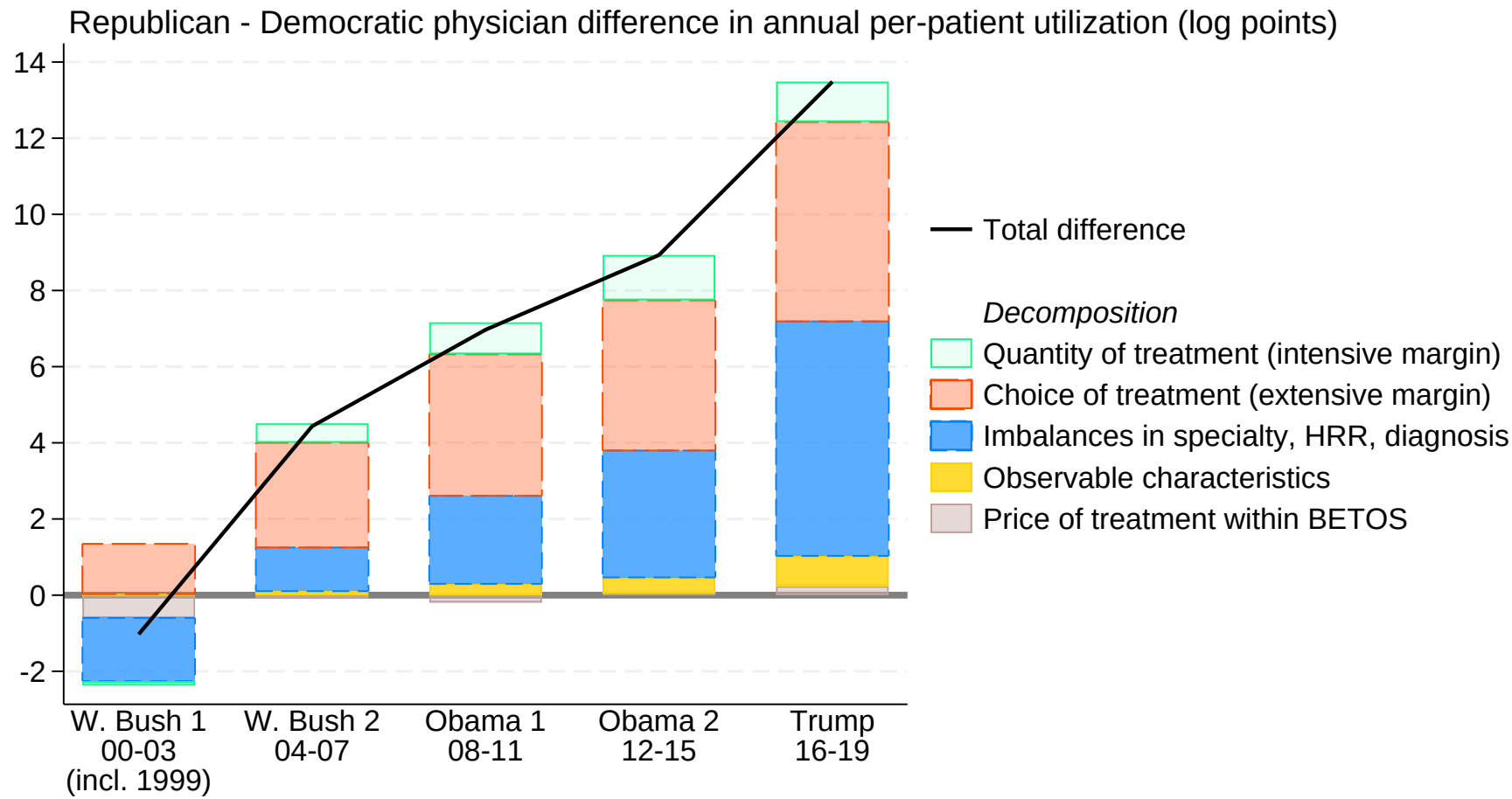
(g) Keeping match rate fixed



This decomposition reproduces Figure 9 but keeps in each year only the top 11% of physicians (i.e., the match rate in 1999), ranked first by the most recent contributors and then by the contributors with the highest cumulative donation amounts.

Figure A.11: Heterogeneity in decomposition of partisan differences

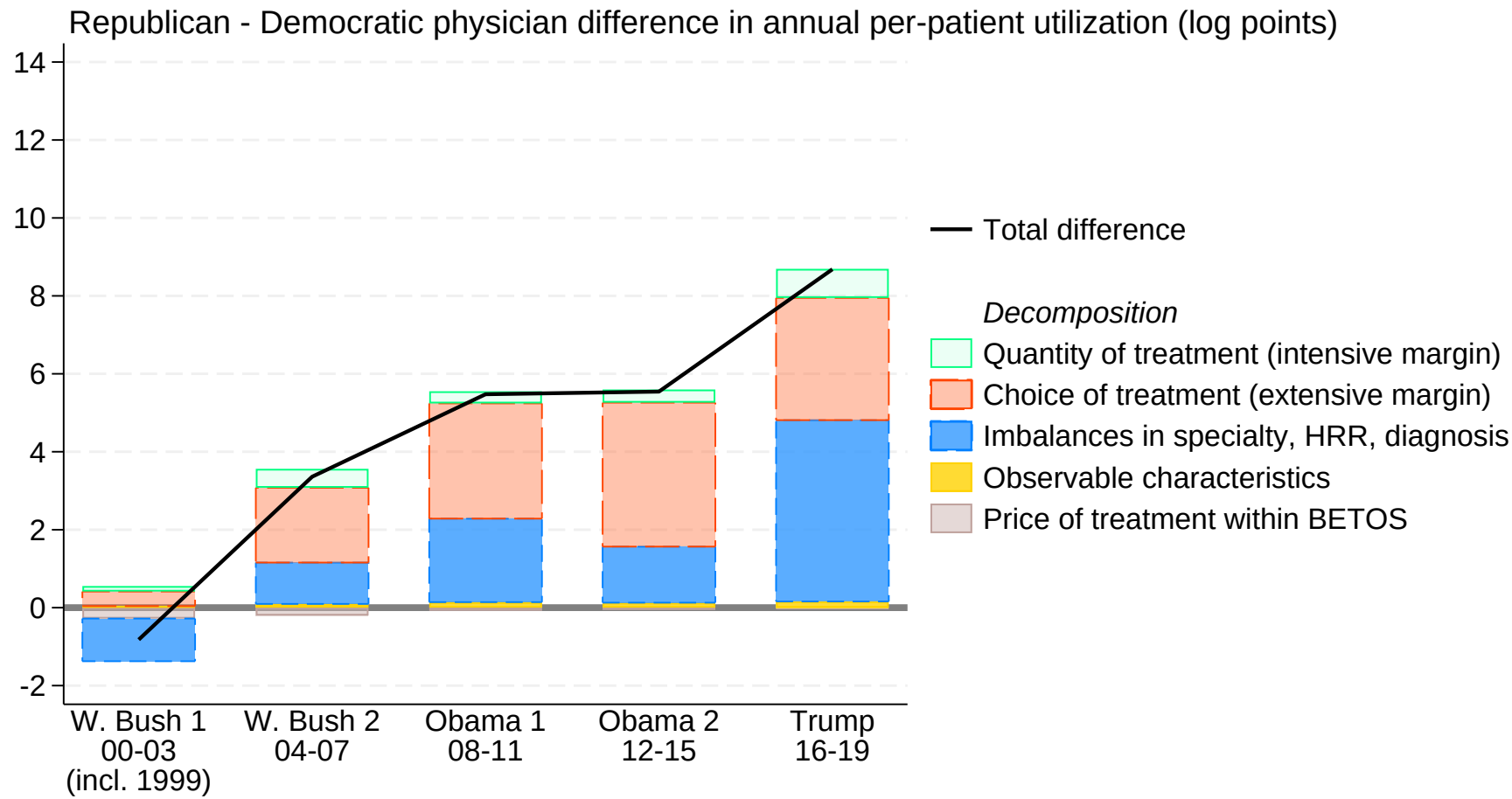
(h) Contributors with < $1000 cumulative donations



This figure aggregates the decomposition estimates from Figure 9 and shows the partisan differences among physicians who have donated less than $1000.

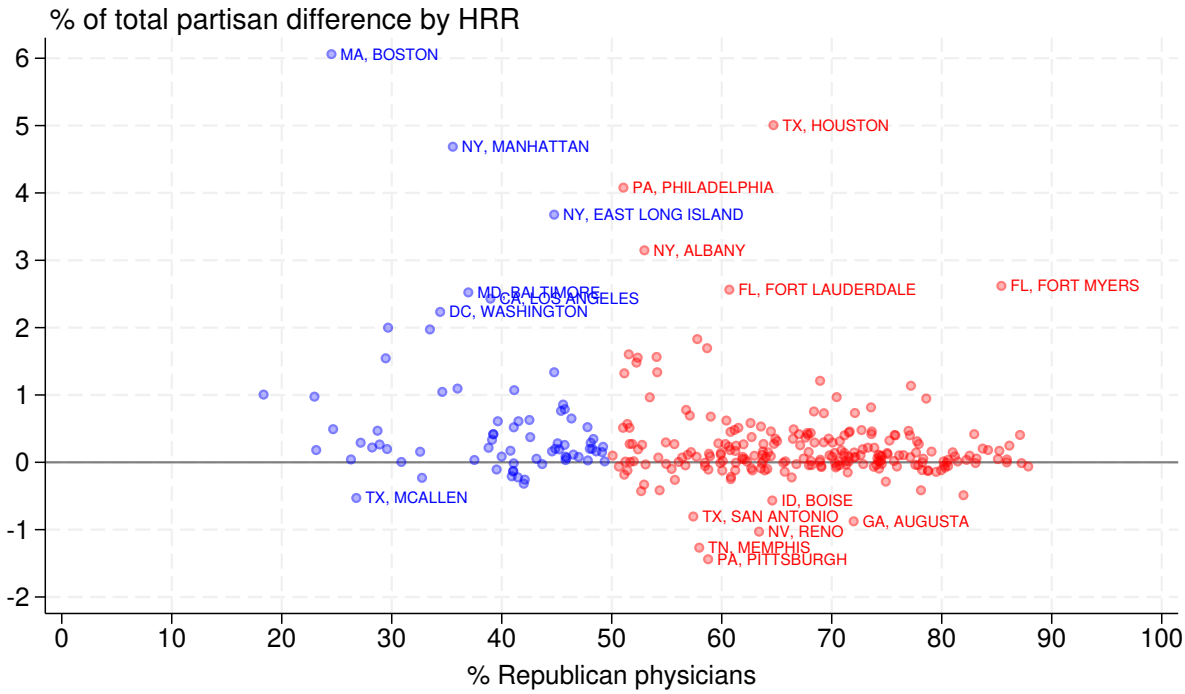
Figure A.11: Heterogeneity in decomposition of partisan differences

(i) Contributors with $\geq$ \$1000 cumulative donations



This figure aggregates the decomposition estimates from Figure 9 and shows the partisan differences among physicians who have donated at least \$1000.

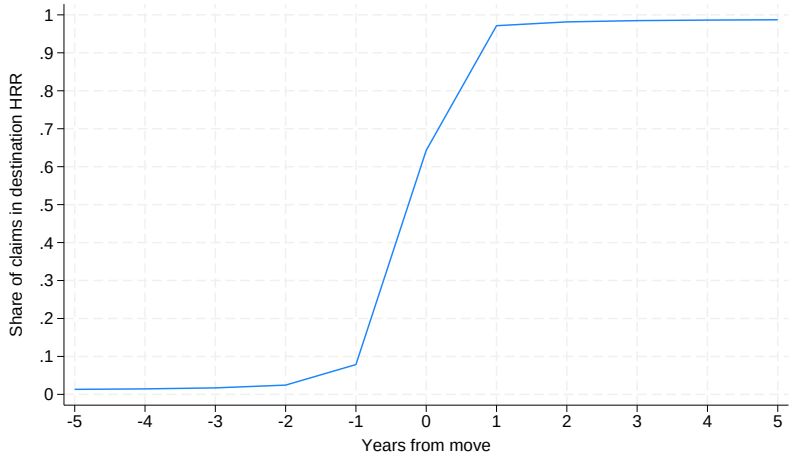
Figure A.12: Decomposition by HRR



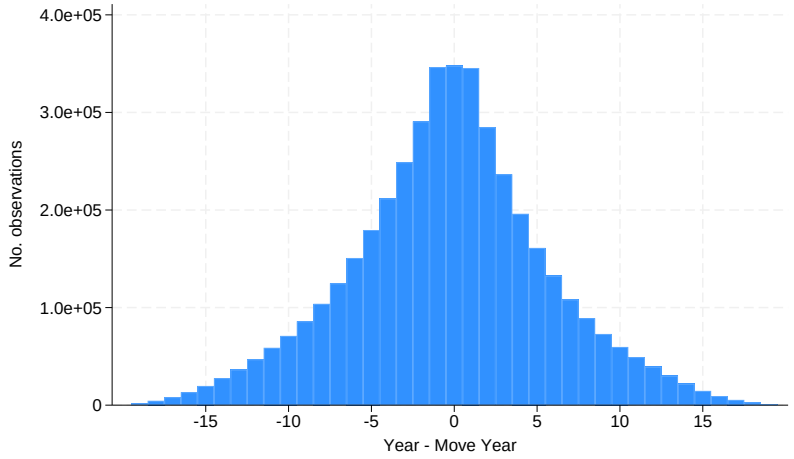
This figure decomposes the percent of the total partisan difference over 1999-2019 by hospital referral region.

Figure A.13: Details on patient movers

(a) Share of claims in origin vs. destination around move year



(b) Distribution of year observations relative to move year



(c) Distribution of the post- vs. pre-move differences in the physician party share

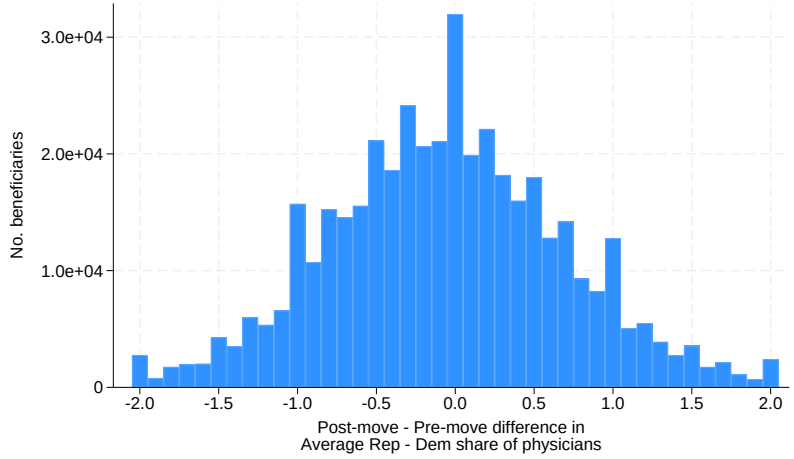
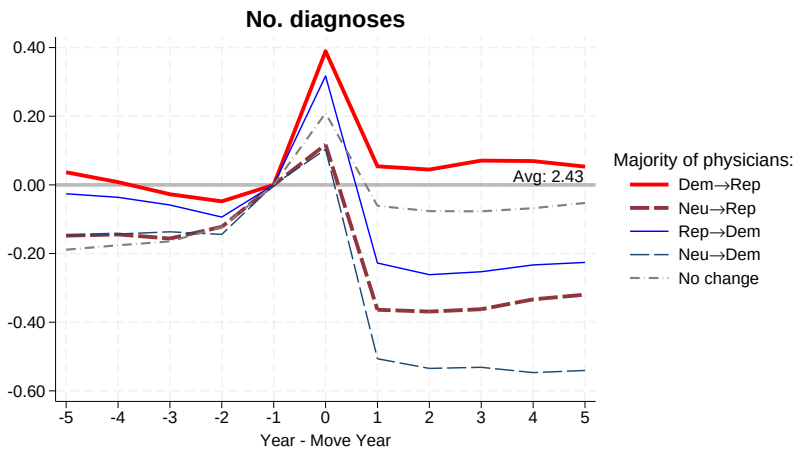
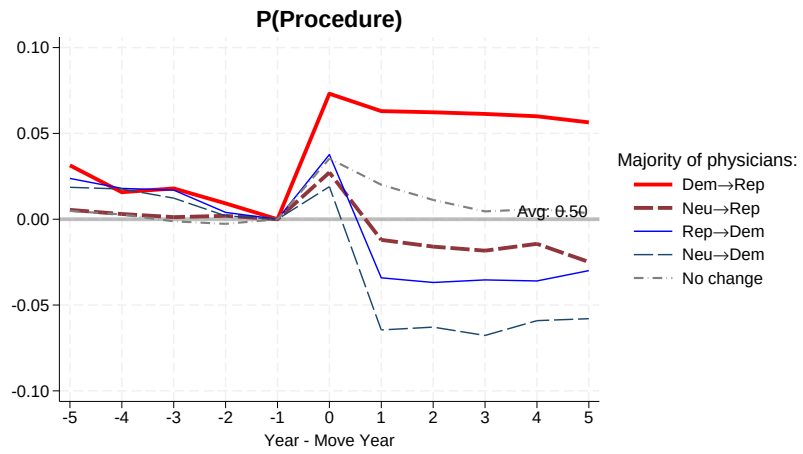


Figure A.14: Trend in levels for other event study outcomes

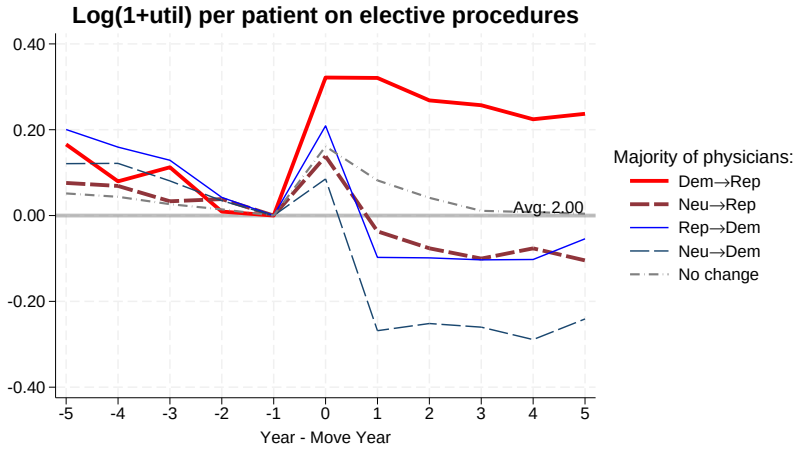
(a) No. diagnoses



(b) Procedure rate



(c) Utilization on elective procedures



(d) Utilization on non-elective procedures

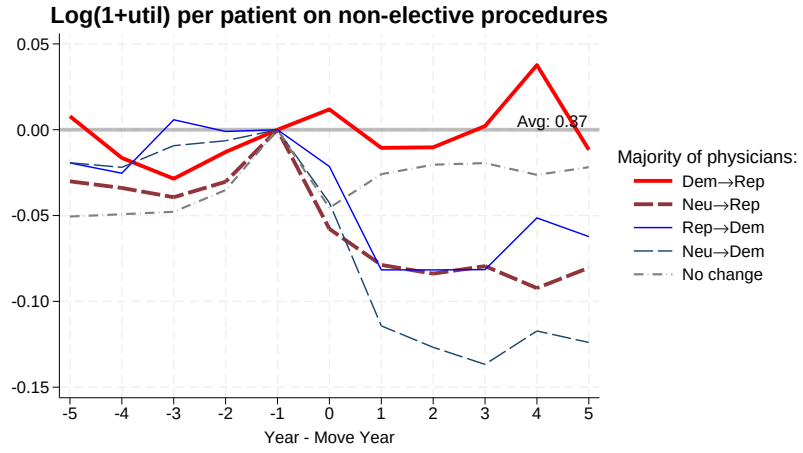
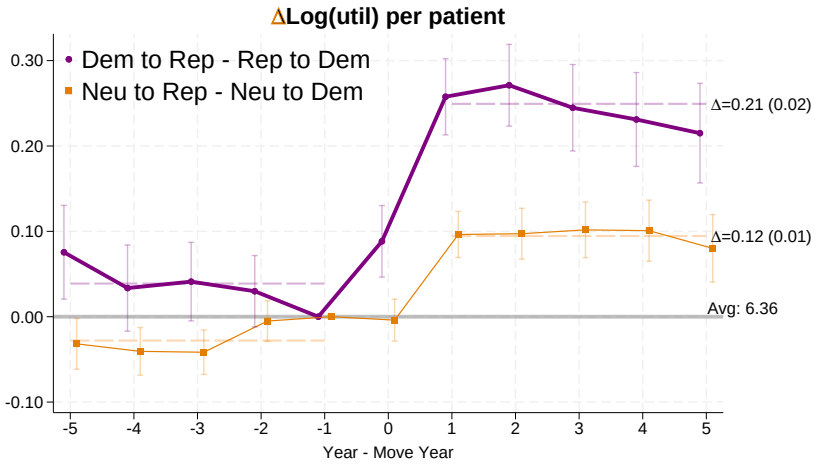
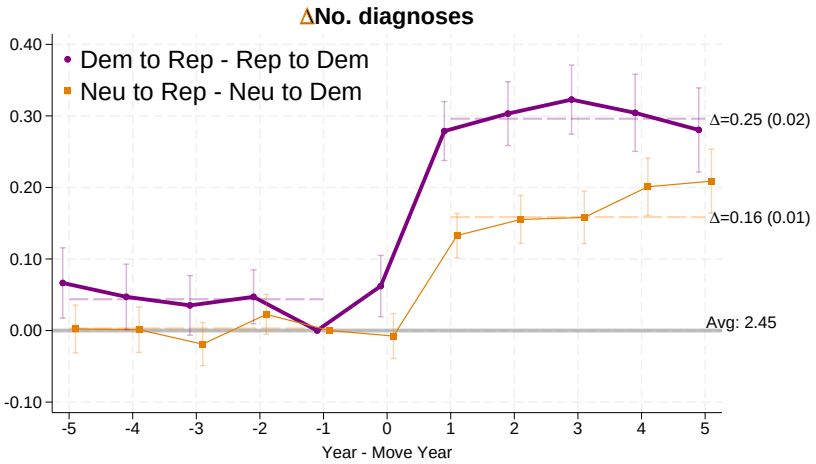


Figure A.15: Patient movers event study robustness: Hospital Service Area (HSA) origin and destination fixed effects

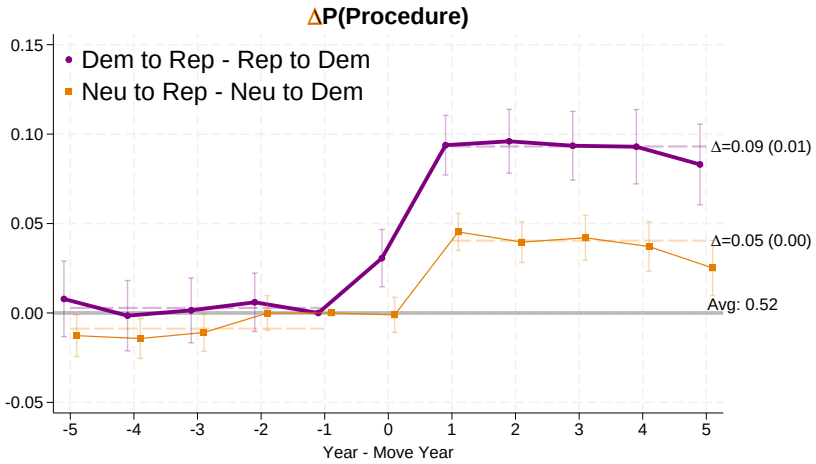
(a) Log(utilization)



(b) No. diagnoses



(c) Procedure rate



(d) Elective vs. non-elective procedures (switch)

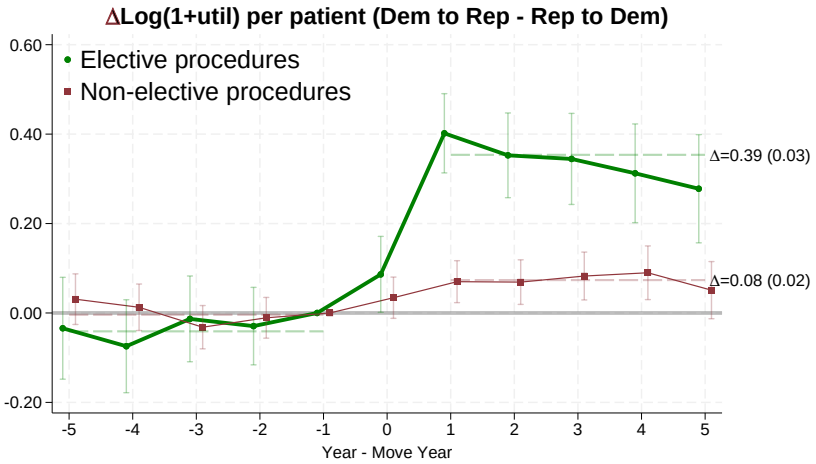
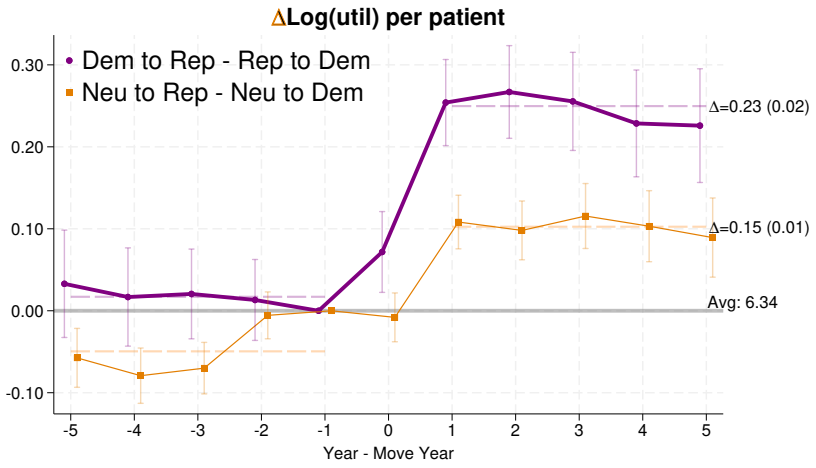
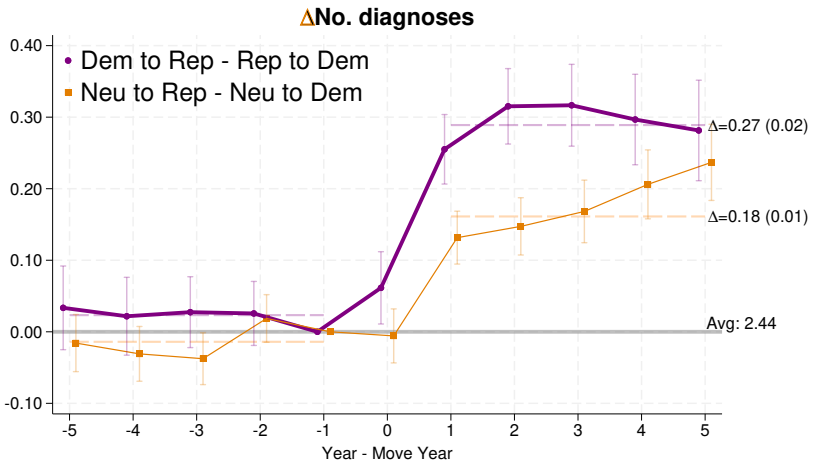


Figure A.15: Patient movers event study robustness: Only movers to destination HRRs with average Republican voteshare between 40-60%

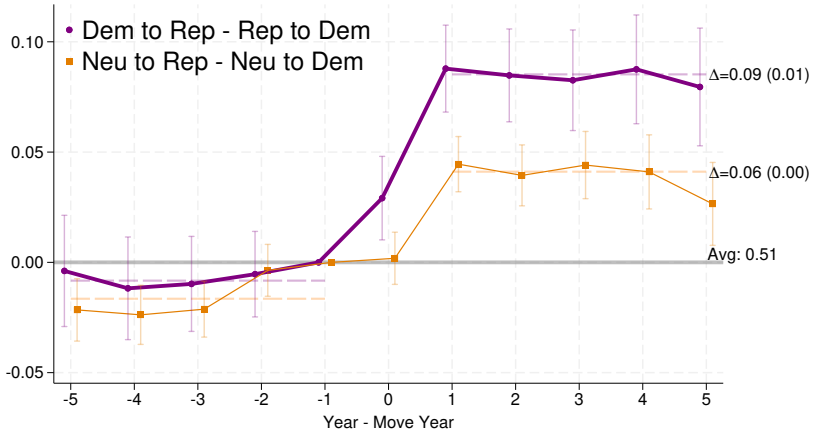
(e) Log(utilization)



(f) No. diagnoses



(g) Procedure rate



(h) Elective vs. non-elective procedures (switch)

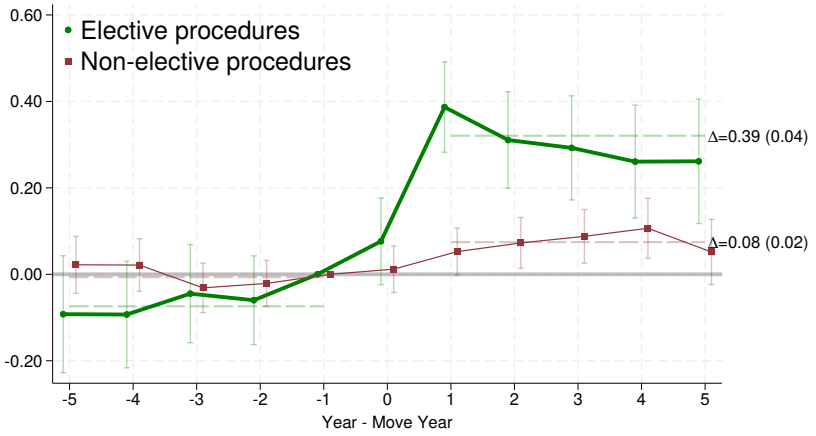
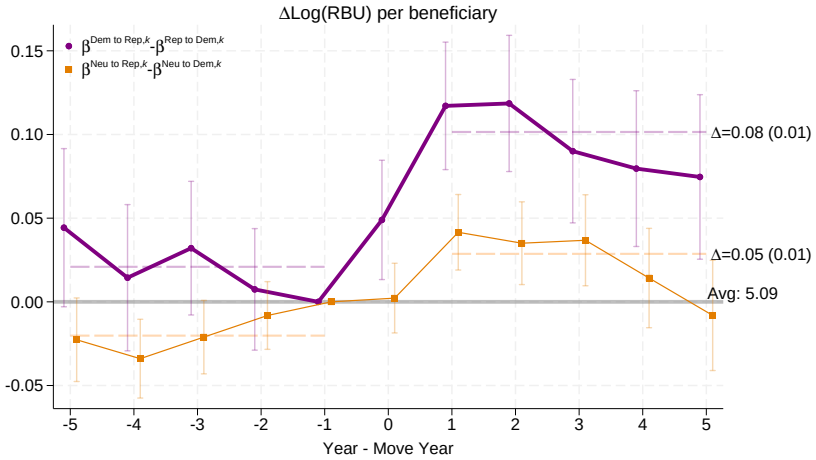
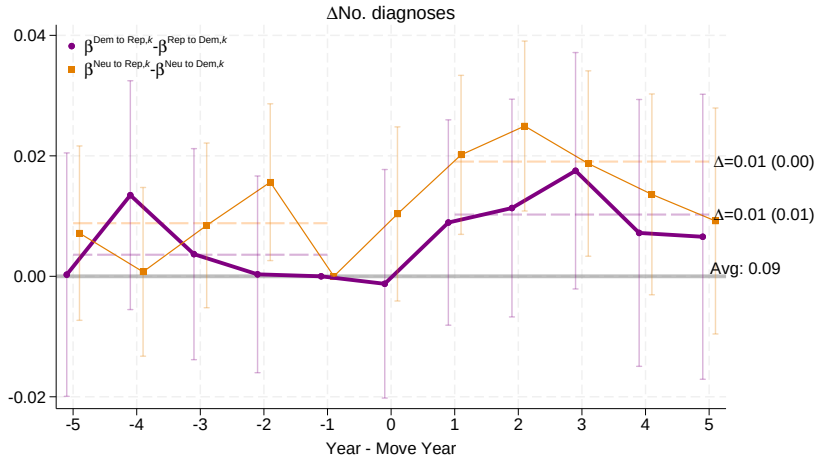


Figure A.15: Patient movers event study robustness: Including controls for specialty seen by patient

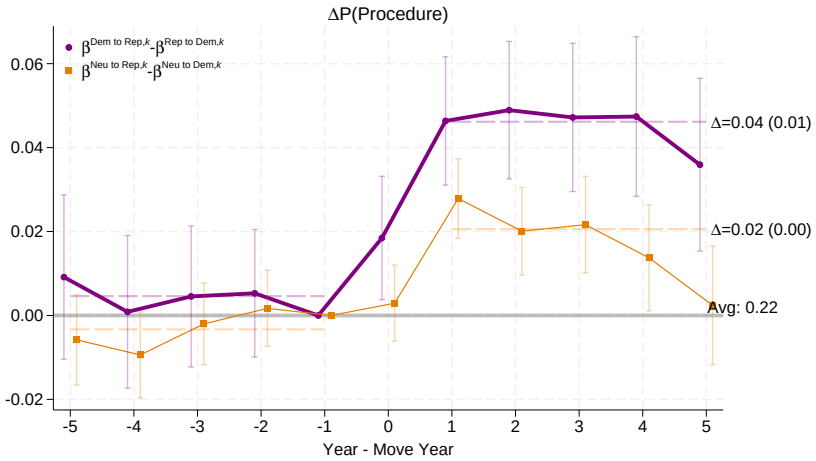
(i) Log(utilization)



(j) No. diagnoses



(k) Procedure rate



(l) Elective vs. non-elective procedures (switch)

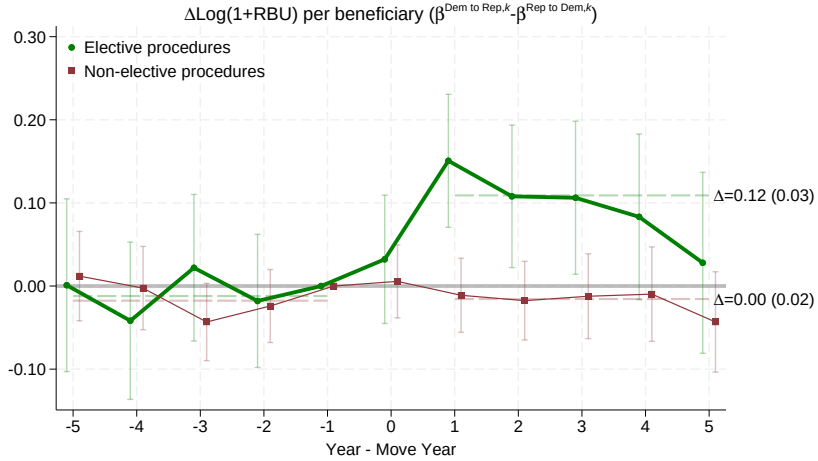


Figure A.16: Share of patients from origin vs. destination HRR for physician movers

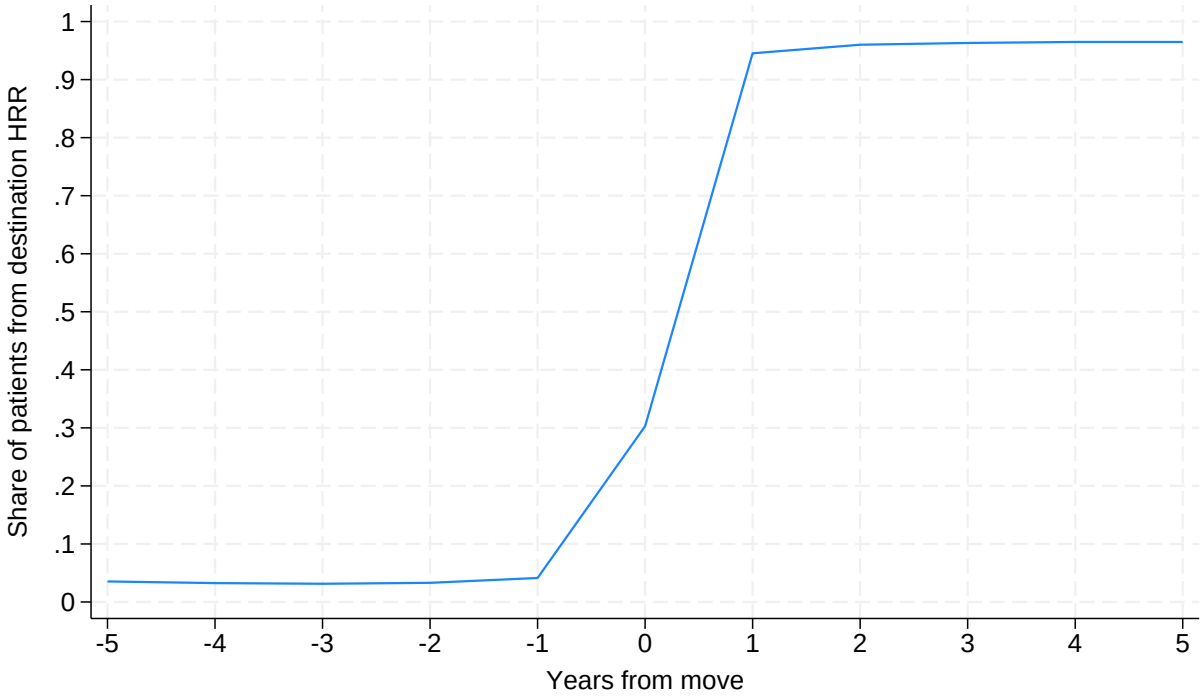
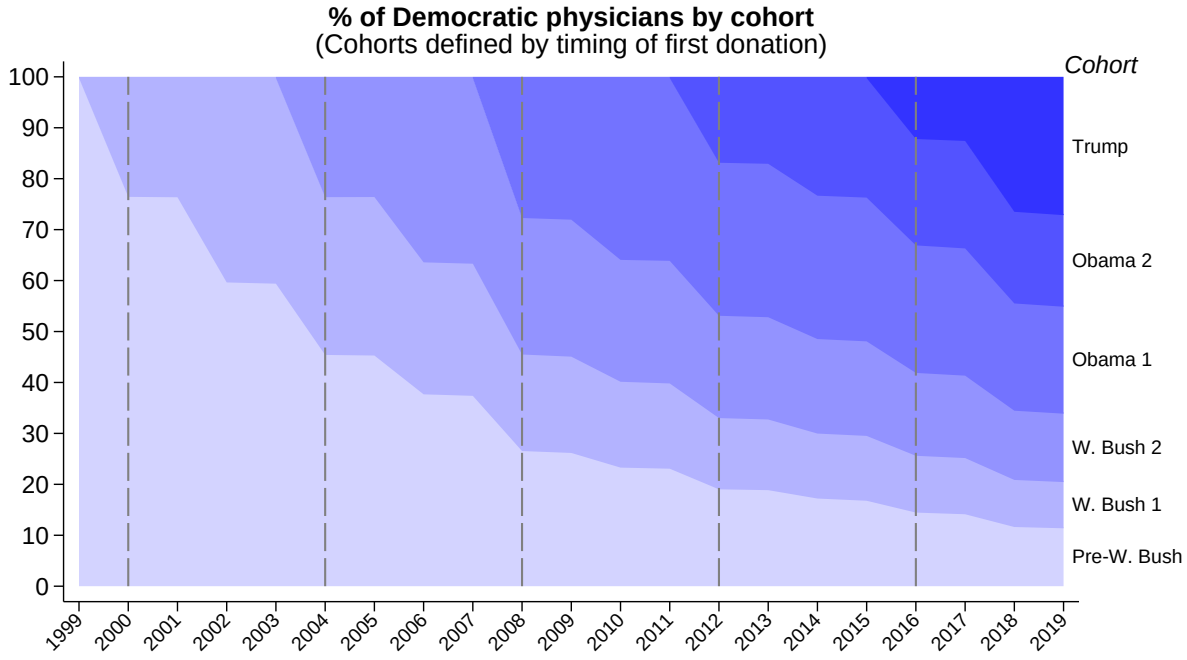
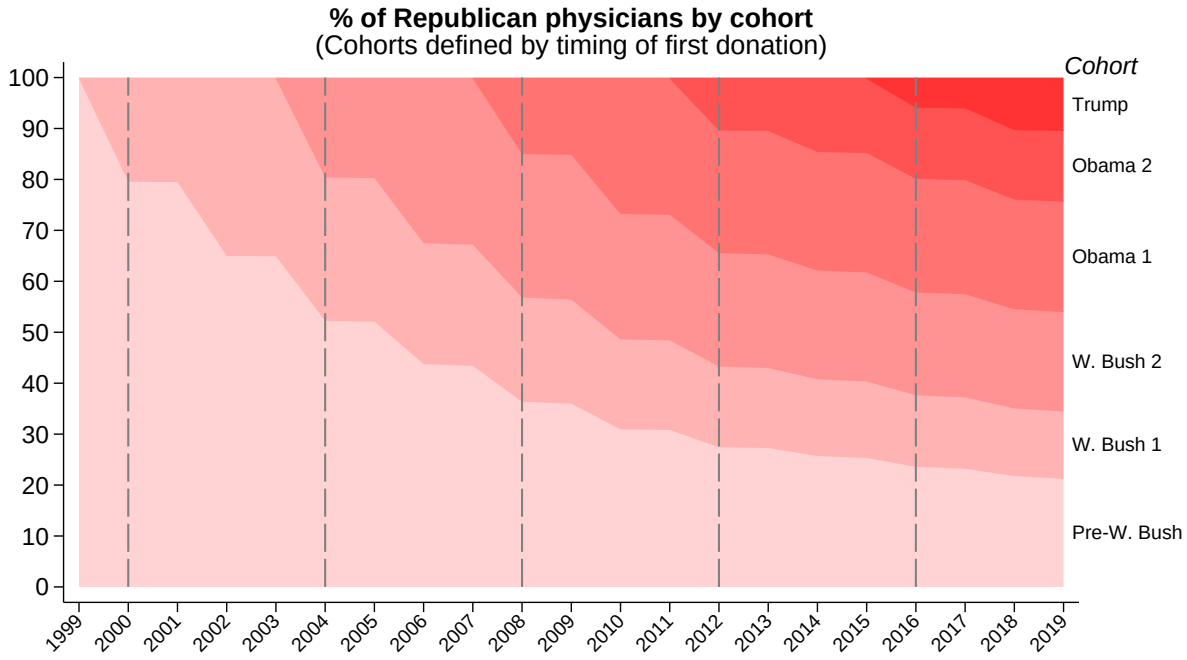


Figure A.17: Composition of physicians by party and cohort

(a) Democratic physicians



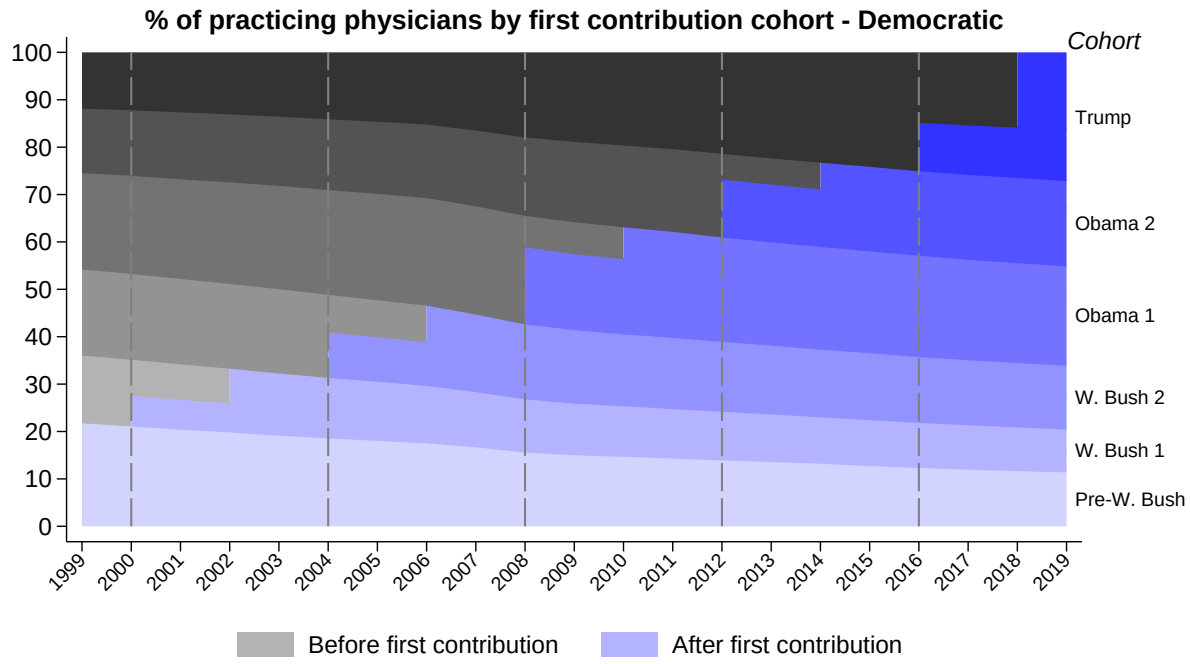
(b) Republican physicians



These figures show the composition of physicians categorized by cohorts, defined by the presidential term when they made their first political contribution. Physicians enter the sample after making their first political contribution.

Figure A.17: Composition of physicians by party and cohort (before first contribution)

(c) Democratic physicians



(d) Republican physicians

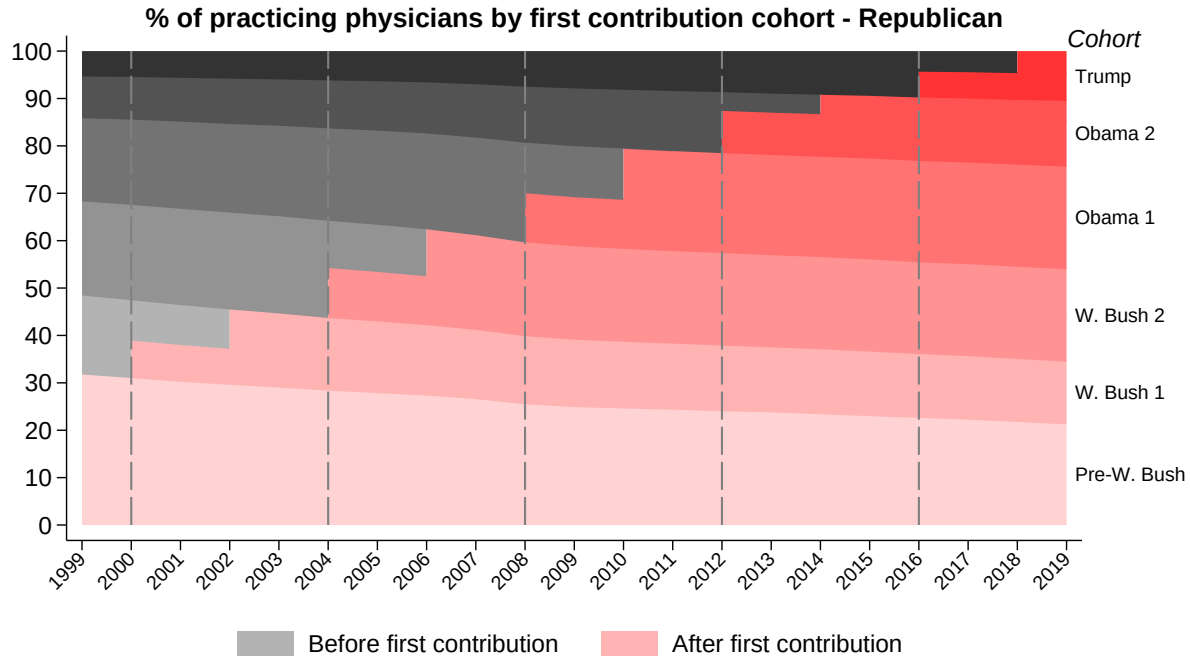
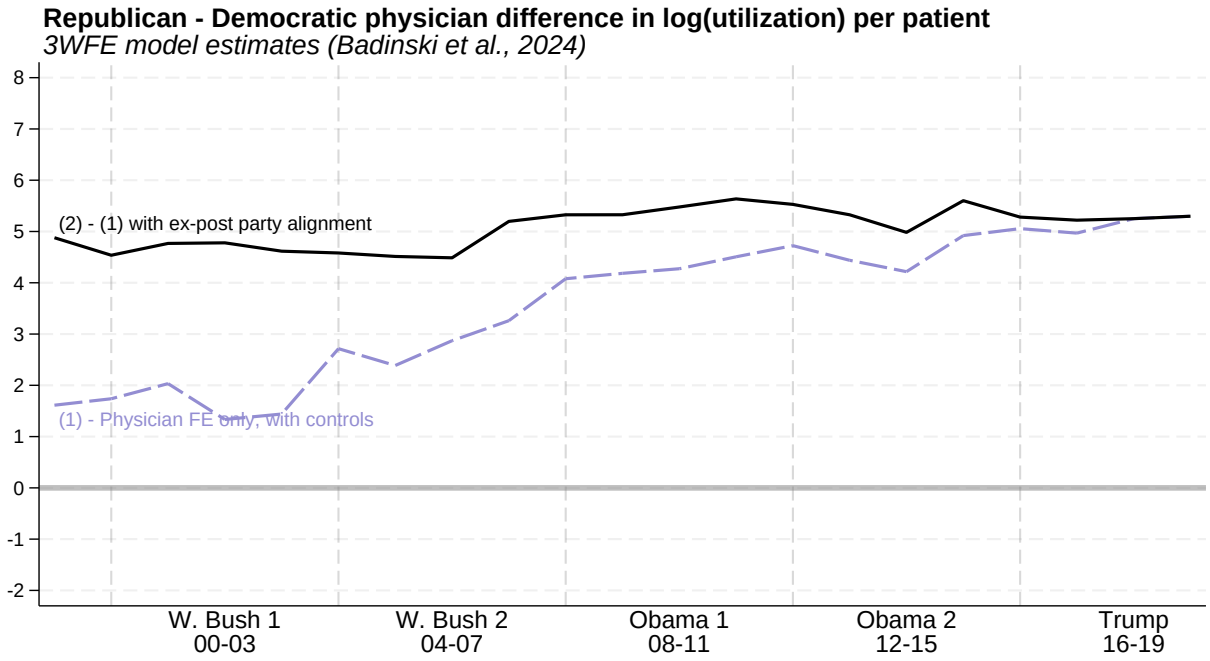
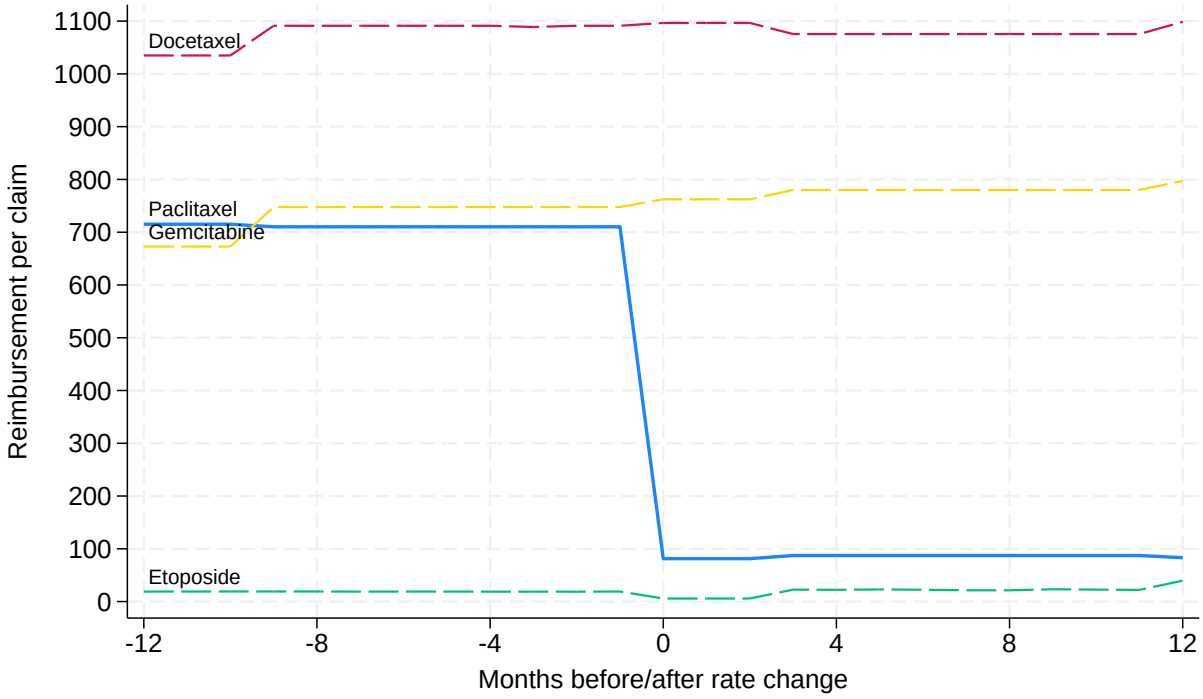


Figure A.18: Partisan difference in practice style with ex-post party alignment



This figure plots the partisan difference practice style, measured by the physician fixed effects in Equation 13, but includes physicians before their first contribution. Physicians are categorized under their final party alignment.

Figure A.19: Chemotherapy drug reimbursement rates around January 2005



This figure shows the average utilization per claim for different chemotherapy drugs in the months before and after January 2005.

B Appendix Tables

Table A.1: Characteristics of physicians matched to campaign contributions

	Nonmissing %	**Overall**	**Matched**	**Unmatched**	
		Mean [SD]	Mean [SD]	Mean [SD]	Diff (SE)
Unweighted / Weighted by util.	(1)	(2)	(3)	(4)	(3)-(4)
Panel A. Physician observations: Total $N = 1093790$, ***Matched*** $N = 308749\,(28\%/47\%)$					
Annual utilization per patient	100	367.79	425.88	344.95	80.93
		[627.37]	[771.58]	[558.93]	(1.53)
No. patients per year	100	34.02	46.06	29.28	16.78
		[45.50]	[55.37]	[39.99]	(0.11)
Female	92 / 99	0.33 / 0.16	0.23 / 0.11	0.37 / 0.21	-0.14 / -0.09
		[0.47 / 0.37]	[0.42 / 0.32]	[0.48 / 0.40]	(0.00 / 0.00)
Med school grad year	75 / 94	1994.19 / 1986.83	1987.37 / 1984.28	1997.14 / 1989.12	-9.77 / -4.84
		[13.80 / 10.99]	[12.30 / 10.00]	[13.36 / 11.33]	(0.03 / 0.05)
PCP	100 / 100	0.31 / 0.34	0.23 / 0.25	0.34 / 0.41	-0.11 / -0.16
		[0.46 / 0.47]	[0.42 / 0.43]	[0.47 / 0.49]	(0.00 / 0.00)
Top 5 non-PCP Specialties by N					
Emergency Medicine	100 / 100	0.06 / 0.03	0.05 / 0.02	0.06 / 0.04	-0.01 / -0.02
		[0.24 / 0.17]	[0.22 / 0.15]	[0.24 / 0.19]	(0.00 / 0.00)
Anesthesiology	100 / 100	0.05 / 0.01	0.07 / 0.01	0.04 / 0.01	0.03 / 0.00
		[0.22 / 0.08]	[0.26 / 0.08]	[0.21 / 0.07]	(0.00 / 0.00)
Obstetrics & Gynecology	100 / 100	0.05 / 0.01	0.06 / 0.01	0.05 / 0.01	0.01 / 0.00
		[0.22 / 0.10]	[0.23 / 0.11]	[0.21 / 0.10]	(0.00 / 0.00)
Psychiatry	100 / 100	0.05 / 0.01	0.05 / 0.01	0.05 / 0.01	-0.00 / -0.00
		[0.22 / 0.08]	[0.21 / 0.07]	[0.22 / 0.09]	(0.00 / 0.00)
Diagnostic Radiology	100 / 100	0.04 / 0.00	0.05 / 0.00	0.04 / 0.00	0.01 / 0.00
		[0.20 / 0.07]	[0.22 / 0.07]	[0.20 / 0.06]	(0.00 / 0.00)
Top 5 non-PCP Specialties by total utilization					
Ophthalmology	100 / 100	0.03 / 0.09	0.04 / 0.13	0.02 / 0.06	0.02 / 0.07
		[0.16 / 0.29]	[0.19 / 0.34]	[0.14 / 0.24]	(0.00 / 0.00)
Cardiology	100 / 100	0.03 / 0.07	0.04 / 0.08	0.03 / 0.06	0.01 / 0.02
		[0.17 / 0.26]	[0.19 / 0.28]	[0.16 / 0.25]	(0.00 / 0.00)
Orthopedic Surgery	100 / 100	0.03 / 0.05	0.05 / 0.07	0.02 / 0.04	0.03 / 0.04
		[0.17 / 0.22]	[0.22 / 0.26]	[0.15 / 0.18]	(0.00 / 0.00)
Hematology-Oncology	100 / 100	0.01 / 0.05	0.01 / 0.06	0.01 / 0.04	0.00 / 0.01
		[0.10 / 0.22]	[0.11 / 0.23]	[0.10 / 0.21]	(0.00 / 0.00)
Dermatology	100 / 100	0.02 / 0.03	0.02 / 0.04	0.01 / 0.03	0.01 / 0.02
		[0.13 / 0.18]	[0.14 / 0.21]	[0.12 / 0.16]	(0.00 / 0.00)
Panel B. Physician-year observations: Total $N{\times}T = 12738271$, ***Matched*** $N{\times}T = 4640717\,(36\%/47\%)$					
Census region					
Northeast	100 / 100	0.23 / 0.20	0.20 / 0.18	0.24 / 0.22	-0.04 / -0.05
		[0.42 / 0.40]	[0.40 / 0.38]	[0.43 / 0.42]	(0.00 / 0.00)
Midwest	100 / 100	0.23 / 0.21	0.20 / 0.18	0.25 / 0.23	-0.05 / -0.05
		[0.42 / 0.41]	[0.40 / 0.39]	[0.43 / 0.42]	(0.00 / 0.00)
South	100 / 100	0.35 / 0.42	0.38 / 0.46	0.33 / 0.39	0.05 / 0.07
		[0.48 / 0.49]	[0.49 / 0.50]	[0.47 / 0.49]	(0.00 / 0.00)
West	100 / 100	0.19 / 0.17	0.22 / 0.18	0.18 / 0.15	0.04 / 0.03
		[0.40 / 0.37]	[0.41 / 0.39]	[0.38 / 0.36]	(0.00 / 0.00)
Practice characteristics					
Sole practitioner	65 / 68	0.22 / 0.22	0.22 / 0.22	0.22 / 0.22	-0.00 / -0.00
		[0.42 / 0.41]	[0.42 / 0.41]	[0.42 / 0.41]	(0.00 / 0.00)
For-profit facility	83 / 96	0.20 / 0.20	0.21 / 0.21	0.20 / 0.19	0.01 / 0.02
		[0.40 / 0.40]	[0.41 / 0.41]	[0.40 / 0.39]	(0.00 / 0.00)
Teaching hospital	78 / 91	0.53 / 0.46	0.51 / 0.44	0.54 / 0.47	-0.04 / -0.03
		[0.50 / 0.50]	[0.50 / 0.50]	[0.50 / 0.50]	(0.00 / 0.00)

This table compares the characteristics of physicians who are matched to campaign contribution records and those who are not matched. Two different averages are shown: the first is the unweighted average over physicians, and the second is the weighted average where the weights correspond to the physician's total utilization over the sample period. Standard deviations are shown in brackets, and standard errors clustered by provider are shown in parentheses.

Table A.2a: Summary statistics on donations of all campaign contributors

			Donation amount			No. election cycles (2-yr)		
Election type	N donators	%	Mean	Std. Dev.	Median	Mean	Std. Dev.	Median
All	308,749	100	4,792	63,919	994	3.40	2.85	2
Federal (non-pres.)	217,866	71	3,891	58,464	825	2.83	2.50	2
Presidential	87,005	28	1,581	3,871	575	1.55	0.90	1
State	199,191	65	2,358	35,438	500	2.79	2.28	2
Local	23,830	8	978	9,096	251	1.59	1.18	1

This table shows summary statistics of the donations for all physician campaign contributors in the sample.

Table A.2b: Summary statistics on donations of partisan campaign contributors

	% donating			log(donation amount)			No. election cycles (2-yr)		
Election type	Rep	Dem	Diff (SE)	Rep	Dem	Diff (SE)	Rep	Dem	Diff (SE)
All	100	100	0 (0.00)	7.51	6.93	0.58 (0.01)	4.30	3.53	0.76 (0.01)
Federal (non-pres.)	80	78	2 (0.17)	7.23	6.48	0.75 (0.01)	3.36	2.80	0.56 (0.01)
Presidential	34	43	-9 (0.21)	6.57	6.28	0.29 (0.01)	1.58	1.57	0.01 (0.01)
State	71	60	12 (0.20)	6.76	6.39	0.37 (0.01)	3.27	2.79	0.49 (0.01)
Local	8	10	-2 (0.12)	5.85	5.89	-0.03 (0.02)	1.60	1.72	-0.11 (0.02)

This table compares the characteristics of the donations from Republican and Democratic physician campaign contributors. Robust standard errors are shown in parentheses.

Table A.2c: Summary statistics on donations of partisan campaign contributors (pre-2004 contributors)

	% donating			log(donation amount)			No. election cycles (2-yr)		
Election type	Rep	Dem	Diff (SE)	Rep	Dem	Diff (SE)	Rep	Dem	Diff (SE)
All	100	100	0 (0.00)	8.02	7.94	0.09 (0.01)	5.97	5.70	0.27 (0.03)
Federal (non-pres.)	87	84	3 (0.27)	7.64	7.54	0.10 (0.01)	4.44	4.22	0.22 (0.03)
Presidential	36	39	-3 (0.37)	6.87	6.97	-0.10 (0.02)	1.83	1.95	-0.12 (0.01)
State	83	82	1 (0.29)	7.11	7.00	0.11 (0.01)	4.15	3.91	0.24 (0.02)
Local	11	17	-6 (0.27)	5.96	6.16	-0.20 (0.03)	1.80	2.08	-0.28 (0.03)

This table compares the characteristics of the donations from Republican and Democratic physician contributors who made their first donation before 2004. Robust standard errors are shown in parentheses.

Table A.2d: Summary statistics on donations of partisan campaign contributors (post-2004 contributors)

	% donating			log(donation amount)			No. election cycles (2-yr)		
Election type	Rep	Dem	Diff (SE)	Rep	Dem	Diff (SE)	Rep	Dem	Diff (SE)
All	100	100	0 (0.00)	7.15	6.59	0.57 (0.01)	3.14	2.81	0.33 (0.01)
Federal (non-pres.)	75	76	-0 (0.23)	6.90	6.09	0.81 (0.01)	2.51	2.28	0.23 (0.01)
Presidential	32	44	-11 (0.25)	6.34	6.08	0.27 (0.01)	1.38	1.45	-0.07 (0.01)
State	64	52	11 (0.26)	6.44	6.07	0.37 (0.01)	2.48	2.20	0.28 (0.01)
Local	6	8	-2 (0.13)	5.71	5.68	0.03 (0.03)	1.34	1.44	-0.10 (0.02)

This table compares the characteristics of the donations from Republican and Democratic physician contributors who made their first donation on or after 2004. Robust standard errors are shown in parentheses.

Table A.3: Partisan differences in medical practice: Decomposition estimates

		Controlling for:		Difference from (4) due to:			Difference from (7) due to:		
(1) Year	(2) Diff.	(3) Price	(4) Price+X	(5) Extensive	(6) Intensive	(7) Weights	(8) HRR	(9) Specialty	(10) CCS
1999	0.59 (1.14)	0.74 (1.14)	0.70 (1.14)	1.11 (0.22)	-0.01 (0.55)	-0.41 (1.00)	-0.18 (0.47)	-1.69 (0.57)	1.46 (0.38)
2000	-1.12 (1.04)	-0.48 (0.97)	-0.51 (0.96)	1.44 (0.23)	-0.28 (0.50)	-1.67 (0.69)	-0.32 (0.33)	-3.19 (0.45)	1.85 (0.39)
2001	-1.02 (0.98)	-0.53 (0.93)	-0.59 (0.94)	1.02 (0.26)	0.09 (0.58)	-1.71 (0.86)	-0.12 (0.35)	-3.21 (0.45)	1.62 (0.36)
2002	-0.82 (0.99)	-0.25 (0.96)	-0.30 (0.95)	1.27 (0.24)	0.12 (0.51)	-1.69 (0.90)	0.28 (0.44)	-3.45 (0.46)	1.47 (0.36)
2003	-0.25 (1.21)	0.14 (1.21)	0.11 (1.22)	0.75 (0.29)	0.18 (0.52)	-0.82 (1.18)	0.63 (0.47)	-3.07 (0.51)	1.61 (0.51)
2004	3.35 (1.21)	3.35 (1.23)	3.24 (1.22)	2.38 (0.29)	0.36 (0.45)	0.51 (1.01)	1.10 (0.38)	-2.57 (0.48)	1.98 (0.45)
2005	3.07 (0.92)	3.17 (0.90)	3.09 (0.89)	1.43 (0.22)	0.47 (0.41)	1.20 (0.81)	1.10 (0.38)	-2.57 (0.37)	2.67 (0.38)
2006	5.51 (1.07)	5.50 (1.04)	5.38 (1.04)	3.66 (0.24)	0.61 (0.47)	1.11 (0.88)	1.56 (0.36)	-2.59 (0.39)	2.13 (0.30)
2007	5.43 (0.90)	5.51 (0.87)	5.38 (0.87)	2.47 (0.23)	0.87 (0.51)	2.05 (0.71)	2.00 (0.30)	-2.37 (0.40)	2.41 (0.32)
2008	6.92 (0.92)	6.97 (0.98)	6.72 (0.98)	3.92 (0.26)	0.91 (0.49)	1.89 (0.64)	2.28 (0.37)	-2.31 (0.36)	1.91 (0.36)
2009	7.06 (1.10)	7.22 (1.07)	6.93 (1.07)	4.10 (0.20)	0.75 (0.46)	2.08 (0.93)	2.46 (0.41)	-2.34 (0.41)	1.97 (0.44)
2010	6.59 (1.09)	6.64 (1.05)	6.36 (1.05)	3.34 (0.21)	0.49 (0.51)	2.53 (0.75)	2.53 (0.30)	-2.15 (0.34)	2.16 (0.44)
2011	6.13 (1.05)	6.10 (1.06)	5.85 (1.07)	3.47 (0.22)	0.73 (0.51)	1.65 (0.87)	2.39 (0.45)	-2.23 (0.42)	1.49 (0.77)
2012	9.16 (0.96)	9.15 (0.86)	8.78 (0.85)	3.97 (0.37)	1.25 (0.44)	3.56 (0.81)	2.19 (0.38)	-1.41 (0.29)	2.78 (0.40)
2013	8.31 (1.24)	7.95 (1.27)	7.62 (1.27)	4.68 (0.24)	0.67 (0.66)	2.28 (1.09)	1.85 (0.57)	-1.70 (0.44)	2.13 (0.52)
2014	6.31 (1.06)	6.22 (1.02)	5.88 (1.02)	4.35 (0.26)	0.57 (0.42)	0.96 (0.86)	0.61 (0.38)	-1.41 (0.39)	1.75 (0.42)
2015	7.66 (1.16)	7.17 (1.12)	6.84 (1.11)	4.27 (0.23)	0.58 (0.47)	1.98 (0.94)	1.46 (0.38)	-1.06 (0.38)	1.59 (0.43)
2016	12.86 (1.28)	12.75 (1.23)	12.23 (1.22)	4.86 (0.29)	1.21 (0.63)	6.17 (1.00)	2.67 (0.36)	0.33 (0.47)	3.17 (0.48)
2017	10.95 (1.79)	10.56 (1.80)	10.01 (1.80)	4.99 (0.21)	0.98 (1.02)	4.04 (1.32)	1.94 (0.46)	-0.09 (0.52)	2.18 (0.71)
2018	12.61 (2.22)	12.43 (2.21)	11.74 (2.21)	5.85 (0.23)	0.85 (0.98)	5.04 (1.55)	2.39 (0.54)	0.48 (0.60)	2.18 (0.80)
2019	12.97 (1.72)	12.67 (1.71)	12.11 (1.71)	2.75 (0.22)	1.07 (0.91)	8.29 (1.51)	2.98 (0.57)	2.13 (0.57)	3.18 (0.77)

This table reports the estimates of the decomposition in Figure 9. Standard errors from 50 bootstrap samples are shown in parentheses.

Table A.4a: Characteristics of patient movers vs. non-movers

	Movers	**Non-movers**	
	Mean	Mean	Diff.
	[std. dev.]	[std. dev.]	(std. err.)
Female	0.615	0.563	0.052
	[0.486]	[0.496]	(0.001)
White	0.911	0.855	0.056
	[0.285]	[0.352]	(0.000)
Age first observed:			
65-74	0.678	0.715	-0.037
	[0.467]	[0.452]	(0.001)
75-84	0.266	0.206	0.059
	[0.442]	[0.405]	(0.001)
85-99	0.056	0.079	-0.023
	[0.230]	[0.269]	(0.000)
First observed residence:			
Northeast	0.194	0.194	0.000
	[0.396]	[0.395]	(0.001)
South	0.427	0.399	0.028
	[0.495]	[0.490]	(0.001)
Midwest	0.183	0.244	-0.060
	[0.387]	[0.429]	(0.001)
West	0.196	0.163	0.032
	[0.397]	[0.370]	(0.001)
Annual utilization	1322.655	1239.688	82.967
	[1738.876]	[2419.691]	(2.767)
log(annual utilization)	6.811	6.498	0.313
	[0.847]	[1.146]	(0.001)
Years observed	9.965	6.186	3.779
	[4.756]	[4.845]	(0.007)
Died during 1999-2019	0.535	0.486	0.048
	[0.499]	[0.500]	(0.001)
N	425,077	10,770,018	

This table compares characteristics of the mover patients versus the non-mover patients in the sample.

Table A.4b: Top 10 most common origin-destination HRRs among patient movers

				% Rep. voteshare		% Rep. physicians	
(1) Origin HRR	(2) Destination HRR	(3) No. movers	(4) % of movers	(5) Origin	(6) Dest.	(7) Origin	(8) Dest
NY, EAST LONG ISLAND	FL, FORT LAUDERDALE	1274	0.30	39.44	40.15	44.76	60.69
NJ, NEWARK	NJ, CAMDEN	859	0.20	28.36	48.76	48.09	58.67
FL, FORT LAUDERDALE	FL, ORLANDO	786	0.18	40.15	53.88	60.69	77.20
CA, LOS ANGELES	CA, ORANGE CO.	719	0.17	30.69	53.57	38.97	57.78
TX, HOUSTON	TX, AUSTIN	691	0.16	58.82	51.58	64.70	61.24
NY, MANHATTAN	NY, EAST LONG ISLAND	669	0.16	20.55	39.44	35.55	44.76
PA, PHILADELPHIA	NJ, CAMDEN	657	0.15	36.66	48.76	51.06	58.67
NY, MANHATTAN	NJ, CAMDEN	643	0.15	20.55	48.76	35.55	58.67
NJ, HACKENSACK	NJ, CAMDEN	558	0.13	41.73	48.76	35.98	58.67
CA, LOS ANGELES	CA, SAN DIEGO	528	0.12	30.69	46.92	38.97	48.22

This table shows the 10 origin-destination hospital referral regions with the highest number of patient movers. Columns 5-6 report the average local two-party Republican voteshare and Columns 7-8 report the average share of Republican physicians in the HRRs over 1999-2019.

Table A.5a: Event study estimates: Log(util) per patient

$t - m_i$	(1) Dem → Rep	(2) Rep → Dem	(3) Neu → Rep	(4) Neu → Dem	(5) Dem → Neu	(6) Rep → Neu	(7) No change	(1)-(2)	(3)-(4)	(5)-(6)
-5	0.097 (0.022)	0.021 (0.018)	-0.047 (0.010)	-0.014 (0.012)	0.034 (0.015)	0.006 (0.009)	-0.054 (0.006)	0.075 (0.028)	-0.033 (0.015)	0.028 (0.017)
-4	0.029 (0.020)	-0.003 (0.017)	-0.052 (0.009)	-0.010 (0.011)	0.015 (0.013)	-0.018 (0.008)	-0.045 (0.005)	0.032 (0.026)	-0.043 (0.014)	0.033 (0.015)
-3	0.033 (0.018)	-0.006 (0.015)	-0.058 (0.008)	-0.016 (0.011)	-0.009 (0.012)	-0.021 (0.007)	-0.048 (0.005)	0.040 (0.024)	-0.042 (0.013)	0.012 (0.014)
-2	-0.007 (0.016)	-0.036 (0.014)	-0.036 (0.007)	-0.031 (0.010)	-0.012 (0.011)	-0.023 (0.007)	-0.037 (0.004)	0.029 (0.021)	-0.006 (0.012)	0.011 (0.013)
-1	0 (-)	0 (-)	0 (-)	0 (-)	0 (-)	0 (-)	0 (-)	0 (-)	0 (-)	0 (-)
0	0.293 (0.017)	0.195 (0.016)	0.108 (0.010)	0.098 (0.012)	0.290 (0.012)	0.207 (0.009)	0.149 (0.006)	0.097 (0.021)	0.010 (0.013)	0.083 (0.012)
1	0.197 (0.018)	-0.074 (0.016)	-0.080 (0.010)	-0.192 (0.013)	0.306 (0.013)	0.193 (0.009)	0.071 (0.006)	0.271 (0.023)	0.112 (0.014)	0.114 (0.013)
2	0.175 (0.019)	-0.110 (0.018)	-0.119 (0.011)	-0.233 (0.014)	0.272 (0.013)	0.151 (0.009)	0.020 (0.006)	0.285 (0.024)	0.114 (0.015)	0.121 (0.014)
3	0.146 (0.019)	-0.113 (0.019)	-0.133 (0.011)	-0.252 (0.015)	0.250 (0.013)	0.127 (0.010)	-0.001 (0.006)	0.260 (0.026)	0.119 (0.017)	0.122 (0.014)
4	0.148 (0.021)	-0.096 (0.020)	-0.133 (0.012)	-0.251 (0.016)	0.231 (0.014)	0.130 (0.010)	-0.002 (0.005)	0.245 (0.028)	0.118 (0.018)	0.101 (0.015)
5	0.151 (0.021)	-0.078 (0.022)	-0.139 (0.012)	-0.237 (0.018)	0.239 (0.014)	0.127 (0.010)	-0.005 (0.005)	0.229 (0.030)	0.098 (0.020)	0.112 (0.016)

Standard errors clustered by physician in parentheses.

Table A.5b: Event study estimates: No. diagnoses

$t - m_i$	(1) Dem → Rep	(2) Rep → Dem	(3) Neu → Rep	(4) Neu → Dem	(5) Dem → Neu	(6) Rep → Neu	(7) No change	(1)-(2)	(3)-(4)	(5)-(6)
-5	0.037 (0.019)	-0.026 (0.017)	-0.148 (0.011)	-0.148 (0.014)	-0.082 (0.014)	-0.091 (0.009)	-0.189 (0.006)	0.063 (0.025)	-0.000 (0.017)	0.009 (0.016)
-4	0.008 (0.017)	-0.036 (0.016)	-0.144 (0.010)	-0.143 (0.013)	-0.089 (0.013)	-0.112 (0.008)	-0.176 (0.006)	0.044 (0.023)	-0.001 (0.016)	0.023 (0.015)
-3	-0.027 (0.015)	-0.059 (0.015)	-0.156 (0.009)	-0.137 (0.013)	-0.102 (0.011)	-0.101 (0.008)	-0.165 (0.005)	0.031 (0.021)	-0.020 (0.015)	-0.001 (0.014)
-2	-0.048 (0.014)	-0.094 (0.014)	-0.122 (0.008)	-0.144 (0.012)	-0.096 (0.010)	-0.088 (0.007)	-0.123 (0.005)	0.046 (0.019)	0.022 (0.014)	-0.008 (0.012)
-1	0 (-)	0 (-)	0 (-)	0 (-)	0 (-)	0 (-)	0 (-)	0 (-)	0 (-)	0 (-)
0	0.390 (0.017)	0.317 (0.017)	0.117 (0.012)	0.103 (0.015)	0.399 (0.014)	0.347 (0.011)	0.209 (0.008)	0.072 (0.022)	0.014 (0.016)	0.052 (0.013)
1	0.054 (0.017)	-0.228 (0.016)	-0.364 (0.012)	-0.506 (0.015)	0.316 (0.014)	0.189 (0.011)	-0.061 (0.008)	0.282 (0.021)	0.143 (0.016)	0.127 (0.014)
2	0.045 (0.018)	-0.262 (0.017)	-0.369 (0.012)	-0.535 (0.016)	0.310 (0.014)	0.179 (0.011)	-0.076 (0.007)	0.306 (0.023)	0.166 (0.017)	0.130 (0.015)
3	0.071 (0.019)	-0.253 (0.019)	-0.362 (0.013)	-0.531 (0.017)	0.308 (0.015)	0.180 (0.011)	-0.077 (0.007)	0.324 (0.025)	0.169 (0.019)	0.128 (0.016)
4	0.069 (0.021)	-0.233 (0.020)	-0.333 (0.014)	-0.547 (0.018)	0.300 (0.016)	0.189 (0.012)	-0.068 (0.007)	0.303 (0.027)	0.213 (0.020)	0.112 (0.017)
5	0.053 (0.022)	-0.226 (0.023)	-0.320 (0.015)	-0.541 (0.020)	0.336 (0.017)	0.201 (0.012)	-0.053 (0.007)	0.279 (0.030)	0.221 (0.023)	0.134 (0.018)

Standard errors clustered by physician in parentheses.

Table A.5c: Event study estimates: P(Procedure)

$t - m_i$	(1) Dem → Rep	(2) Rep → Dem	(3) Neu → Rep	(4) Neu → Dem	(5) Dem → Neu	(6) Rep → Neu	(7) No change	(1)-(2)	(3)-(4)	(5)-(6)
-5	0.031 (0.008)	0.024 (0.007)	0.005 (0.004)	0.019 (0.005)	0.010 (0.006)	0.016 (0.003)	0.005 (0.002)	0.008 (0.011)	-0.013 (0.006)	-0.006 (0.007)
-4	0.016 (0.008)	0.018 (0.006)	0.003 (0.003)	0.018 (0.005)	0.009 (0.005)	0.010 (0.003)	0.003 (0.002)	-0.002 (0.010)	-0.015 (0.006)	-0.002 (0.006)
-3	0.018 (0.007)	0.017 (0.006)	0.001 (0.003)	0.012 (0.004)	-0.001 (0.005)	0.008 (0.003)	-0.001 (0.002)	0.001 (0.009)	-0.011 (0.005)	-0.008 (0.005)
-2	0.009 (0.006)	0.004 (0.006)	0.002 (0.003)	0.002 (0.004)	-0.004 (0.004)	0.006 (0.003)	-0.003 (0.002)	0.005 (0.008)	-0.000 (0.005)	-0.009 (0.005)
-1	0 (-)	0 (-)	0 (-)	0 (-)	0 (-)	0 (-)	0 (-)	0 (-)	0 (-)	0 (-)
0	0.073 (0.006)	0.038 (0.006)	0.027 (0.004)	0.019 (0.005)	0.068 (0.005)	0.050 (0.003)	0.035 (0.002)	0.035 (0.008)	0.008 (0.005)	0.018 (0.005)
1	0.063 (0.007)	-0.034 (0.006)	-0.012 (0.004)	-0.065 (0.005)	0.081 (0.005)	0.045 (0.004)	0.020 (0.002)	0.097 (0.008)	0.052 (0.005)	0.036 (0.005)
2	0.062 (0.007)	-0.037 (0.007)	-0.016 (0.004)	-0.063 (0.005)	0.073 (0.005)	0.037 (0.004)	0.011 (0.002)	0.099 (0.009)	0.047 (0.006)	0.036 (0.005)
3	0.061 (0.007)	-0.035 (0.007)	-0.018 (0.004)	-0.068 (0.006)	0.069 (0.005)	0.029 (0.004)	0.005 (0.002)	0.097 (0.010)	0.049 (0.006)	0.040 (0.005)
4	0.060 (0.008)	-0.036 (0.008)	-0.014 (0.004)	-0.059 (0.006)	0.065 (0.005)	0.033 (0.004)	0.006 (0.002)	0.096 (0.011)	0.045 (0.007)	0.033 (0.006)
5	0.056 (0.008)	-0.030 (0.009)	-0.025 (0.005)	-0.058 (0.007)	0.066 (0.005)	0.028 (0.004)	0.004 (0.002)	0.086 (0.011)	0.033 (0.008)	0.037 (0.006)

Standard errors clustered by physician in parentheses.

Table A.5d: Event study estimates: Log(1+util) per patient on elective procedures

$t - m_i$	(1) Dem → Rep	(2) Rep → Dem	(3) Neu → Rep	(4) Neu → Dem	(5) Dem → Neu	(6) Rep → Neu	(7) No change	(1)-(2)	(3)-(4)	(5)-(6)
-5	0.166 (0.045)	0.201 (0.037)	0.076 (0.021)	0.121 (0.027)	0.083 (0.030)	0.092 (0.019)	0.052 (0.012)	-0.035 (0.058)	-0.045 (0.034)	-0.009 (0.035)
-4	0.080 (0.040)	0.160 (0.035)	0.069 (0.020)	0.122 (0.026)	0.062 (0.027)	0.069 (0.017)	0.044 (0.011)	-0.080 (0.053)	-0.053 (0.032)	-0.007 (0.032)
-3	0.113 (0.036)	0.129 (0.033)	0.033 (0.018)	0.081 (0.024)	0.000 (0.025)	0.049 (0.016)	0.027 (0.010)	-0.016 (0.049)	-0.047 (0.030)	-0.048 (0.029)
-2	0.009 (0.032)	0.042 (0.030)	0.038 (0.017)	0.035 (0.022)	0.003 (0.022)	0.040 (0.015)	0.014 (0.009)	-0.033 (0.044)	0.004 (0.028)	-0.037 (0.026)
-1	0 (-)	0 (-)	0 (-)	0 (-)	0 (-)	0 (-)	0 (-)	0 (-)	0 (-)	0 (-)
0	0.322 (0.034)	0.209 (0.032)	0.138 (0.022)	0.085 (0.026)	0.321 (0.025)	0.229 (0.020)	0.161 (0.014)	0.113 (0.043)	0.053 (0.028)	0.092 (0.026)
1	0.321 (0.036)	-0.097 (0.033)	-0.037 (0.022)	-0.268 (0.026)	0.392 (0.026)	0.197 (0.020)	0.082 (0.013)	0.418 (0.045)	0.231 (0.029)	0.195 (0.027)
2	0.268 (0.038)	-0.099 (0.035)	-0.076 (0.023)	-0.252 (0.028)	0.336 (0.027)	0.155 (0.020)	0.041 (0.013)	0.367 (0.048)	0.175 (0.032)	0.181 (0.028)
3	0.257 (0.040)	-0.103 (0.037)	-0.100 (0.024)	-0.260 (0.030)	0.284 (0.028)	0.110 (0.020)	0.011 (0.012)	0.360 (0.052)	0.160 (0.035)	0.175 (0.030)
4	0.224 (0.042)	-0.102 (0.041)	-0.076 (0.025)	-0.289 (0.033)	0.260 (0.028)	0.133 (0.021)	0.008 (0.012)	0.327 (0.056)	0.213 (0.038)	0.127 (0.031)
5	0.237 (0.045)	-0.054 (0.045)	-0.105 (0.026)	-0.241 (0.036)	0.258 (0.030)	0.111 (0.021)	0.004 (0.012)	0.291 (0.062)	0.136 (0.042)	0.147 (0.033)

Standard errors clustered by physician in parentheses.

Table A.5e: Event study estimates: Log(1+util) per patient on non-elective procedures

$t - m_i$	(1) Dem → Rep	(2) Rep → Dem	(3) Neu → Rep	(4) Neu → Dem	(5) Dem → Neu	(6) Rep → Neu	(7) No change	(1)-(2)	(3)-(4)	(5)-(6)
-5	0.008 (0.022)	-0.019 (0.019)	-0.030 (0.011)	-0.019 (0.015)	-0.004 (0.015)	-0.021 (0.010)	-0.051 (0.007)	0.027 (0.029)	-0.011 (0.018)	0.017 (0.018)
-4	-0.016 (0.019)	-0.025 (0.018)	-0.034 (0.011)	-0.022 (0.014)	-0.015 (0.013)	-0.028 (0.009)	-0.049 (0.006)	0.009 (0.026)	-0.012 (0.018)	0.012 (0.016)
-3	-0.029 (0.017)	0.006 (0.018)	-0.039 (0.010)	-0.009 (0.014)	-0.039 (0.012)	-0.025 (0.009)	-0.048 (0.006)	-0.034 (0.025)	-0.030 (0.017)	-0.014 (0.015)
-2	-0.013 (0.017)	-0.001 (0.016)	-0.030 (0.010)	-0.006 (0.013)	-0.025 (0.011)	-0.017 (0.008)	-0.035 (0.005)	-0.012 (0.023)	-0.024 (0.016)	-0.008 (0.014)
-1	0 (-)	0 (-)	0 (-)	0 (-)	0 (-)	0 (-)	0 (-)	0 (-)	0 (-)	0 (-)
0	0.012 (0.018)	-0.021 (0.018)	-0.058 (0.012)	-0.043 (0.015)	0.008 (0.014)	-0.025 (0.011)	-0.046 (0.007)	0.033 (0.023)	-0.015 (0.016)	0.033 (0.014)
1	-0.011 (0.019)	-0.082 (0.018)	-0.079 (0.012)	-0.114 (0.015)	0.079 (0.015)	0.027 (0.011)	-0.026 (0.007)	0.071 (0.024)	0.036 (0.016)	0.051 (0.015)
2	-0.010 (0.020)	-0.082 (0.018)	-0.084 (0.013)	-0.127 (0.015)	0.063 (0.015)	0.015 (0.011)	-0.020 (0.007)	0.071 (0.025)	0.043 (0.018)	0.048 (0.016)
3	0.002 (0.021)	-0.081 (0.020)	-0.079 (0.013)	-0.137 (0.016)	0.080 (0.015)	0.026 (0.011)	-0.019 (0.007)	0.084 (0.027)	0.057 (0.019)	0.054 (0.017)
4	0.038 (0.023)	-0.051 (0.022)	-0.092 (0.014)	-0.117 (0.018)	0.064 (0.016)	0.026 (0.012)	-0.026 (0.007)	0.089 (0.031)	0.025 (0.021)	0.037 (0.017)
5	-0.012 (0.024)	-0.062 (0.023)	-0.080 (0.015)	-0.124 (0.019)	0.049 (0.016)	0.025 (0.012)	-0.022 (0.007)	0.051 (0.032)	0.044 (0.023)	0.024 (0.018)

Standard errors clustered by physician in parentheses.

Table A.6: Characteristics of physician movers vs. non-movers

	Nonmissing %	**Overall**	**Mover**	**Non-mover**	
		Mean [SD]	Mean [SD]	Mean [SD]	Diff (SE)
Unweighted / Weighted by util.	(1)	(2)	(3)	(4)	(3)-(4)
Panel A. Physician observations: Total $N = 308749$, ***Mover*** $N = 29263\,(9\%/8\%)$					
Annual utilization per patient	100	425.88	403.95	428.17	-24.23
		[771.58]	[390.05]	[801.05]	(2.74)
No. patients per year	100	46.06	45.67	46.11	-0.44
		[55.37]	[44.54]	[56.38]	(0.28)
Female	96 / 99	0.23 / 0.11	0.25 / 0.15	0.22 / 0.11	0.03 / 0.04
		[0.42 / 0.32]	[0.43 / 0.36]	[0.42 / 0.31]	(0.00 / 0.00)
Med school grad year	80 / 95	1987.37 / 1984.28	1991.71 / 1990.17	1986.86 / 1983.76	4.86 / 6.41
		[12.30 / 10.00]	[11.20 / 9.42]	[12.33 / 9.88]	(0.07 / 0.11)
PCP	100 / 100	0.23 / 0.25	0.26 / 0.24	0.23 / 0.25	0.04 / -0.01
		[0.42 / 0.43]	[0.44 / 0.42]	[0.42 / 0.43]	(0.00 / 0.00)
Top 5 non-PCP Specialties by N					
Anesthesiology	100 / 100	0.07 / 0.01	0.06 / 0.01	0.07 / 0.01	-0.01 / 0.00
		[0.26 / 0.08]	[0.24 / 0.09]	[0.26 / 0.08]	(0.00 / 0.00)
Obstetrics & Gynecology	100 / 100	0.06 / 0.01	0.04 / 0.01	0.06 / 0.01	-0.01 / -0.00
		[0.23 / 0.11]	[0.21 / 0.09]	[0.23 / 0.11]	(0.00 / 0.00)
Diagnostic Radiology	100 / 100	0.05 / 0.00	0.06 / 0.01	0.05 / 0.00	0.01 / 0.00
		[0.22 / 0.07]	[0.24 / 0.09]	[0.22 / 0.07]	(0.00 / 0.00)
Orthopedic Surgery	100 / 100	0.05 / 0.07	0.05 / 0.07	0.05 / 0.07	0.00 / 0.00
		[0.22 / 0.26]	[0.22 / 0.26]	[0.22 / 0.26]	(0.00 / 0.00)
Emergency Medicine	100 / 100	0.05 / 0.02	0.10 / 0.05	0.05 / 0.02	0.05 / 0.03
		[0.22 / 0.15]	[0.30 / 0.22]	[0.21 / 0.14]	(0.00 / 0.00)
Top 5 non-PCP Specialties by total utilization					
Ophthalmology	100 / 100	0.04 / 0.13	0.03 / 0.10	0.04 / 0.14	-0.01 / -0.04
		[0.19 / 0.34]	[0.17 / 0.30]	[0.20 / 0.34]	(0.00 / 0.01)
Cardiology	100 / 100	0.04 / 0.08	0.04 / 0.09	0.04 / 0.08	0.00 / 0.00
		[0.19 / 0.28]	[0.20 / 0.28]	[0.19 / 0.28]	(0.00 / 0.00)
Orthopedic Surgery	100 / 100	0.05 / 0.07	0.05 / 0.07	0.05 / 0.07	0.00 / 0.00
		[0.22 / 0.26]	[0.22 / 0.26]	[0.22 / 0.26]	(0.00 / 0.00)
Hematology-Oncology	100 / 100	0.01 / 0.06	0.01 / 0.07	0.01 / 0.06	0.00 / 0.01
		[0.11 / 0.23]	[0.11 / 0.25]	[0.11 / 0.23]	(0.00 / 0.01)
Urology	100 / 100	0.02 / 0.05	0.02 / 0.04	0.02 / 0.05	-0.00 / -0.00
		[0.14 / 0.21]	[0.14 / 0.21]	[0.14 / 0.21]	(0.00 / 0.00)
Panel B. Physician-year observations: Total $N{\times}T = 4640717$, ***Mover*** $N{\times}T = 466792\,(10\%/8\%)$					
Census region					
Northeast	100 / 100	0.20 / 0.18	0.18 / 0.13	0.20 / 0.18	-0.02 / -0.05
		[0.40 / 0.38]	[0.38 / 0.34]	[0.40 / 0.38]	(0.00 / 0.00)
Midwest	100 / 100	0.20 / 0.18	0.19 / 0.17	0.20 / 0.18	-0.01 / -0.01
		[0.40 / 0.39]	[0.39 / 0.38]	[0.40 / 0.39]	(0.00 / 0.00)
South	100 / 100	0.38 / 0.46	0.40 / 0.50	0.38 / 0.46	0.02 / 0.05
		[0.49 / 0.50]	[0.49 / 0.50]	[0.49 / 0.50]	(0.00 / 0.01)
West	100 / 100	0.22 / 0.18	0.23 / 0.20	0.22 / 0.18	0.01 / 0.02
		[0.41 / 0.39]	[0.42 / 0.40]	[0.41 / 0.39]	(0.00 / 0.00)
Practice characteristics					
Sole practitioner	61 / 66	0.22 / 0.22	0.19 / 0.17	0.23 / 0.22	-0.04 / -0.05
		[0.42 / 0.41]	[0.39 / 0.38]	[0.42 / 0.41]	(0.00 / 0.00)
For-profit facility	85 / 96	0.21 / 0.21	0.22 / 0.23	0.21 / 0.21	0.01 / 0.03
		[0.41 / 0.41]	[0.41 / 0.42]	[0.41 / 0.41]	(0.00 / 0.00)
Teaching hospital	80 / 92	0.51 / 0.44	0.47 / 0.40	0.51 / 0.44	-0.04 / -0.04
		[0.50 / 0.50]	[0.50 / 0.49]	[0.50 / 0.50]	(0.00 / 0.00)

This table compares characteristics of the mover physicians versus the non-mover physicians in the sample. See Table A.1 for details. Standard errors clustered by physician are shown in parentheses.

Table A.7a: Partisan differences in response to January 2005 chemotherapy drug reimbursement rate changes (including Carboplatin)

Administered Carboplatin/Paclitaxel (pp.)	(1)	(2)	(3)	(4)
Post-January 2005	0.86	0.29		
	(1.44)	(1.53)		
Interactions with Post-January 2005				
Republican physician	-1.37	-1.18		
	(1.96)	(2.04)		
Pre-2004 contributor			2.20	2.45
			(2.14)	(2.30)
Pre-2004 contributor × Rep			-2.51	-2.04
			(2.90)	(3.02)
Post-2004 contributor			0.04	-1.09
			(1.86)	(1.98)
Post-2004 contributor × Rep			-0.70	-0.99
			(2.63)	(2.73)
Republican physician	-0.34		1.06	
	(1.58)		(2.26)	
Post-2004 contributor			0.30	
			(2.30)	
Post-2004 contributor × Rep			-2.72	
			(3.07)	
Constant	65.97	66.02	65.81	66.03
	(1.13)	(0.57)	(1.70)	(0.57)
Physicians controls	✓		✓	
Physician fixed effects		✓		✓
Physician N	1842	1842	1842	1842
Patient N	7598	7598	7598	7598
N(Phys-Patient-Month)	27629	27629	27629	27629
R^2	0.07	0.29	0.07	0.29

Coefficients are in percentage points. All regressions include controls for hospital referral regions and five-year bins for patient age. Physician controls include specialty, gender, and five-year bins for medical school graduation year. Standard errors are clustered by physician and patient.

Table A.7b: Partisan differences in response to January 2005 chemotherapy drug reimbursement rate changes (2-year window)

Administered Paclitaxel (pp.)	(1)	(2)	(3)	(4)
Post-January 2005	-3.43	-3.11		
	(1.44)	(1.46)		
Interactions with Post-January 2005				
Republican physician	2.35	2.17		
	(1.88)	(1.89)		
Pre-2004 contributor			-4.53	-4.95
			(2.29)	(2.28)
Pre-2004 contributor × Rep			4.94	5.32
			(2.93)	(2.93)
Post-2004 contributor			-2.78	-1.90
			(1.80)	(1.84)
Post-2004 contributor × Rep			0.46	-0.26
			(2.46)	(2.47)
Republican physician	-2.74		-1.55	
	(1.38)		(2.04)	
Post-2004 contributor			0.29	
			(2.12)	
Post-2004 contributor × Rep			-2.46	
			(2.72)	
Constant	40.50	38.88	40.37	38.87
	(1.00)	(0.42)	(1.63)	(0.42)
Physicians controls	✓		✓	
Physician fixed effects		✓		✓
Physician N	1872	1872	1872	1872
Patient N	10774	10774	10774	10774
N(Phys-Patient-Month)	40924	40924	40924	40924
R^2	0.06	0.26	0.06	0.26

Coefficients are in percentage points. All regressions include controls for hospital referral regions and five-year bins for patient age. Physician controls include specialty, gender, and five-year bins for medical school graduation year. Standard errors are clustered by physician and patient.

Table A.8a: Partisan differences in response to MRI acquisition (only orthopedic surgeons and neurologists)

MRI referral rate (%)	(1)	(2)	(3)	(4)
Post-MRI acquisition	3.57	3.71		
	(0.53)	(0.51)		
Interactions with Post-MRI acquisition				
Republican physician	0.07	-0.13		
	(0.59)	(0.58)		
Pre-2004 contributor			3.47	3.43
			(1.29)	(1.20)
Pre-2004 contributor × Rep			0.26	0.16
			(1.35)	(1.26)
Post-2004 contributor			3.63	3.87
			(0.41)	(0.43)
Post-2004 contributor × Rep			-0.05	-0.29
			(0.55)	(0.57)
Republican physician	-0.22		-0.94	
	(0.45)		(0.75)	
Post-2004 contributor			-1.09	
			(0.75)	
Post-2004 contributor × Rep			1.14	
			(0.87)	
Constant	6.30	6.15	7.00	6.15
	(0.37)	(0.14)	(0.62)	(0.14)
Physicians controls	✓		✓	
Physician fixed effects		✓		✓
Physician N	3262	3262	3262	3262
N(Phys-Quarter)	28171	28171	28171	28171
R^2	0.08	0.36	0.08	0.36

The outcome is the number of MRI referrals divided by the number of patients seen for an Evaluation and Management visit. Coefficients are in percentage points. All regressions include controls for hospital referral regions. Physician controls include specialty, gender, and five-year bins for medical school graduation year. Standard errors are clustered by physician.

Table A.8b: Partisan differences in response to MRI acquisition (2-year window)

MRI referral rate (%)	(1)	(2)	(3)	(4)
Post-MRI acquisition	3.09	3.27		
	(0.38)	(0.42)		
Interactions with Post-MRI acquisition				
Republican physician	0.24	0.10		
	(0.41)	(0.44)		
Pre-2004 contributor			3.33	3.65
			(1.00)	(1.09)
Pre-2004 contributor × Rep			0.01	-0.30
			(1.04)	(1.11)
Post-2004 contributor			2.97	3.08
			(0.31)	(0.32)
Post-2004 contributor × Rep			0.34	0.30
			(0.37)	(0.38)
Republican physician	-0.33		-0.40	
	(0.29)		(0.53)	
Post-2004 contributor			-0.62	
			(0.55)	
Post-2004 contributor × Rep			0.10	
			(0.63)	
Constant	5.28	5.00	5.69	5.00
	(0.24)	(0.10)	(0.45)	(0.10)
Physicians controls	✓		✓	
Physician fixed effects		✓		✓
Physician N	5486	5486	5486	5486
N(Phys-Quarter)	85862	85862	85862	85862
R^2	0.08	0.35	0.08	0.35

The outcome is the number of MRI referrals divided by the number of patients seen for an Evaluation and Management visit. Coefficients are in percentage points. All regressions include controls for hospital referral regions. Physician controls include specialty, gender, and five-year bins for medical school graduation year. Standard errors are clustered by physician.

Table A.9: Partisan differences in end-of-life cancer care (referring physicians)

	ΔRep-Dem $\overline{\text{Util.}}$ (log pt.) (1)	Δ due to Extensive (%) (2)	EOL Chemo Rate among Dem (%) (3)	ΔRep-Dem EOL Chemo Rate (pp.) (4)	Relative Risk (5)
Post-2004 contributors	10.87 (3.40)	101	2.85	0.36 (0.08)	1.13 (0.03)
Pre-2004 contributors	-5.86 (3.64)	83	3.32	-0.03 (0.09)	0.99 (0.03)
Difference	16.74 (4.92)			0.39 (0.10)	0.14 (0.03)

This figure reproduces the analysis in Figure 5b, but assigns claims to the referring physician for non-office-visit claims. Standard errors from 50 bootstrap samples are shown in parentheses.

C Data on physicians

C.1 Sources of data

We combine data on physicians from several sources. For gender and sole practitioner status, we use yearly snapshots of the National Plan and Provider Enumeration System (NPPES). Coverage of sole practitioner is available for some physicians from 2005, but is not comprehensive until 2007. For medical school information (i.e., program and graduation year), we use the National Downloadable File. We manually clean the medical school names and link programs together (e.g., "Dartmouth Medical School" with "Geisel School of Medicine at Dartmouth"). Information on the average MCAT score by program is taken from Motivate MD.

For specialty, we use the information from the Carrier Claims. In particular, the claims record the specialty code of the performing physician. We assign physicians to the specialty code that accounts for the greatest number of their claims. We also supplement missing specialty codes using information from NPPES and the National Downloadable File.

For data on the type of facility where physicians practice (i.e., medical school facility, number of physicians, and for-profit status), we first find the physicians in the Medicare Inpatient and Outpatient Claims. Unlike the Carrier Claims, the Inpatient and Outpatient Claims record the provider number, which can be linked to medical facilities in the Provider of Service Files. The Provider of Service Files contain the data on the type of facility. For physicians that appear under multiple facilities, we prioritize the facilities that are in the Provider of Service Files. If there are still multiple matches, we assign the physician to the facility that has the most physicians.

C.2 Matching to DIME

We use the NPPES registry to find the history of mailing addresses for the physicians in the medical data. We record the state and hospital referral region (HRR) from the mailing addresses. Then for each physician in the medical data, we search for a self-identified physician in the DIME data who has the exact same first and last names, middle name initial, state, and HRR. We unlink any matches with inconsistent middle names (e.g., John vs. Jake). If there is a unique match between the two datasets, we assign the contributor to the matching physician. We match 24% of the physicians in the Medicare data according to this criteria, which forms the group of "exact" matches.

We then expand the criteria to include "likely" matches. When a contributor is matched to multiple physicians by full name and location, but only one has a history of

contributing in another location, we assign the contributor to that physician, on the premise that a past contributor is more likely to contribute than someone who has not contributed before. If a contributor does not have any matches among physicians in the same state and HRR, we look for physicians outside the HRR but in the same state or in neighboring states. These expansions accommodate physicians who practice in one location but live across a HRR or state border.

These additional criteria increase the overall match rate to 28%, or 308,749 out of 1,093,790 physicians. This match rate is similar to that achieved in Bonica et al. (2014). The matched physicians account for close to half (47%) of all physician utilization in the medical data. We use this sample of matched physicians for the rest of the analysis in the paper (though the partisan differences are similar with only exact matches as well in Figure A.11a).

D Medical practice decomposition details

D.1 Derivation of Equation 6

This section derives the decomposition framework in Section 4.2. In a given year, we have patients indexed by i and physicians by d. Let y_{id} be the utilization per encounter, D the number of physicians, I_d the set of patients that physician d sees, and N_d the number of patients that physician d sees. Then with each physician assigned equal weight regardless of how many patients they see, the average utilization per encounter is:

$$\overline{y} = \frac{1}{D} \sum_{d} \frac{1}{N_d} \sum_{i \in I_d} y_{id}$$

We then separate the utilization within each BETOS category, indexed by b:

$$\overline{y} = \sum_{b} \frac{1}{D} \sum_{d} \frac{1}{N_d} \sum_{i \in I_d} y_{bid} \tag{16}$$

Next, we group the physicians by specialty, where S is the set of physicians with specialty s, as well as the patients by hospital referral region r and CCS diagnosis code c. Now the set I_{drc} contains the patients seen by physician d who are from region r and

diagnosed with condition c. The expression then becomes:

$$\begin{aligned}\overline{y} &= \sum_b \sum_s \frac{1}{D} \sum_{d \in S} \frac{1}{N_d} \sum_{rc} \sum_{i \in I_{drc}} y_{bid} \\ &= \sum_b \sum_{rsc} \frac{1}{D} \sum_{d \in S} \sum_{i \in I_{drc}} \frac{1}{N_d} y_{bid} \\ &= \sum_b \sum_{rsc} \overline{y}_{brsc} w_{rsc} \end{aligned} \tag{17}$$

where $\overline{y}_{brsc} = \left(1/\sum_{d \in S} \sum_{i \in I_{drc}} \frac{1}{N_d}\right) \sum_{d \in S} \sum_{i \in I_{drc}} \frac{1}{N_d} y_{bid}$ is the weighted average of utilization per encounter for treatment b in region r among physicians with specialty s treating patients with condition c, and $w_{rsc} = \left(\sum_{d \in S} \sum_{i \in I_{drc}} \frac{1}{N_d}\right)/D$ is the weight for the number of physicians represented in rsc. Note that $\sum_{rsc} w_{rsc} = 1$.

The same procedure starting from Equation 16 can be applied to the number of claims in each BETOS category q_{bid}, the extensive margin indicator $e_{bid} = \mathbf{1}\{q_{bid} > 0\}$, and the number of claims conditional on the treatment being selected q^+_{bid}. Defining $\overline{p}_{brsc} = \overline{y}_{brsc}/\overline{q}_{brsc}$ as the average price per claim in the BETOS category b within rsc, we can then rewrite Equation 17 as:

$$\overline{y} = \sum_b \sum_{rsc} \overline{p}_{brsc} \overline{e}_{brsc} \overline{q}^+_{brsc} w_{rsc}$$

D.2 Derivation of Equation 11

Equation 11 is equivalent to:

$$\begin{aligned} &\left(\Gamma + \delta^R\right)\left(\Pi + \theta^R\right) w_{rsc} - \left(\Gamma + \delta^D\right)\left(\Pi + \theta^D\right) w_{rsc} \\ =& \left(\Gamma + \delta\right)\left(\Pi + \theta^R\right) w_{rsc} - \left(\Gamma + \delta\right)\left(\Pi + \theta^D\right) w_{rsc} \\ +& \left(\Gamma + \delta^R\right)\left(\Pi + \theta\right) w_{rsc} - \left(\Gamma + \delta^D\right)\left(\Pi + \theta\right) w_{rsc} \end{aligned}$$

where $\delta_{brsc} = (\delta^R_{brsc} + \delta^D_{brsc})/2$, $\theta_{brsc} = (\theta^R_{brsc} + \theta^D_{brsc})/2$, and $w_{rsc} = (w^R_{rsc} + w^D_{rsc})/2$, and for clarity, we have dropped indices, defined $\Gamma = \Gamma^e_b \overline{W}$ and $\Pi = \Gamma^{q^+}_b \overline{W}^+$, and divided through by $\overline{p}_{brsc}$.

Suppose we equalize the extensive margin first and then the intensive margin by

writing the left-hand side as:

$$\begin{aligned}
&\left(\Gamma+\delta^R\right)\left(\Pi+\theta^R\right)w_{rsc}-\left(\Gamma+\delta^D\right)\left(\Pi+\theta^D\right)w_{rsc}\\
=&\left(\Gamma+\delta^R\right)\left(\Pi+\theta^R\right)w_{rsc}-\left(\Gamma+\delta^D\right)\left(\Pi+\theta^R\right)w_{rsc}\\
+&\left(\Gamma+\delta^D\right)\left(\Pi+\theta^R\right)w_{rsc}-\left(\Gamma+\delta^D\right)\left(\Pi+\theta^D\right)w_{rsc}
\end{aligned}\tag{18}$$

We can also do the reverse and equalize the intensive margin first and then the extensive margin:

$$\begin{aligned}
&\left(\Gamma+\delta^R\right)\left(\Pi+\theta^R\right)w_{rsc}-\left(\Gamma+\delta^D\right)\left(\Pi+\theta^D\right)w_{rsc}\\
=&\left(\Gamma+\delta^R\right)\left(\Pi+\theta^R\right)w_{rsc}-\left(\Gamma+\delta^R\right)\left(\Pi+\theta^D\right)w_{rsc}\\
+&\left(\Gamma+\delta^R\right)\left(\Pi+\theta^D\right)w_{rsc}-\left(\Gamma+\delta^D\right)\left(\Pi+\theta^D\right)w_{rsc}
\end{aligned}\tag{19}$$

Averaging Equations 18 and 19 gives:

$$\begin{aligned}
&\left(\Gamma+\delta^R\right)\left(\Pi+\theta^R\right)w_{rsc}-\left(\Gamma+\delta^D\right)\left(\Pi+\theta^D\right)w_{rsc}\\
=&\frac{1}{2}\left(\Gamma+\delta^R\right)\left(\Pi+\theta^R\right)w_{rsc}-\frac{1}{2}\left(\Gamma+\delta^D\right)\left(\Pi+\theta^R\right)w_{rsc}\\
+&\frac{1}{2}\left(\Gamma+\delta^D\right)\left(\Pi+\theta^R\right)w_{rsc}-\frac{1}{2}\left(\Gamma+\delta^D\right)\left(\Pi+\theta^D\right)w_{rsc}\\
+&\frac{1}{2}\left(\Gamma+\delta^R\right)\left(\Pi+\theta^R\right)w_{rsc}-\frac{1}{2}\left(\Gamma+\delta^R\right)\left(\Pi+\theta^D\right)w_{rsc}\\
+&\frac{1}{2}\left(\Gamma+\delta^R\right)\left(\Pi+\theta^D\right)w_{rsc}-\frac{1}{2}\left(\Gamma+\delta^D\right)\left(\Pi+\theta^D\right)w_{rsc}
\end{aligned}$$

Finally, note that:

$$\begin{aligned}
\frac{1}{2}\left(\Gamma+\delta^R\right)\left(\Pi+\theta^R\right)w_{rsc}+\frac{1}{2}\left(\Gamma+\delta^D\right)\left(\Pi+\theta^R\right)w_{rsc}&=\left(\Gamma+\frac{\delta^R+\delta^D}{2}\right)\left(\Pi+\theta^R\right)w_{rsc}\\
&=\left(\Gamma+\delta\right)\left(\Pi+\theta^R\right)w_{rsc}\\
\frac{1}{2}\left(\Gamma+\delta^R\right)\left(\Pi+\theta^R\right)w_{rsc}+\frac{1}{2}\left(\Gamma+\delta^R\right)\left(\Pi+\theta^D\right)w_{rsc}&=\left(\Gamma+\delta^R\right)\left(\Pi+\theta\right)w_{rsc}\\
-\frac{1}{2}\left(\Gamma+\delta^D\right)\left(\Pi+\theta^R\right)w_{rsc}-\frac{1}{2}\left(\Gamma+\delta^D\right)\left(\Pi+\theta^D\right)w_{rsc}&=-\left(\Gamma+\delta^D\right)\left(\Pi+\theta\right)w_{rsc}\\
-\frac{1}{2}\left(\Gamma+\delta^D\right)\left(\Pi+\theta^D\right)w_{rsc}-\frac{1}{2}\left(\Gamma+\delta^R\right)\left(\Pi+\theta^D\right)w_{rsc}&=-\left(\Gamma+\delta\right)\left(\Pi+\theta^D\right)w_{rsc}
\end{aligned}$$

D.3 Decomposition of weights

The weights w_{rsc} represent the number of physicians in each HRR-specialty-CCS cell. These imbalances reflect the differences between Republican and Democratic physicians in geographic distribution, specialization, patient condition, or interactions among these three dimensions. But how can we separately measure the role of each component?

In the decomposition framework of Section 4.2.1, we can calculate how much of the partisan differences in medical utilization is due to the weights by normalizing all other margins except for the weights, and then aggregating the remaining difference. We start from Equation 10 with all else equalized besides the weights:

$$\Delta \log\left(\overline{\text{utilization}}\right) = \log\left(\sum_b \sum_{rsc} \overline{p}_{brsc}\left(\Gamma_b^e \overline{W} + \delta_{brsc}\right)\left(\Gamma_b^{q^+}\overline{W}^+ + \theta_{brsc}\right)\left(w_{rsc}^R - w_{rsc}^D\right)\right) \quad (20)$$

Our objective is to separate the difference in the weights $w_{rsc}^R - w_{rsc}^D$ into parts explained by the HRR, the specialty, and the CCS diagnosis code.

Consider an approach where we first normalize the geographic distribution. Then, within each HRR, we normalize the distribution across specialties. Finally, within HRR-specialty, we normalize the distribution across CCS diagnosis codes. To begin, we define:

$$\begin{aligned} w_{\tilde{r}} &= \left(\sum_{sc} w_{rsc}^R + \sum_{sc} w_{rsc}^D\right)/2 \\ w_{\tilde{r}sc}^R &= w_{rsc}^R \times \frac{w_{\tilde{r}}}{\sum_{sc} w_{rsc}^R} \\ w_{\tilde{r}sc}^D &= w_{rsc}^D \times \frac{w_{\tilde{r}}}{\sum_{r} w_{rsc}^D} \end{aligned}$$

Note that the $\tilde{r}$ in the subscript denotes that the weight on r has been normalized. Summing $w_{\tilde{r}sc}^R$ or $w_{\tilde{r}sc}^D$ across sc results in $w_{\tilde{r}}$.

Next within each r, we normalize the weights on specialty:

$$\begin{aligned} w_{\tilde{r}s} &= \left(\sum_{c} w_{\tilde{r}sc}^R + \sum_{c} w_{\tilde{r}sc}^D\right)/2 \\ w_{\tilde{r}\tilde{s}c}^R &= w_{\tilde{r}sc}^R \times \frac{w_{\tilde{r}s}}{\sum_{c} w_{\tilde{r}sc}^R} \\ w_{\tilde{r}\tilde{s}c}^D &= w_{\tilde{r}sc}^D \times \frac{w_{\tilde{r}s}}{\sum_{c} w_{\tilde{r}sc}^D} \end{aligned}$$

If we sum $w_{\tilde{r}\tilde{s}c}^R$ across c, which gives $w_{\tilde{r}s}$, and then sum $w_{\tilde{r}s}$ across s, we return to $w_{\tilde{r}}$.

Finally, we normalize the weights on CCS codes within rs:

$$\begin{aligned} w_{\tilde{r}\tilde{s}\tilde{c}} &= (w^R_{\tilde{r}\tilde{s}c} + w^D_{\tilde{r}\tilde{s}c})/2 \\ &= w^R_{\tilde{r}\tilde{s}\tilde{c}} \\ &= w^D_{\tilde{r}\tilde{s}\tilde{c}} \end{aligned}$$

We can then express the partisan difference in the weights for a given rsc as the sum of the differences after normalizing each component sequentially:

$$\begin{aligned} w^R_{rsc} - w^D_{rsc} = &(w^R_{rsc} - w^D_{rsc}) - (w^R_{\tilde{r}sc} - w^D_{\tilde{r}sc}) \\ &+ (w^R_{\tilde{r}sc} - w^D_{\tilde{r}sc}) - (w^R_{\tilde{r}\tilde{s}c} - w^D_{\tilde{r}\tilde{s}c}) \\ &+ (w^R_{\tilde{r}\tilde{s}c} - w^D_{\tilde{r}\tilde{s}c}) \end{aligned}$$

where the first line $(w^R_{rsc} - w^D_{rsc}) - (w^R_{\tilde{r}sc} - w^D_{\tilde{r}sc})$ is the amount of the partisan difference in the weights due to the HRR imbalances, the second line is the amount due to specialty imbalances, and the third is the amount due to imbalances in diagnoses. By plugging this weight decomposition formula into Equation 20, we can calculate the component due to each dimension.

This weight decomposition, however, is not order invariant. For example, we could normalize the specialty first, and then the HRR. There are six potential sequences: rsc, rcs, src, scr, csr, and crs We do all six, and for each sequence, we calculate the amount due to each component. We then average across all six components, which provides the estimates in Columns 8-10 of Table A.3.