Trust in Medicine and the Demand for Health Care*

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Abstract

This paper studies how trust in medicine affects the demand for health care and subsequent health outcomes. I leverage the aftermath of the Covid-19 pandemic, with Republicans and Democrats drifting far apart in their views of the medical profession, as a shock to trust that differentially impacted local areas by political orientation. I first show that since 2019, the relative use of routine care among Medicare beneficiaries has declined sharply in more Republican areas. By 2023, a 10 percentage point increase in the 2020 Republican county vote share reduces routine visits by around 0.8% and the number of beneficiaries per primary care provider by 2%. Consistent with pandemic-related dissatisfaction driving changes in trust, I exploit variation in state and local Covid-19 restrictions to show that these shifts are larger in places that had more stringent policies. I also find that patient volume declines in Republican areas are much larger for Democratic physicians, highlighting the importance of belief concordance in maintaining trust. Finally, I link declining trust to worse health, documenting substantial relative increases in mortality across the age distribution in more Republican areas. By 2025, a 10 percentage point increase in the 2020 Republican vote share implies a roughly 1% increase in the mortality rate. The results emphasize the key influence played by trust in both care utilization and health outcomes and suggest efforts to rebuild it will be critical moving forward.

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1 Introduction

Across a range of settings, the last two decades have witnessed a dramatic decline in trust toward institutions and expertise in the United States.[1] Until the Covid-19 pandemic, the medical profession had largely avoided these trends, but from a base of 65% describing doctors as honest and ethical in 2019, the share rose to an all-time high of over 75% in 2020 before collapsing to 53% by 2024 (Gallup, 2025). Equally striking has been the partisan nature of these declines — in 2019, there was little difference between Republicans and Democrats in their views of the profession, but by 2023, Republicans were 20 percentage points less likely to describe doctors positively. The importance of trust in the health care sector has long been theorized, with Arrow (1963) writing that "Delegation and trust are the social institutions designed to obviate the problem of informational inequality." However, the difficulty finding sources of variation to test this hypothesized importance has led to limited empirical evidence on the subject.

This paper focuses on the pandemic-induced shock to trust, exploiting its partisan nature to establish a causal link between declining trust in medicine, demand for care, and health outcomes. Proxying differential exposure to declining trust with county-level 2020 Trump vote shares, I first document large post-pandemic relative reductions in the use of routine health care in more Republican areas by Medicare beneficiaries, consistent with a mistrust-driven decline in demand. Motivated by prior work linking Republican declines in trust to backlash against pandemic-era public health (O'Brian and Kent, 2025), I then show that the negative relationship between Republican vote shares and routine care use is stronger in places that had more stringent pandemic restrictions. Moreover, consistent with the politicization of the pandemic among both physicians and patients (Levin et al., 2023), I find that declining patient volumes in Republican areas are larger for Democratic primary care physicians than Republicans, suggesting mismatched beliefs exacerbated mistrust. Importantly, I do not find corresponding reductions in hospital-based care, which in a simple theory of demand for care should be less influenced by trust than routine care, and I rule out several alternative explanations, including changes in economic conditions, beneficiary composition, and the supply of care. Finally, I test for subsequent health effects, documenting substantial relative increases in mortality in Republican areas across the age distribution. Together, these results suggest that declining trust has altered whether and with whom Americans access medical care, with evidence of deleterious health effects already emerging.

I begin by documenting the evolution of views toward the medical profession in recent

[1] At the start of the 21st century, clergy were seen as honest by 64%, professors by 58%, judges by 47%, and state governors by 31%. Today, these numbers have fallen to 30% (clergy), 42% (professors), 28% (judges), and 16% (governors).

years. At the onset of the Covid-19 pandemic, roughly even shares of Republicans and Democrats expressed trust in both medical doctors and public health authorities.[2] In the years since, however, these views diverged sharply, with partisan gaps continuing to grow. By 2024, less than half of Republicans viewed doctors as honest or ethical compared with nearly 70% of Democrats. These patterns are not restricted to the profession in the abstract — by 2025, Republicans were 30 percentage points less likely to report a great deal of trust in their *personal* doctor about vaccines (Gallup, 2025; Kaiser Family Foundation, 2025).

To fix ideas around the potential consequences of these shifting views, I next develop a model that nests both the patient care-seeking decision and provider treatment choice. The model yields two important testable implications of declining trust. First, the utilization of medical care should fall. Second, particularly for the population under study, declines in utilization should be greater for more routine categories of care. The model also highlights the normative ambiguity of distrust — whether lower trust is rational on the part of patients ultimately depends on whether it influences health outcomes.

To test these predictions empirically, my baseline specification is an event study with a continuous treatment, where the event is the Covid-19 pandemic and the treatment is a county's 2020 Republican vote share. Intuitively, places with greater Republican vote shares will be more exposed to partisan declines in trust in the years since the pandemic. Using data from Medicare's public use files, both at the county and provider level, I document a sharp polarization in the utilization of health care between Republican and Democratic areas post-pandemic, consistent with the concurrent polarization of trust. Relative to 2019, I find that by 2023 a 10 percentage point increase in a county's share of the 2020 vote cast for Donald Trump implies a 0.8% decrease in the number of evaluation and management visits per Medicare beneficiary and a roughly 2% decrease in the average number of unique beneficiaries seen by primary care providers (PCPs) in the county.

I next shift to a triple differences approach to examine two core sources of heterogeneity that may influence the extent of declines in trust. First, I exploit the wide heterogeneity across local areas in gathering and mask restrictions during the pandemic. Since many of these policies were implemented at the state level, a substantial number of Republican areas had strict restrictions while many Democratic ones did not. Recent work by O'Brian and Kent (2025) has found that among Republicans, increasing the salience of the pandemic to survey respondents reduced reported trust in personal doctors, suggesting that the strictness of local policies could influence declines in trust. Indeed, using data from the CDC on the

[2]Pew found roughly even shares reporting positive views of doctors in 2019, with 77% of Republicans and 73% of Democrats doing so (Funk et al., 2020). Meanwhile, in early 2020, Republicans (90%) and Democrats (85%) both expressed a high degree of trust in the Centers for Disease Control (Hamel et al., 2020b)

share of days in each county between April 2020 and August 2021 with an active gathering restriction or mask mandate, I find that effects are concentrated in Republican areas that had more stringent pandemic policies. I find that moving from the 25th to 75th percentiles of my restriction measure implies an (absolute) increase in the coefficient on the 2020 Republican vote share of 40-60% for evaluation and management visits and 33% for PCP patient volumes by 2023.

Second, I consider the match in beliefs between patients and providers. A growing literature has documented differences in both the practice style of Republican and Democratic physicians and their beliefs relating to the pandemic (Kim, 2025; Levin et al., 2023). In this context, Republican physicians may be more adept at communicating with or have views on vaccines that are more closely aligned with Republican patients, helping to mitigate some of the reductions in trust observed elsewhere. After identifying physician partisan affiliation from a combination of political donations and party registration data, I find that declining patient volumes in more Republican areas are substantially larger for Democratic physicians than Republican physicians. Importantly, these shifts only emerge when focusing on primary care doctors, who will be more closely related to vaccination efforts and have more repeated interactions with patients during which a mismatch in beliefs could become evident. Moreover, though noisy, estimates are especially large when focusing on the subset of primary care doctors who have donated to a political campaign, a potential proxy for the intensity of beliefs.

The assumption underlying interpretation of the coefficients is that, had trust remained relatively non-partisan, utilization would have trended similarly between Republican and Democratic areas following the pandemic. In the triple difference analyses, the equivalent assumption is that differences in utilization trends between Republican and Democratic areas would have been the same for places with more or less restrictive Covid-19 policies or for Democratic versus Republican physicians. Though inherently untestable, I provide several pieces of evidence in support of these assumptions. First, one potential concern is that comparing counties across different states may mix effects from shifting trust with other state health policies. In specifications that include state-year fixed effects to restrict comparisons to the same state, I find qualitatively similar results throughout.

Second, I examine patterns for utilization per beneficiary across a broader set of care categories ranging from hospital-based care (emergency room visits, inpatient stays, and outpatient visits) to several potentially more discretionary categories (tests and imagings, procedures, and treatments). Consistent with the theoretical prediction from my model, I find evidence of declining utilization in more Republican areas for tests and imagings as well as treatments, while procedures, inpatient stays, and outpatient visits remain relatively flat.

Meanwhile, I document increases in emergency room visits that began during the pandemic and have persisted even as Covid-19 morbidity and mortality declined, potentially indicating worse health outcomes. I also report results for two other plausibly trust-dependent outcomes — influenza vaccinations and home births — with more Republican areas seeing sharp decreases in vaccine uptake and sharp increases in the share of births taking place at home. Together, these patterns provide further evidence that shifting trust has altered the relationship of many Americans with the health care system while ruling out systematic health improvements that would violate the parallel trends assumption.

Third, I show that results are robust to a wide range of modifications, including alterations in the construction of outcomes, the use of the 2016 or 2024 election to construct vote shares, and the inclusion of controls for a range of beneficiary characteristics. Finally, I consider several potential alternative explanations for these shifting utilization patterns — changes in the local economic environment, Medicare beneficiary characteristics, and the supply of care — finding that each is inconsistent with the documented shifts in care use.

The first concern is that changing economic conditions during by the pandemic have altered demand for care or population health. Evidence on care-seeking behavior shows that socioeconomic status is strongly predictive of greater utilization of routine care (Darden and Macis, 2024). Though most of my sample will be retired, some could still be working and local economic conditions could influence material wealth. Reassuringly, I show that local unemployment rates were actually lower in the years following 2020 in more Republican areas. Moreover, these better economic conditions have not resulted in improved health — I show that rates of obesity and chronic conditions are largely stable if not increasing in more Republican areas during this time.

The second possibility is that differential trends in the composition of beneficiaries have altered demand for care. Changes in the age distribution, socioeconomic makeup, racial composition, or take-up of Medicare Advantage (MA) could alter aggregate patterns without individual demand changing. Indeed substantial differences do exist between Republican and Democratic areas in the cross-section, and there have been significant national shifts on these measures. However, these trends cannot explain the polarization of demand for care I document. First, the average age of fee-for-service (FFS) Medicare beneficiaries has risen overall, but increases have been relatively even across local political orientation. Second, the share of beneficiaries who were dually eligible for Medicaid (a proxy for socioeconomic status) has declined as many shifted into MA, but trends have been stable between Republican and Democratic areas. Third, though the white share of beneficiaries has increased in Democratic areas relative to Republican ones, I show that Republican declines in utilization occur specifically for white beneficiaries and do not simply reflect a compositional shift. Finally,

though national increases in the share of Medicare beneficiaries opting into MA has been more rapid in Republican areas, this pattern preceded the pandemic and is driven largely by pre-pandemic differences in MA prevalence. Republican areas had lower initial MA penetration and have converged over the last decade; accounting for 2019 MA prevalence eliminates most of the MA trend differences without influencing results for routine care. Moreover, these differential trends are absent in the triple-difference specifications. Together, these results suggest compositional shifts are not responsible for the changes in demand.

The final alternative I consider is that it was not reduced demand but rather a supply side contraction driving changing utilization. Given that the number of patients per PCP declines, the findings are inconsistent with a pure provider exit story. And though provider location data has limitations, I show that the supply of providers actually increased somewhat in more Republican areas immediately after the pandemic. Interestingly, this pattern has reversed since 2023, which may indicate a supply side response to reduced demand rather than the other way around. It is also possible that an intensive margin contraction in the number of hours worked has reduced utilization, potentially due to burnout or staffing shortages. However, I show that the number of nurses per capita has actually risen somewhat in more Republican counties in recent years. Moreover, I provide evidence that effects are largely driven by white beneficiaries, who are more likely to be Republican than non-white individuals but would face a similar local supply of care. Thus, the shifts in utilization are inconsistent with a supply side change and point rather to changing demand for care.

I close by examining whether declining trust has affected health outcomes. As highlighted by my model, trust-induced shifts in utilization lack clear normative implications without a direct examination of subsequent health. On one hand, reduced utilization of routine and preventive care may result in worse health outcomes. On the other, the care being foregone may be largely unnecessary, with reduced care-seeking resulting in a closer to optimal use of medical services. To shed light on this theoretical ambiguity, I examine patterns for mortality rates over the last decade. I find substantial increases in infant and overall mortality rates in Republican areas, persisting after the height of the pandemic and accelerating in the last 2-3 years. Relative to 2019, a 10 percentage point increase in the Trump vote share corresponded to an increase of over 1 death per 10,000 by 2024 and 2025 in infant and overall mortality or roughly 2% and 1% increases relative to the mean, respectively. Importantly, these patterns are only apparent among white Americans, consistent with non-white individuals being much less likely to be Republican, and appear throughout the age distribution, assuaging concerns that they are driven by compositional shifts or population aging.

Together, the findings in this paper highlight the broad importance of trust in medicine. In the years since the pandemic, media discussion has focused in large part upon vaccines

as a flash point in health care politics and seldom on the broader relationship of Americans with the health care system. The findings in this paper emphasize the large set of health care services whose use are influenced by declining trust, with serious implications for health outcomes. Rebuilding this trust and undoing the rising polarization in the use of health care will be a core challenge for the medical profession in the years to come.

This paper adds to a small literature in health economics on the role of trust in medicine. Though trust has been theoretically recognized as an important factor for decades (Arrow, 1963), empirical work on the subject remains more limited. There has been research on the effects of the revelation of the Tuskegee syphilis experiment, which reduced trust in medicine among Black men, and in turn led to lower utilization and increased mortality (Alsan and Wanamaker, 2017). In a more recent setting, Darden and Macis (2024) conduct a detailed survey on trust, health care utilization, and other characteristics to highlight the robust correlation between reported trust in medicine and use of care. My paper exploits the dramatic shift in trust brought about by the pandemic to provide novel evidence on the causal impact of trust on the demand for care and subsequent health in a contemporary setting. The findings underscore the first order importance of trust in medicine, particularly as it has grown more polarized in recent years.

The paper also contributes to a more extensive recent literature studying the role of political beliefs in health behaviors and outcomes amid the Covid-19 pandemic (see Camacho-Garcia et al., 2025, for a more extensive review). Research has studied the influence of conservative media on stay-at-home behavior (Bursztyn et al., 2022) and has documented wide political gradients in beliefs (Kerr et al., 2021; Levin et al., 2023), behaviors (Allcott et al., 2020; Fan et al., 2025), and Covid-19 mortality (Sehgal et al., 2022). There has also been survey work studying the effect of the pandemic and corresponding public health measures in reducing reported trust in medicine, particularly among Republicans (Perlis et al., 2024; O'Brian and Kent, 2025). The current paper adds to this body of research by documenting a novel impact of pandemic-related polarization — reduced Republican utilization of routine care — mediated through its influence on trust.

Beyond the pandemic, there has also been a wider body of research studying the importance of political beliefs in the health care sector. This includes work showing lower take-up of Affordable Care Act insurance plans among Republicans (Lerman et al., 2017; Bursztyn et al., 2025), the role of the opioid epidemic in driving Republican support (Arteaga and Barone, 2025), and the influence of physician political ideology on practice style (Kim, 2025). Most related, Darden and Macis (2024) show that political ideology is correlated with a series of care-seeking behaviors in survey data. I extend this by highlighting the influence of politicized trust in shifting demand for health care while also leveraging data on physician

political identity to highlight the importance of the match between patient and provider politics in the preservation of trust.

Finally, this paper relates to a broader set of work studying the drivers of care-seeking behavior. Much of this has focused on the role of health insurance in influencing the extent and composition of health care utilization (Finkelstein et al., 2012; Aron-Dine et al., 2013; Brot-Goldberg et al., 2017) and, in general, finds that routine care is more sensitive to the prices facing consumers. Other factors, including education and income (Darden and Macis, 2024), health history (see the large literature on selection, e.g. Handel, 2013) and distance to providers (Ho, 2006) have been shown to predict care use as well. The results in this paper highlight patient trust as another important driver of utilization, particularly for routine and preventive services.

The remainder of the paper proceeds as follows. Section 2 provides an overview of shifting trust in the years following the onset of the Covid-19 pandemic before developing a theoretical model of care-seeking in the presence of trust. Section 3 discusses the data used in the paper and provides and overview of the empirical methodology. Section 4 presents results, first showing the main results on the use of routine care, then examining other care categories and considering alternative explanations, and finally reporting results for mortality. Section 5 concludes.

2 Background

2.1 Covid-19 and Trust

The Covid-19 pandemic resulted in a sharp break in the way that Americans view the health care system. For decades, Gallup has asked respondents whether they consider medical doctors honest or ethical, alongside a range of other professions. The public's view of doctors has consistently been above 50%, and between 2000 and 2019, hovered steadily between 65 and 70% describing high or very high levels of honesty in the profession (see Appendix Figure A.1 for the full time series). This stability occurred even as other elite professions, including political figures, journalists, clergy, and academics, saw their standing steadily erode.

In addition to stability over time, there was also little partisan divide in views of doctors, with Republicans as likely or even slightly more likely to describe them as honest or ethical pre-2020. In part, this may have reflected the relatively balanced partisan split of doctors themselves (Kim, 2025). Rather, the main fault lines in trust of the profession were along other dimensions; for instance, Black Americans were less likely to report positive views of

doctors as a legacy of long-standing mistreatment (Musa et al., 2009; Alsan and Wanamaker, 2017). Thus, the onset of the pandemic occurred amid a relatively nonpartisan trust landscape. This balance in views of doctors was also reflected in baseline views of public health authorities, at least with a Republican in the White House. In early 2020, Republicans (90%) and Democrats (85%) both expressed a high degree of trust in the Centers for Disease Control (Hamel et al., 2020b). And as of March/April 2020, while there were some partisan disagreements over the danger posed by the disease, reported social distancing behavior was actually relatively balanced between members of both parties (Blumenthal, 2020).

Over the course of 2020, however, deep partisan fissures emerged over the perceived severity of the disease and the proper response to it. By May 2020, under two months after the onset of most state lockdowns, Republicans were three times as likely as Democrats to say their state was reopening too slowly while Democrats were three times as likely to say that their state was reopening too fast (Hamel et al., 2020a). Meanwhile, Democrats were around twice as likely as Republicans to report wearing a mask every time they left the house. And by July-August of 2020, whereas 94% of Democrats supported reducing infections first before opening businesses, Republicans were split evenly between prioritizing infections and the economy (Deane et al., 2021). As of October 2020, the share expressing a great deal or fair amount of trust in the CDC had also plummeted 30 percentage points to 60% among Republicans, with the share of Democrats unchanged (Kirzinger et al., 2020). This polarization in views of the pandemic carried through to the mass roll-out of vaccines. In the first 9 months of the vaccination campaign, roughly 90% of Democrats received an initial dose, compared to only 58% of Republicans (Hamel et al., 2021), a gap that widened further for subsequent doses (Tyson and Pasquini, 2024).

A broader literature in political science has studied the drivers of these partisan divides amid the pandemic. Delineating the exact causes of this stark polarization is beyond the scope of this paper, but it is worth considering several possibilities. First, it is not necessarily surprising that conservatives, with a greater emphasis on individual liberty, would be opposed to government mandated business closures, mask requirements, or vaccinations. Indeed, across a broad set of countries, right wing respondents were more likely to believe there should have been fewer Covid-19 restrictions (Kat et al., 2021). In these responses, though, the US clearly stands out in the degree of polarization if not the general pattern.

Prior work has highlighted several key distinguishing features of the United States. First, in most other developed countries, mainstream political parties regardless of ideology maintained support for public health measures through the pandemic. By contrast, President Trump's views on the severity of the disease were mixed from the start, at times downplaying its seriousness and expressing opposition to government restrictions. This theory of

elite cueing suggests that what made the US unique was that Republican political leaders signaled to members of the party that they should oppose restrictions and be skeptical of public health authorities (Green et al., 2020). In conjunction with this explanation, the United States began the pandemic toward the lower end of OECD countries in baseline trust in government and scientific expertise and with a higher level of political polarization, which may have made elite cues more important (Organisation for Economic Cooperation and Development, 2019; Boxell et al., 2024). Third, the US media landscape is highly fragmented along partisan lines, meaning that Republicans and Democrats consumed significantly different information about the pandemic and vaccine efficacy (Allcott et al., 2020). Finally, because pandemic policy in the US was fragmented at the state level and the pandemic took place during an election year, there may have simply been more incentive and more opportunities for politicians to politicize the pandemic (Adolph et al., 2022). Regardless of the explanation, the last five years have seen views of public health diverge sharply along partisan lines.

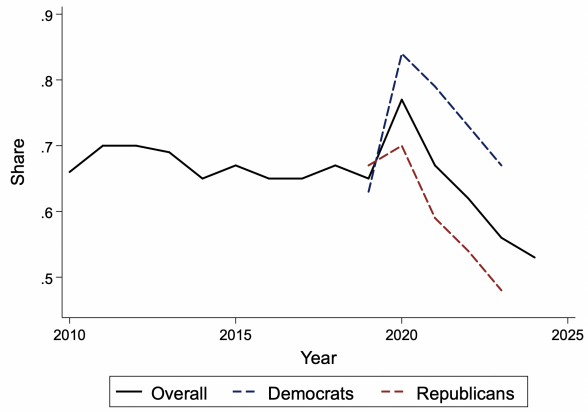
Importantly, this partisanship has spilled over to views of the medical profession more generally, as doctors became associated with polarizing pandemic restrictions and vaccinations. As shown in Figure 1a, a relatively stable 65-70% of Americans viewed doctors as honest or ethical in the two decades before 2020. With the onset of the pandemic, the share spiked to over 75% in 2020 before falling steadily to just over 50% by 2024, the lowest level in decades. When splitting by party, the shifts are even more striking. Views among Democrats increased during the pandemic but by 2023 had roughly returned to the pre-pandemic level. Meanwhile, Republican views began to plummet in 2021 and by 2023 fewer than half of Republicans described doctors positively. These patterns are not exclusive to abstract questions about doctors in general — by the end of 2020, Republicans were much less likely to report a great deal of trust in their own person doctor about vaccines, and this share has continued to decline through 2025 (Figure 1b).

2.2 Trust

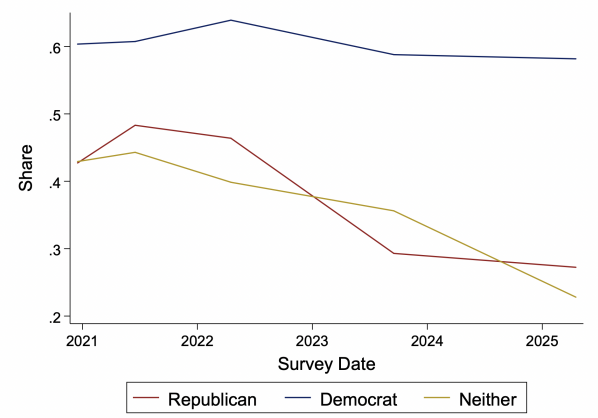
I next consider the meaning of trust in medicine and its potential role in shaping the demand for health care. To do so, I present a simple model of physician behavior in conjunction with a model of the care-seeking decision adapted from Currie et al. (2024) and Darden and Macis (2024), respectively. The model proceeds in two periods, $t \in \{1, 2\}$. In the first period, individuals realize a health state ($\alpha_{1i} \sim F_1(.)$) and decide whether to seek out care ($m_i = 1$). If they do, physician j sees them and chooses the level of treatment intensity $\tau_i \in [0, 1]$ for the patient. In the second period, each individual's new health state,

Figure 1: Trust in Doctors over Time

(a) Share Describing Doctors as Honest or Ethical



(b) Share with a Great Deal of Trust in Personal Doctor about Vaccines



Notes: Data from Gallup (L) and Kaiser Family Foundation (R). Gallup has published partisan split sporadically but only since 2020, so the breakdown by party in 2019 is from Pew (Funk et al., 2020), re-normalized to match the Gallup top-line. A Gallup party split in 2013 roughly matches the relative finding from 2019 (Jones, 2013). Kaiser changed the wording of its question to ask about vaccines in general rather than the Covid-19 vaccine in 2023.

α_{2i}, is realized, with the conditional distribution $F_2(.; \alpha_{1i}, m_i \cdot \tau_i)$ a function of initial health and treatment intensity (if care is received) in period 1. When choosing whether to seek out care, the individual will have subjective beliefs about the treatment decision a physician will make as well as the effect it will have on their health, both of which will be influenced by trust. I begin by describing the physician's treatment decision in more detail.

Physician j chooses the treatment intensity, τ_i, for a patient i based upon their need level α_{1i}. When choosing the patient's treatment intensity, the provider weighs two competing forces — the expected benefit to the patient and the private payoff from more intensive care. The physician expects the health state to evolve according to $\hat{F}_{2j}(\alpha_{2i}; \alpha_{1i}, \tau_i)$ and receives private payoff $\pi_j(\tau_i)$. The private payoff will include financial incentives from more intensive treatment but will also encompass a range of other factors — the opportunity cost of spending more time with one individual, the risk of losing dissatisfied patients, psychic costs from excessive care provision, reputational concerns, and legal considerations.

In this setup, physicians are heterogeneous on two dimensions. First, physicians may have incorrect beliefs about the proper treatment intensity for the patient's level of need, making decisions based upon a potentially erroneous $\hat{F}_{2j}(.)$ as opposed to the true conditional distribution of period two health $F_2(.)$. Second, physicians will vary in their private payoffs,

both due to differences in the financial incentives they face and differences in their altruism regarding patient versus private well-being.

Given patient second period utility from health, $v(\alpha_{2i})$, physician j has objective function:

$$\begin{aligned} U(\tau_i; \alpha_{1i}, j) = &\int v(\alpha_{2i}) d\hat{F}_{2j}(\alpha_{2i}; \alpha_{1i}, \tau_i) + \pi_j(\tau_i) \\ :=&\hat{E}_j[v(\alpha_{2i})|\alpha_{1i}, \tau_i)] + \pi_j(\tau_i) \end{aligned}$$

Intuitively, the physician will choose the level of treatment intensity at which the expected marginal benefit (or harm) to the patient equals the marginal private cost (or benefit) to the physician. Under the assumption of concave, increasing expected patient benefit (i.e. the expected returns to treatment intensity diminish) and concave, increasing marginal private benefits (i.e. financial returns diminish while marginal opportunity and psychic costs increase), the physician will choose τ_i^* such that $\frac{\partial}{\partial \tau} \hat{E}_j[v(\alpha_{2i})|\alpha_{1i}, \tau_i^*)] = -\pi_j'(\tau_i^*)$.

Next, consider the individual's choice of whether to access the health care system. For simplicity, suppose that they have full insurance and do not pay any financial cost of care. In $t = 1$, person i chooses whether to access medical care or not, $m_i \in \{0, 1\}$. The individual draws a health state α_{1i} and receives flow utility $v(\alpha_{1i}) - \phi_i \cdot m_i$, where ϕ_i is the hassle and time cost of seeking care and $v(\alpha_{1i})$ is an increasing function of health. Importantly, the decision to seek out care influences the person's utility in the second period by affecting their subsequent health. The true expected benefit of accessing care depends on their health state in period 1, α_{1i}, the relative weight placed by the provider on patient health versus private payoffs, and the beliefs of the provider in the value of treatment intensity.

The individual will face two levels of uncertainty when choosing whether to seek out care. First, there is uncertainty about the physician's type, both relating to the physician's beliefs and altruism. Second, the individual will be uncertain about the benefit of the care itself, both because of the innate uncertainty in a person's ultimate 2nd period health state and because of the individual's incomplete knowledge regarding the benefits of treatment.

Define $E[v(\alpha_{2i})|\alpha_{1i}, m_i]$ as the true expected utility of patient i in the second period, which depends upon both their first period health as well as their decision of whether to access care. The expectation operator implicitly nests both uncertainty over the type (altruism and beliefs) of the physician a patient sees and over the progression of health over time with and without treatment. However, patients may have mistaken beliefs about any of these points of uncertainty — they may be overly optimistic or pessimistic about provider knowledge and altruism or about the effects of treatment. I therefore define $\tilde{E}_i[v(\alpha_{2i})|\alpha_{1i}, m_i]$ as the individual's analogous, potentially incorrect, subjective expected utility. Then, the objective

function for person i is:

$$V(m_i; \alpha_{1i}) = v(\alpha_{1i}) - \phi_i \cdot m_i + \beta \cdot \tilde{E}_i[v(\alpha_{2i})|\alpha_{1i}, m_i]$$

The individual will choose to access medicare care if

$$\begin{aligned} v(\alpha_{1i}) - \phi_i + \beta \cdot \tilde{E}_i[v(\alpha_{2i})|\alpha_{1i}, 1] &> v(\alpha_{1i}) + \beta \cdot \tilde{E}_i[v(\alpha_{2i})|\alpha_{1i}, 0] \\ \Leftrightarrow \beta \cdot (\underbrace{\tilde{E}_i[v(\alpha_{2i})|\alpha_{1i}, 1] - \tilde{E}_i[v(\alpha_{2i})|\alpha_{1i}, 0]}_{:=\tilde{\Delta}_i(\alpha_{1i})}) &> \phi_i \end{aligned}$$

This intuitive criterion simply says that an individual will access medical care if the discounted subjective expected benefit of care, $\beta \cdot \tilde{\Delta}_i(\alpha_{1i})$, exceeds the hassle cost. Under the reasonable assumption that the perceived value of care is greater in worse health ($\frac{\partial \tilde{\Delta}(\alpha)}{\partial \alpha} < 0$), there will exist a threshold α^* such that $\forall \alpha < \alpha^*$, an individual chooses to access medical care.

It is useful to define, as a benchmark, the true expected value of seeking out care, $\Delta(\alpha_{1i}) := E[v(\alpha_{2i}|\alpha_{1i}, 1] - E[v(\alpha_{2i}|\alpha_{1i}, 0]$, in which the individual has rational expectations about the distribution of physician types and the value of medical care. I then define trust in medicine as simply the difference $\tilde{\Delta}_i(\alpha_{1i}) - \Delta(\alpha_{1i})$, i.e. the gap between a person's subjective and true expected benefit from accessing medical care. Similarly, when comparing trust levels, I define person i as more trusting than person j if, $\forall \alpha$, $\tilde{\Delta}_i(\alpha) - \tilde{\Delta}_j(\alpha) \geq 0$. In the care-seeking decision, the threshold α^* is therefore increasing in the level of trust of an individual. In turn, when aggregating over health states to the population level, the model has a straightforward prediction for the effect of reduced trust: a decline in the demand for care.

Several things are important to note. First, trust in medicine is multifaceted. In the model presented above, trust can be separated into two types — trust in *motive* and trust in *ability*. The former is tied to the weight placed on patient benefit versus private payoff by physicians (in particular, the patient's perception of $\pi_j(\tau_i)$), while the latter encapsulates the difference between physician and patient beliefs about the benefits of treatment (in effect, the gap between $\hat{E}[.]$ and $\tilde{E}[.]$). For example, someone who suspects doctors of ordering unnecessary tests to generate revenue will have a low level of trust in physician motives. Meanwhile, someone rejecting vaccines due to concerns about their side-effects, even when their doctor recommends them, will have low trust in physician ability. The trends in Figure 1 suggest that both trust in motive and trust in ability have declined substantially among Republicans in the last 5 years. Importantly, though, the model prediction is the same in either case — reduced demand as patients expect the treatment choice of their

physician to benefit them less.

Second, the type of care foregone in the event of a decline in trust will depend critically upon the initial threshold α^*. In the primarily elderly or disabled population under study, utilization of routine care is quite high, suggesting a relatively lenient threshold for care-seeking at least within the distribution of elderly health.[3] In this case, the implication of the model is that the marginal health states in which care would be foregone from reduced trust will be relatively high and we would expect declines in utilization to be concentrated in routine rather than acute care. In other words, a heart attack patient will be less likely to avoid the emergency room due to distrust than a relatively health 65 year-old will be to skip an annual wellness visit. The prediction of the model in this context is that the types of visits associated with more intense care needs, such as emergency room visits and hospital stays, ought to be less responsive to the polarization of trust than routine care.[4]

Finally, it is important to note that a reduction in trust is ambiguous from a normative perspective. A person who previously expected their physician to be able to resolve any issue that arose would move closer to the correct view with a reduction in trust. On the other hand, someone starting with rational expectations of the benefits of care-seeking will forego care that would have been beneficial. Thus, whether these declines in trust have led to patient harm is ultimately an empirical question, requiring an examination of health outcomes.

3 Methodology

3.1 Data

The paper uses outcome data from two primary sources: Medicare public-use files and Center for Disease Control and Prevention (CDC) birth and death data. The Medicare data consists of two sets of files: the Medicare Geographic Variation public data (Centers for Medicare and Medicaid Services, 2025c), running from 2014 to 2023, and the Physicians and Other Practitioners data, from 2013 to 2023 (Centers for Medicare and Medicaid Services, 2025d). In my analyses, I restrict to the period 2015 and later to remove ACA-related policy shifts that could have had disparate impacts across areas.

The Geographic Variation files include county-year-level information on the general char-

[3]For instance, the share of beneficiary with at least one evaluation and management visit each year is nearly 90%.

[4]Importantly, in a population with a lower level of attachment to the health care system, either because of generally good health, high hassle costs, or low baseline trust, a decline in trust could also influence the use of acute care. Patterns may look quite different in a study focused on those aged 18-35, for example.

acteristics of Medicare's fee-for-service beneficiaries, including average age, racial composition, and the share dual-eligible, as well as summary utilization measures for a series of categories. The categories used in this paper include emergency room visits, inpatient stays, and outpatient visits, as well the Restructured BETOS Classification System groups for Part B services — evaluation and management visits, treatments, procedures, tests, and imagings. For each (mutually exclusive) category, there are variables for the average number of events, the share of beneficiaries with any event, and the average total spending in each category. In the analyses that follow, I report results for all categories, but the primary outcome is for evaluation and management visits, which includes Medicare Part B visits aimed at assessing patient symptoms or managing conditions — importantly, this category will most closely align with a reasonable definition of routine or primary care.

These measures are not without issue, though. For one, the categorizations are broad, with the evaluation and management category including both primary care and some specialist visits, as well as some evaluations that occur in an emergency department or inpatient setting. Because of this breadth, the share of beneficiaries with any visit is around 90%, making my main outcome the number of visits per beneficiary. Second, the number of visits will double-count within episodes of care. Whereas an ideal measure of care-seeking would include the number of times a person initiated contact with the health care system, these variables will capture every visit taking place within an episode. For instance, a patient who visits their PCP and is referred to multiple specialists will be counted as having several visits by this measure.

Meanwhile, the Physicians and Other Practitioners data includes provider location information and the number of unique beneficiaries seen each year per provider, restricted to those who see at least 10 beneficiaries a year through Medicare Part B. Additionally, some patient volume sub-categories, such as male versus female and white versus non-white, are reported if both categories include more than 10 people. Information on provider specialty is also included, allowing for comparisons across provider types. In most analyses, I aggregate the data to the county level, which is where I measure local political affiliation, by calculating the average patient volume of providers in the county across provider types (PCPs and specialists).

These provider measures have their own issues as well. First, these measures are subject to changes in the size of the local beneficiary population. To address this, I include controls for the county-level number of fee-for-service beneficiaries per provider to adjust for shifts in the number of potential patients and also report versions in which I rescale the number of patients per provider by the county-level ratio of the 2019 to current beneficiary population. Second, these variables are sensitive to shifts in the composition of providers through re-

tirements and entry. To address this, I include versions with the patient volumes generated from either a balanced or an unbalanced panel of providers. Third, the location information is derived from the NPPES and is often out of date, so I show robustness to using CMS' Doctors and Clinicians files, which has better location information but is only available from 2018 onward (Centers for Medicare and Medicaid Services, 2025a).

The most significant issue, which affects both sets of outcomes and which I will consider in-depth later in the paper, is that the variables are only recorded for Fee-for-Service (FFS) (or Traditional Medicare, TM) beneficiaries. During the sample frame, the share of people in TM has fallen steadily, meaning that these measures are subject to concerns of compositional shifts in the beneficiary population (in addition to the mechanical effect that could be produced in the patient volume measure). Finally, due to limited data availability amid the fragmented US health care landscape, these measures only cover care utilization by the elderly (and those with disabilities), who are covered by Medicare. Thus, this paper will be more limited in what it can say about the implications of declining trust across the full US population.

I merge the county-level panel generated from the Medicare data with a range of other sources. First, I use the CMS Mapping Medicare Disparities tool to calculate the annual share of fee-for-service beneficiaries that received a flu shot, beneficiary obesity rates, and the share with 3 or more chronic conditions (Centers for Medicare and Medicaid Services, 2025b). Second, I use the CDC's natality data to calculate the county-level share of births taking place at home by year. (Centers for Disease Control and Prevention, 2025b). Home birth counts are reported only for counties with more than 10 of the relevant events, with all other counties in each state aggregated as an additional observation. In that analysis, I thus calculate a weighted average vote share across the censored counties and treat the grouped counties as one combined county. Third, I use county-level presidential voting data from the MIT Election Data and Science Lab (2023), which includes data for presidential elections since 1976. From here, I generate my primary explanatory variable, the Trump share of a county's vote in 2020, though I also test robustness to using vote shares from 2016 and 2024. Fourth, I use data from the CDC on Covid-19 restrictions in each county between April 2020 to August 2021, constructing a measure of policy stringency by calculating the share of days in this window in which either a mask or gathering restriction was in place (Centers for Disease Control and Prevention, 2021). In robustness checks, I also merge on data from the Bureau of Labor Statistics' Local Area Unemployment Statistics to measure shifts in economic conditions during the pandemic (U.S. Bureau of Labor Statistics, 2025).

I use several other sources of provider-level data. First, I use data from the CMS' Doctors and Clinicians file mentioned earlier to identify graduation year in addition to location. In

all physician level analyses, I restrict to providers at least ten years out of medical school to remove both residents and early-stage providers in the process of building up a patient panel. Second, I use two data sources for identifying physician political ideology. The first is the Database on Ideology, Money in Politics, and Elections (DIME), which provides information on political donations linked to physician NPIs from 1991-2012 (Bonica, 2024). I add more recent election cycles — 2014 to 2020 — by linking to physician names (first, matching on state + name and then, for unique names, on name alone). Because many physicians have not donated, I supplement this with information from the L2 2025 voter files (L2, 2025). These files contain party registration for the majority of states for those registered to vote, and in the subset of states without party registration, use a prediction algorithm to impute individual party. In matching to lists of providers, I first search for matches within state and name. For physicians matched to multiple names in the L2 data, I prioritize those whose practice locations are in the same county as the voter's address. If there remain multiple matches, I prioritize those who are recorded as working in the medical profession or in the "Other" category (which in spot-checking was a common occurrence). If there remained ambiguity for the matches, providers were then dropped.

In total, almost 1,000,000 unique providers were matched to the L2 data, of whom just under 700,000 were identified as either Democrats or Republicans, though the majority were removed when restricting to a balanced panel of those seeing at least 10 patients in all years of data. In contrast, the sample of donating physicians included around 270,000 unique NPIs, though the majority again were not preserved in the balanced panel. I combine these by first taking provider political party from L2 for those who were matched to the voter file, and supplementing with the DIME version where the NPI was unmatched or party was not assigned. I also report results that restrict to the set of donors, given that these are likely to be more politically engaged and potentially more outspoken than the broader set of providers. In the political analysis, I restrict to physicians since the DIME data does as well, but other analyses include nurse practitioners and physician's assistants.

In my analysis of health outcomes, I also use the CDC's county-level mortality data to obtain overall and infant annual mortality rates, as well as rates by age bin and race (Centers for Disease Control and Prevention, 2025a). Variables are reported only for counties with more than 10 of the relevant events, so I restrict to a balanced panel of counties in the mortality analyses.

In Table 1, I report descriptive statistics for my main county-level utilization dataset. Several things are apparent. First, the large majority of counties voted Republican, even as the national vote was relatively evenly split, reflecting the relatively large number of less populated rural counties in the US and motivating the use of population weights in the

analyses that follow. Second, on many dimensions, the rates of utilization between more Republican and Democratic areas are quite similar — beneficiaries in both Republican and Democratic counties had around 0.6 ER visits and just over 0.2 inpatient stays per beneficiary in 2023. At the same time, Republican counties get somewhat higher outpatient care and have fewer EM visits per person. And while age (among Medicare beneficiaries) is relatively balanced, Republican counties are much whiter on average and have lower rates of dual-eligibility with Medicaid. Though the cross-sectional differences in routine care utilization are suggestive, the other potentially biasing demographic differences across areas motivate my analysis over time as described next.

Table 1: Descriptive Statistics — County-Level CMS Sample

	GOP	Dem.
Trump 2020 Share	0.64	0.36
ER Visits per Beneficiary	0.60	0.58
Inpatient Stays per Beneficiary	0.22	0.23
Outpatient Visits per Beneficiary	5.06	4.17
EM Visits per Beneficiary	13.01	15.71
Beneficiary Avg. Age	72.69	73.04
Beneficiary White Share	0.87	0.70
Beneficiary Dual Elg. Share	0.14	0.20
Observations	2445	557

Notes: Table reports 2023 weighted means by whether a county gave over or under 50% of the 2020 vote to Trump.

3.2 Empirical Strategy

In an ideal experiment, we would be able to randomize trust in the population and assess its impact on the utilization of health care. Given the aggregated level of my data and the impracticality of directly altering patient trust, my approach is instead to exploit the shock induced by the Covid-19 pandemic and examine utilization across areas differentially exposed to the reduction in trust. I do so by tracing out utilization of care in recent years across geographic political orientation over time. This approach leverages the politically polarized nature of recent declines in trust, though it also requires a thorough consideration of alternative possible explanations for shifts.

My baseline regression specification is:

$$y_{ct} = \sum_{k \neq 2019} \beta_k \times GOP_c \times \mathcal{I}[t = k] + \phi_t + \psi_c + \epsilon_{ct}$$

where GOP_c is the county-level 2020 Trump vote share, ϕ_t and ψ_c are year and county fixed

effects, ϵ_{ct} is an error term, and y_{ct} is a county-year level outcome such as log evaluation and management visits per beneficiary. The coefficients of interest are β_k for k between 2015 and 2023, leaving out 2019, which reflect shifts in the relationship between vote share and the outcome relative to 2019. In some specifications, I include state-year fixed effects as well, restricting to within-state cross-county comparisons. This has the benefit of removing any state-level economic, social, or policy shocks that could bias results, but at the expense of shutting off potentially useful variation across states with different pandemic related policies, media landscapes, or cultural attributes that could influence trust. In versions that examine the log number of beneficiaries per provider, I also control for the log number of beneficiaries in the county relative to the number of providers since these measures are sensitive to the size of the local Medicare population.

A core assumption in these analyses is that it is not the politics of a location but rather the politics of individuals in the location that drive these patterns. In other words, if more Republican areas see lower utilization post-Covid, I interpret this as reflecting reduced utilization *among Republicans*. Though this is not directly testable, I provide evidence looking at demographic heterogeneity to suggest this is reasonable. Taking this further, if we assume that a person's trends in utilization conditional on their own political preferences are independent of the political preferences of their location (and, that county vote reflects the political preferences of the Medicare population), the coefficients can be interpreted as the relative change in utilization between Democrats and Republicans over time. This is likely not exactly true, but may be a reasonable approximation with which to interpret magnitudes, though I generally avoid doing so directly.

When I examine the role trust-relevant sources of heterogeneity, I add a third difference to the estimating equation. First, to assess the role of Covid restrictions, I modify the above specification by adding the interaction term $Restr_c$:

$$y_{ct} = \sum_{k \neq 2019} (\beta_k \times GOP_c \times Restr_c + \alpha_k^G \times GOP_c + \alpha_k^R \times Restr_c) \times \mathcal{I}[t = k] + \phi_t + \psi_c + \epsilon_{ct}$$

Where $Restr_c$ is the county-level share of days between April 2020 and August 2021 in which a county had either a mask mandate or gathering restriction in place. In this case, β_k represents the extent to which changing utilization across political geography is exacerbated or mitigated by local Covid-19 policies.

Meanwhile, when examining heterogeneity by physician political affiliation, I shift to running analyses at the provider j level and include the interaction Dem_j for whether a

physician is a Democrat:

$$y_{jct} = \sum_{k \neq 2019} (\beta_k \times GOP_c \times Dem_j + \alpha_k^G \times GOP_c + \alpha_k^{ch} \times Dem_j) \times \mathcal{I}[t = k] + \psi_{ct} + \epsilon_{jct}$$

In these analyses, I include county-year fixed effects, both to remove the influence of shifts in the local FFS population and because physician characteristics influence sorting across political geography (and local politics may influence those of providers as well). Now, β_k represents the extent to which changing utilization across local political affiliation is exacerbated or mitigated by the identity of the provider.

In all analyses, I cluster standard errors at the county level and weight by the population. I show robustness to several weighting approaches, but my primary specifications weights by the 2010 population with the aim of holding this fixed so that coefficients are not driven by changes in weights.

Across these specifications, the identifying assumption in order to interpret the results as indicating the effect of trust is that the β_k estimates would be zero in the absence of post-pandemic trust polarization. In words, more or less Republican areas would have trended similarly since 2020 and neither the restrictiveness of pandemic policies nor physician politics would have influenced trends across local political orientation.

4 Results

4.1 Trust and the Demand for Routine Care

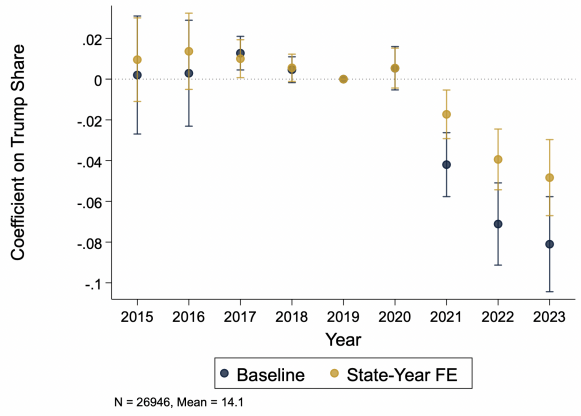
I now turn to my main results on the effect of declining trust on the demand for care. Throughout, I report event study figures, but tables with all corresponding coefficients are reported in the Appendix. I begin by examining trends in the number of evaluation and management visits per beneficiary across the political orientation of counties. Given the polarized nature of recent declines in trust, I interpret Republican vote shares as a measure of exposure to reduced trust. Then, I proceed to an examination of two sources of heterogeneity that may exacerbate polarized trust — the stringency of pandemic restrictions and the political affiliation of physicians.

First, in Figure 2a, I report continuous event study estimates for the log number of evaluation and management visits per beneficiary, with each point estimate reflecting the relative influence of an increase in the Republican vote share in a given year, relative to 2019. The figure reports versions both without (blue) and with (gold) state-year fixed

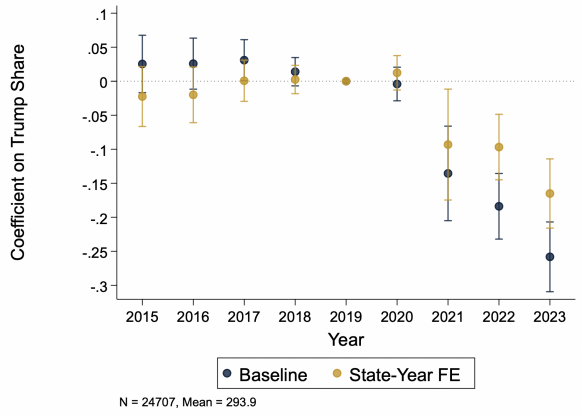
effects included. In the pre-period, the influence of county-level political affiliation was relatively stable, with Republican counties trending similarly to Democratic ones. Beginning in 2021 and continuing through 2023, more Republican areas saw steep relative declines in the number of visits per beneficiary. Notably, these declines have continued as time since the pandemic has gone on, paralleling the continued decline in trust seen among Republicans. By 2023, a 10 percentage point increase in the Trump 2020 vote share implied a 0.8% reduction in the number of visits per beneficiary. When restricting to within-state comparisons, the coefficient falls somewhat, but still implies a roughly 0.5% reduction for a 10 percentage point increase.

Figure 2: Event Study Results - Utilization of Routine Care

(a) Log E&M Visits per Beneficiary



(b) Log Beneficiaries per PCP



Notes: Figures report coefficients on the 2020 Trump vote share interacted with year dummies for either the baseline specification (blue) or the specification with state-year fixed effects included (gold). Samples restrict to counties with 9 years of non-missing data, which requires at least ten beneficiaries (left) and at least one PCP (right). Regressions are at the county level, weighting by the 2010 population, with standard errors clustered at the county level. Evaluation and Management visits are defined by CMS based on the Revised BETOS Classification System (RBCS) and beneficiaries per PCP are for a balanced panel of providers who appear in all years of data.

In Figure 2b, I turn to the patient volume of local providers, focusing on PCPs since their patients are likely to come from nearby (so provider county will be a reasonable approximation to patient location) and because they will be most responsible for routine and preventive care. In each regression, I control for the log number of fee-for-service beneficiaries relative to the number of PCPs in the county to try and absorb shifts caused by changes in the size of a provider's potential pool of patients. As with the evaluation and management measure, there are limited pre-trends before a rapid relative decline in Republican areas in

patient volumes beginning in 2021 and continuing through 2023. As before, estimates are somewhat smaller with state-year fixed effects included, but between the two specifications a consistent story emerges. By 2023, a 10 percentage point increase in the local Trump vote share implied a 1.5-2.5% decline in patient volume for PCPs. And as with the E&M results, this polarization has continued growing in the years since the pandemic as trust in medicine among Republicans decreased further.

In Appendix Figure A.2a and Figure A.3a, I show that the evaluation and management patterns are robust to simply considering whether or not a county voted for Trump and that they are replicated when using levels rather than logs. Moreover, though an aging Medicare population means utilization has been rising over time, Appendix Figure A.4 shows that in Republican counties, the number of visits has not returned to the long-run trend and that conditional on beneficiary population characteristics, utilization has remained lower in Republican counties. Thus, these shifts appear to be driven by reduced utilization in more Republican areas rather than simply increased utilization in more Democratic ones. I also examine the share of beneficiaries with any evaluation and management visit in Figure A.5, with a decline in the share post-Covid in more Republican areas following an increase during the pandemic. However, given that the share of beneficiaries with any visit is around 90% and many non-routine events, including evaluations at the emergency room, are included in this measure, it is unsurprising that the effect sizes are more muted than in the number of visits measure where there is more variation and the majority of visits would fall under a reasonable definition of routine care.

As with the evaluation and management results, similar patterns emerge for PCP patient volumes when using levels rather than logs or a binary Trump-county variable, and an examination of raw and residualized trends suggests that it is declining utilization in more Republican areas rather than increases in more Democratic areas driving the shifts (Appendix Figure A.2b, Figure A.3b, and Figure A.4). Several other considerations are necessary for the provider-level variables. First, my main outcome is generated from a balanced panel given that shifts in the composition of providers from entry or retirement could shift average patient volume without indicating changing demand. However, differential entry or exit could also impact the patient volume of the balanced panel of providers. In Appendix Figure A.6, I report versions of analyses with an unbalanced panel, documenting similar patterns. Second, shifts in the number of local fee-for-service Medicare beneficiaries, whether because of population aging, mortality, or exit to Medicare Advantage, could all influence patient volume. In the core specification, I control for the log of the ratio of Medicare FFS beneficiaries to PCPs in the county. In Appendix Figure A.6, I also show results removing any control, controlling for just the log number of fee-for-service beneficiaries, and finally

when directly rescaling average patient volume by the ratio of the 2019 county-level FFS population to the current population, each yielding similar results. I also report a version that replaces physician locations from the CMS' Physicians and Other Practitioners files with those in the Doctors and Clinicians files, which are more up-to-date but begin only in 2018, with similar results.

In Appendix Figure A.7, I show that these routine care patterns are robust to a variety of other alterations. Changing the election year used to calculate vote shares makes almost no difference to the results. Nor does the inclusion of a range of beneficiary composition controls or modifications to the weighting approach alter results meaningfully. Though estimates are much noisier when removing county-level population weights altogether, which is unsurprising given the large number of small counties in the US, the general qualitative patterns remain.

Together, these patterns indicate a substantial shift in the way Americans, particularly in more conservative areas, have interacted with the health care system in recent years. The rapid decline in reported trust among Republicans has coincided with sharp declines in routine care utilization. I next examine the relationship between local political orientation and demand for routine care across two sources of trust-related heterogeneity — pandemic-related public health measures and the political affiliation of physicians.

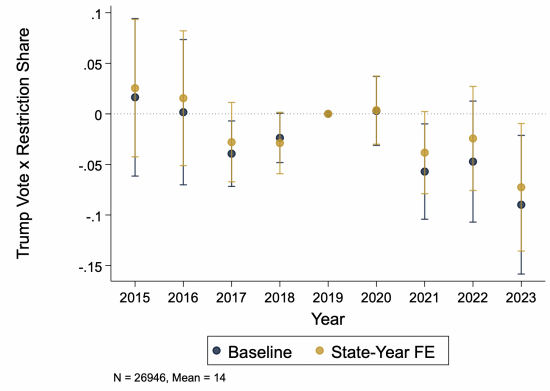
I begin by analyzing the influence of Covid-19 policies in driving changes in the utilization of routine care. Importantly, because many policies were implemented at the state-level, a substantial number of Republican counties had stringent restrictions while many Democratic counties had lax ones. Given the role of Republican dissatisfaction toward public health in driving shifts in attitudes toward medicine and doctors (O'Brian and Kent, 2025), I hypothesize that the influence of political affiliation will be larger in places that had stronger restrictions.

In Figure 3a and Figure 3b, I test this proposition directly, examining both evaluation and management visits (a) and PCP patient volumes (b). In each case, declining utilization in more Republican areas is concentrated in places that had more restrictive policies. For Evaluation and Management visits, I estimate that moving from the 25th to 75th percentile of policy restrictiveness (an increase from roughly 50% of days under restriction to nearly 90%), increases (in absolute terms) the coefficient on the Republican vote share by around 0.03, a roughly 40-60% increase relative to the estimates in Figure 2a. For PCP patient volumes, the analogous estimate is an absolute increase in the coefficients of 0.05-0.08, or roughly a third of the estimates in Figure 2b. These findings suggest that the pandemic, and dissatisfaction with restrictions among Republicans, have played a key role in driving shifts in utilization of routine care. And given the link between the pandemic and distrust, they

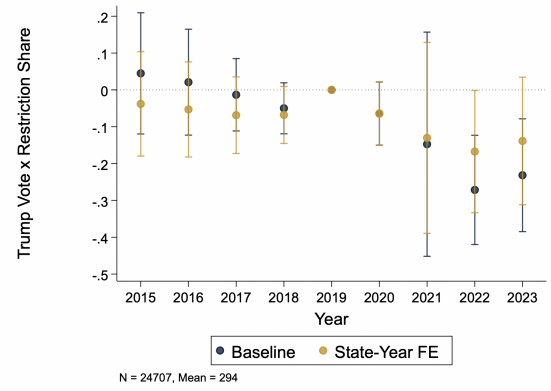
provide further evidence to support the conclusion that declining trust has driven shifts in routine care use.

Figure 3: Heterogeneity in the Demand for Routine Care

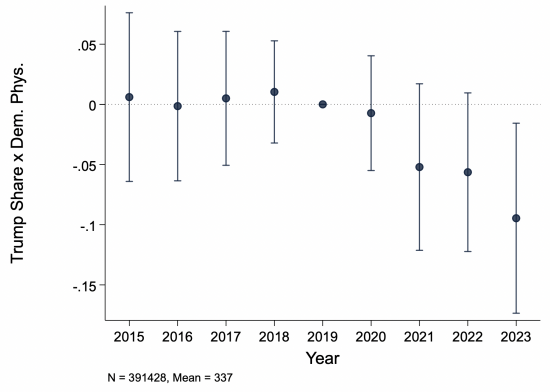
(a) Log E&M Visits by Covid-19 Policies



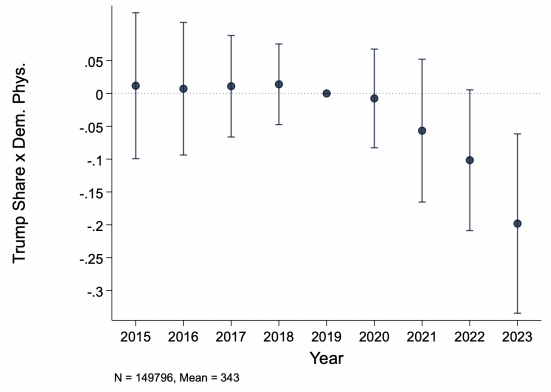
(b) Log PCP Patients by Covid Policies



(c) Log Patients by Party — PCPs



(d) Log Patients by Party — PCP Donors



Notes: Figures report coefficients on the 2020 Trump vote share interacted with year dummies and (a-b) a the county-level share of days from April 2020 and August 2021 with a mask mandate or gathering restriction or (c-d) whether the physician is a Democrat. Parts (a-b) report both the baseline specification (blue) or the specification with state-year fixed effects included (gold) and are run at the county level, weighting by the 2010 population, with standard errors clustered at the county level. Meanwhile, (c-d) are run at the provider level, include a county-year fixed effect, and cluster standard errors at the county level. Evaluation and Management visits are defined by CMS based on the Revised BETOS Classification System (RBCS) and beneficiaries per PCP are for a balanced panel of PCPs.

I next consider the role of the match between patient-provider beliefs using data from DIME and L2 on political orientation of providers. Under the assumption that the county-level vote share is a reasonable approximation of the political beliefs of the patients seen by a given provider, I interpret differences in the effect of the Republican share on patient

volumes between Democratic and Republican physicians as evidence on the importance of belief concordance in shaping trust and care utilization. While it may not necessarily be the case that individuals directly observe the political affiliation of their provider, past work has highlighted divergent practice styles and beliefs surrounding Covid-19, which may well be apparent to patients when discussing issues such as vaccinations (Kim, 2025; Levin et al., 2023). Moreover, survey evidence since the pandemic has shown that patients have a strong preference for political alignment with their provider (O'Brian and Kent, 2025). It would not be overly surprising if patients read into pandemic-related cues or assessed other provider characteristics to infer their political views.

In Figure 3c, I report coefficients on interactions between physicians being a Democrat, the Trump vote share in a county, and the year. In these specifications, I include county-year fixed effects to restrict to comparisons between Democrats and Republicans in the same counties to account for substantial differences in average location characteristics between the two groups. The results are striking — a 10% increase in the Republican vote share implies a 1 percentage point larger decrease in patient volumes for Democratic versus Republican PCPs. Though the sample is considerably smaller, Figure 3d restricts to the set of primary care physicians who have made political donations. This subset of physicians is likely to be more politically engaged, and given that political identity in the L2 is sometimes imputed, their political views may be less affected by mis-measurement. In this sample, the effect sizes are even larger, with coefficients around 2 times those for the full set of PCPs (though with large standard errors, I cannot reject the null hypothesis of no difference between the coefficients).

Importantly, as shown in Figure A.9 these patterns are only evident when focusing on primary care physicians, with no change over time in patient patterns between Republican and Democratic specialists. This is consistent with both the important role PCPs play in vaccinations, one of the most politically contentious issues in health care, and the fact that patients typically have more frequent, repeated interactions with PCPs in which a mismatch in beliefs would become evident.

There remain several relevant caveats to the physician politics findings, though. First, though political affiliation is available for a large number of physicians, many do not match to the Medicare sample (either because they practice only in an inpatient setting or do not see 10 or more Medicare patients). When restricting further to a balanced panel of providers who saw at least 10 FFS Medicare patients in all years between 2015-2023, several hundred thousand additional providers are removed. I also remove providers that moved during the sample period to avoid confounding patient demand with supply side shifts, and I restrict to those who graduated at least 10 years earlier from medical school to ensure they have had

time to build their own patient panels. Additionally, the inclusion of county-year fixed effects restricts comparisons to physicians practicing in counties with at least one other provider in the sample. Altogether, these sample restrictions results in a balanced panel of around 150,000 unique providers. In Appendix Figure A.10, I show results for PCPs when removing balanced panel restrictions, allowing providers to move counties, or replacing locations with those from the Doctors and Clinicians files. In some cases, results are slightly noisier but the general patterns remain robust.

These estimates highlight two key points. First, what was once a relatively bipartisan sector, both in the views of providers and patients, has followed the rest of the country in its politicization. This shift has important implications for health care politics, the implementation of policy, medical spending, and population health moving forward. Second, the match between provider and patient beliefs appears central to the building of trust. To some extent, the sorting of Democratic and Republican physicians into Democratic and Republican areas may have mitigated even greater declines in trust. However, directly sorting physicians and patients by political views is not a feasible policy, meaning that improved communication between patients and physicians of different beliefs will be important in bridging gaps of trust.

Together, this section has presented three sets of results indicative of a trust-induced fall in demand for routine care among Republicans. First, I documented substantial reductions in routine care use in Republican areas since the pandemic, with the timing of these declines closely aligning with reductions in reported trust in medicine by Republicans. Second, I showed that these reductions have been concentrated in places with more stringent pandemic restrictions, consistent with backlash against public health measures driving declines in trust. Third, I showed that falling patient volumes in Republican areas are particularly pronounced for Democratic PCPs, in line with the partisan nature of rising distrust and suggesting the potential for mismatched beliefs to exacerbate distrust. Next, I examine the role of shifting trust in the use other categories of care.

4.2 Trust and the Composition of Care

One of the main implications of the theoretical model presented earlier is that, in an elderly population with a high level of connection to the health care system, routine care ought to be most influenced by declining trust. In contrast, reductions in utilization of acute care may indicate more general health improvements that could confound estimates of the effects of trust. In this section, I examine a broader set of care measures, ranging from hospital based care to other more routine categories. Before discussing the results, several

important points are necessary.

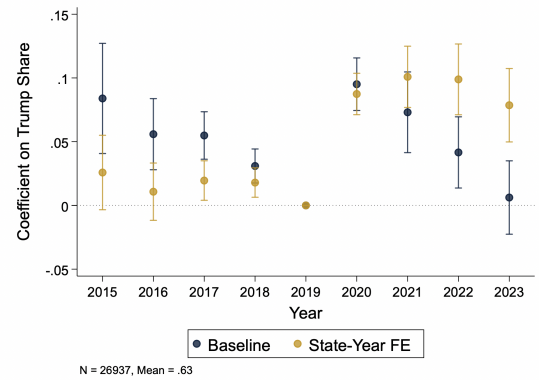
First, these outcomes exhibit more substantial pre-trends than had been the case for the routine care measures, though they generally improve when considering within-state variation, particularly for the hospital based-measures. One potential reason for this is that state policy may be especially important for hospital care, given that policies such Medicaid expansion are at state discretion and may influence hospital closures and consolidation directly. Second, these measures may be directly influenced by the pandemic more significantly than evaluation and management visits. Given the risk of ER visits and hospitalizations among those infected with Covid-19, higher utilization may be expected among Republicans in some categories given their lower adherence to social distancing and vaccination guidelines. Additionally, these services can generally not be performed remotely, meaning that delayed use of elective care by Democrats during the pandemic will be more apparent here. Third, some of these measures, particularly the ER visit category, may reflect the influence of trust on health outcomes and move inversely with routine care utilization. Despite their limitations, the patterns reported across these categories are consistent with the theoretical prediction of the model.

Beginning with Figure 4a, I show estimates for the log number emergency-room visits per beneficiary. As noted before, the baseline specification shows a declining pre-trend that disappears when focusing on within-state variation, suggesting a potential role for state-level policy in driving these trends. Beginning in 2020, emergency room visits increased substantially in more Republican areas and remained elevated through 2023. Initially, this likely reflected a mix of stay-at-home behavior and severe Covid-19 infections. However, the fact that these shifts persist to 2023, even after rates of infection had fallen substantially, is striking. One possibility is that this is driven by the ongoing effects of past severe cases (i.e. long Covid). Another is that it reflects the health consequences of reduced utilization of preventive and routine care or delayed care-seeking upon the onset of illness. Importantly, the magnitudes are not large enough to suggest that people are simply substituting from routine to emergency care when they get sick — focusing on the version with state-year fixed effects, the coefficient for 2023 implies that a 10 percentage point increase in the Trump vote share results in roughly 0.005 more visits per person, in contrast to more than 0.1 fewer implied E&M visits.

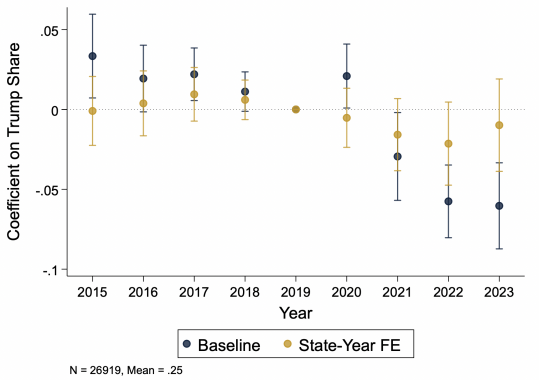
Next, in Figure 4b and Figure 4c, I show results for the log number of inpatient stays and outpatient visits per person. As with emergency room visits, inpatient stays were declining prior to 2020 in more Republican areas, though in this case they continued to do so after 2020. And again, the inclusion of state-year fixed effects removes most of this trend (as well as most of the post-pandemic decline), suggesting the potential influence of state policy. For

Figure 4: Event Study Results — Other Care Categories

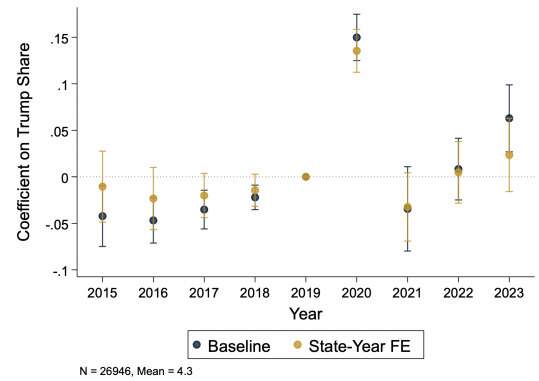
(a) Log ER Visits per Beneficiary



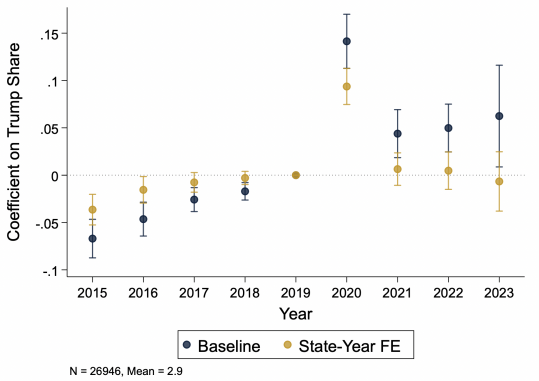
(b) Log Inpatient Stays per Beneficiary



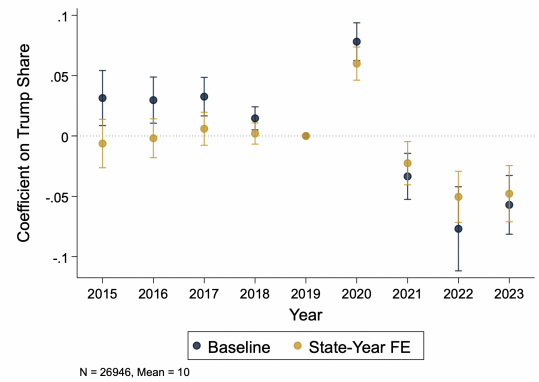
(c) Log Outpatient Visits per Beneficiary



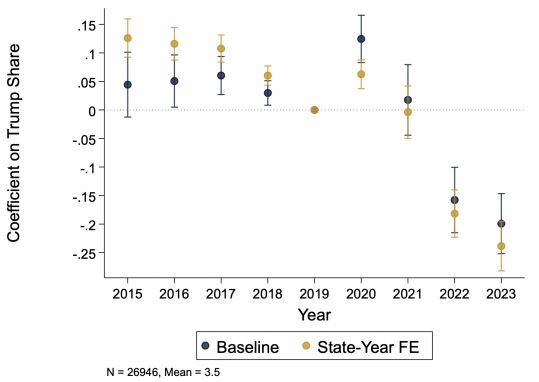
(d) Log Procedures per Beneficiary



(e) Log Tests/Imag. per Beneficiary



(f) Log Treatments per Beneficiary



Notes: Figures report coefficients on the 2020 Trump vote share interacted with year dummies for either the baseline specification (blue) or the specification with state-year fixed effects included (gold). Regressions are at the county level, weighting by the 2010 population, with standard errors clustered at the county level. Category variables are generated by CMS from fee-for-service Medicare claims under the Revised BETOS Classification System.

hospital outpatient visits, the inclusion of state-year fixed effects again attenuates both the pre-trend and post-pandemic coefficients. In either case, the number of outpatient visits was trending up somewhat before the pandemic, spiked in 2020 in more Republican areas as Democrats avoided in-person activity, and then returned roughly to its pre-trend by 2023.

Altogether, the hospital-based care measures highlight several key points. First, though results are noisier than for routine care, they are instructive in what they do not show. In each case, there is no evidence of improved underlying health in Republican areas which would depress the use of care across the board. Second, the results are consistent with the theory that demand for acute care will be less directly influenced by patient trust. Finally, as is discussed later when examining mortality rates, the results for ER visits are indicative of a continued deterioration of health in more Republican areas relative to Democratic ones, even as pandemic-related mortality has abated.

In parts d-f of Figure 4, I report results for three other care categories, derived by CMS, as with the E&M measure, from Medicare Part B claims using the Revised BETOS Classification System: Procedures, Tests+Imagings, and Treatments. In two of three cases, with the exception of procedures, these categories exhibit significant declines post-Covid. These patterns are consistent with the E&M results — a reduced number of visits will naturally result in fewer tests and imagings. Additionally, given that vaccinations fall under the treatments category, lower utilization in more Republican areas is unsurprising. Importantly, these reductions in tests, imagings, and treatments confirm that not only are fewer visits occurring but that people are receiving less actual care. At the level of aggregation available, it is unclear whether the care being foregone is of high or low value, though it presumably includes some of both. In the final set analyses, focused on health behaviors and outcomes, I return to this question with the goal of understanding whether the broad set of trust-related changes in health behaviors and care utilization have had an impact on health outcomes.

I also report results for the patient volumes of specialists, though the interpretation is less immediately clear. On the one hand, specialty care may be viewed as more urgent than non-specialty care, reducing the role of patient trust. On the other hand, many specialty visits will be generated from referrals by PCPs, patients may lack longer-term relationships with specialists during which trust has been built, and much specialty care will be with the purpose of managing ongoing, non-emergent conditions for which patient care-seeking is important. It is also important to note that this measure is generated from Part B claims and thus does not involve inpatient care provided by specialists. Results are reported in Appendix Figure A.8, showing some evidence of reduced specialist patient volumes, though there tends to be more of a pre-trend and less evidence of a clear trend break across the varying specifications.

Finally, I report results for two other highly trust-dependent measures — flu vaccinations among the elderly and home births. Flu vaccinations, and vaccines more generally, have been a flash-point of trust in medicine following the deeply partisan roll-out of Covid-19 vaccines. Meanwhile, media coverage of intended home births frequently references concern about intrusive and unnecessary care at hospitals as a driver of this decision (O'Brien, 2026). In each case, there have been substantial shifts in recent years, with vaccination rates declining and home births increasing sharply. Moreover, each behavior is associated with a clear risk — illness and mortality for vaccinations and birth complications and infant mortality in the case of home births — and are encouraged or discouraged, respectively, by the medical establishment.[5]

In Figure 5a, I report estimates for the influence of the Republican vote share over time on influenza vaccination rates. As shown in Appendix Figure A.11a, in the years running up to the pandemic, annual influenza vaccination rates were actually rising among the Medicare population, both in Republican and Democratic areas. This changed rapidly with the pandemic, however. By 2023, the share receiving an annual dose had declined by 5 percentage points in counties won by Trump relative to 2019, compared to a 2 percentage point decline in Democratic counties. With the continuous measure, I find that by 2023, a 10 percentage point increase in the Trump vote share implies a 1 percentage point decrease in the vaccination rate. Given that these decreases were off a mean of less than 50%, the effects are sizable and could have substantial implications for population health.

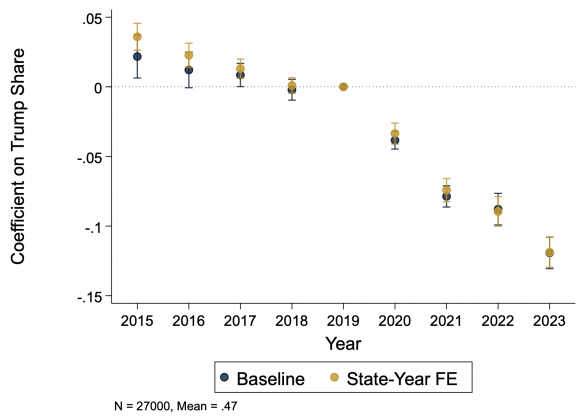
Next, in Figure 5b, I report equivalent results for the fraction of births occurring at home intentionally, which past work has found to be associated with much higher rates of complications and mortality (Grünebaum et al., 2020). Importantly, data censoring required that many smaller counties be combined within each state, with the explanatory variable being the weighted average of the Trump 2020 vote share. Home births remain rare, but have grown rapidly in prevalence in the years since the pandemic as illustrated in Appendix Figure A.11b. Importantly, much of this increase has been driven by more Republican areas, with Trump-voting counties experiencing double the increase of Democratic counties. In continuous terms, a 10 percentage point increase in the Trump vote share implies, by 2024, a 0.15 percentage point increase in the share of births intentionally occurring at home. Given

[5]On flu shots, the American Medical Association's website states "everyone six months and older should get an annual flu shot. Influenza vaccination remains one of the best preventive measures for containing the spread and severity of flu." On Home births, the American College of Obstetricians and Gynecologists is more nuanced, stating that it "believes that hospitals and accredited birth centers are the safest settings for birth" while also noting that "each woman has the right to make a medically informed decision about delivery."
https://www.ama-assn.org/topics/influenza-seasonal-flu
https://www.acog.org/clinical/clinical-guidance/committee-opinion/articles/2017/04/planned-home-birth

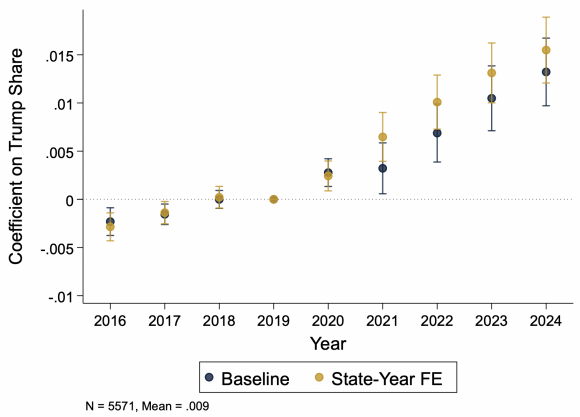
the still-low home birth share of a little over 1% post-pandemic, this implies a more than 10% increase relative to the mean.

Figure 5: Event Study Results - Trust-Related Measures

(a) Flu Vaccination Rate



(b) Intended Home Birth Share



Notes: Influenza vaccination rates are for the FFS Medicare beneficiary population, from the Mapping Medicare Disparities tool, while home birth rates are from CDC Wonder's natality data. Each figure reports coefficients from regressions of flu vaccination rates on the Trump 2020 vote share interacted with year dummies and (gold) state-year fixed effects. Regressions are at the county level, weighting by the 2010 population, with standard errors clustered at the county level.

Together, the results in this section provide further evidence of the effect of declining trust on demand for health care. Consistent with the theoretical prediction of my model, declines in utilization in Republican areas are pronounced for routine care and generally absent for acute care measures. Meanwhile, flu vaccine take-up has declined rapidly while the share of births intentionally occurring at home have spiked in more Republican counties, in line with the close link these outcomes have with trust in medicine. Next, I consider several alternative explanations for the shifting utilization patterns across political geography. Though the core patterns and heterogeneity analyses are compelling, it is important to rule out alternative stories that could drive changing utilization across different geographic areas.

4.3 Alternative Explanations

First, I consider the possibility that financial conditions or costs are driving these shifts. On the one hand, this should in general be less of a concern for my sample of Medicare beneficiaries given that the large majority are not working and prices are set centrally. At the same time, given extensive past work highlighting the positive relationship between income

and health care utilization, local economic shifts could affect non-Medicare demand and in turn influence the supply side, or impact the wealth of Medicare beneficiaries. Reassuringly, as shown in Appendix Figure A.12, in the post-Covid period, unemployment was actually lower in more Republican areas, potentially due to the lingering impacts of restrictions or stay-at-home behavior. A related concern is that shifts in the share of dual-eligible beneficiaries, those covered by both Medicaid and Medicare, could alter the price facing patients. In Appendix Figure A.13a, I test for this, finding little evidence of post-pandemic changes.

Next, I examine the possibility that better health or other compositional shifts in the Medicare fee-for-service population are driving the observed patterns. The estimates in Figure 4a showing increases rather than decreases in the number of emergency room visits per beneficiary suggest that if anything, the health needs of the population may be increasing. However, there are several other factors I can examine. In Appendix Figure A.14a and Figure A.14b, I report estimates for two other measures from CMS' Mapping Medicare Disparities data — first, the share of beneficiaries with a past diagnosis for 3 or more of a set chronic conditions, and second, the obesity rate among beneficiaries.[6] In neither case is there evidence of health improvements among the FFS Medicare population. In Appendix Figure A.14c, I report estimates for the average age of the FFS population at the county level, again finding no evidence of shifts that might drive reduced need for routine care.

In Appendix Figure A.13, I report patterns for two other compositional measures: the white share of FFS beneficiaries and the share of all Medicare beneficiaries who are in traditional fee-for-service Medicare, though it is important to note that data censoring means the former is only available for a subset of counties. The white share coefficients begin declining in the years prior to the pandemic and accelerate somewhat in the years since. Given the large racial differences between more Republican and Democratic areas, it is perhaps not surprising that trends differ on this measure between them. However, these shifts are very unlikely to be driving the results, for several reasons. First, the shifts appear largely driven by a broader increase in the white share of FFS beneficiaries after 2019, and since Republican counties were already predominantly white the increases were concentrated in Democratic ones (Appendix Figure A.15a). When including controls for the 2019 white share of FFS beneficiaries interacted with year dummies to control for the influence of baseline rates in subsequent shifts, the magnitude of coefficients falls substantially, without meaningfully al-

[6]The conditions are AMI, ADRD, Anemia, Asthma, Atrial Fibrillation, Benign Prostate Hyperplasia, Cancer (Colorectal, Breast, Prostate, Lung, Urologic, or Endometrial), Cataracts, Chronic Kidney Disease, COPD, Depression, Diabetes, Glaucoma, Heart Failure, Hip/Pelvic Fracture, Hyperlipidemia, Hypertension, Hypothyroidism, Ischemic Heart Disease, Obesity, Osteoporosis, Parkinson's Disease, Pneumonia, Rheumatoid Arthritis, Schizophrenia/Other Psychotic Disorders, and Stroke.

tering the routine care estimates (Appendix Figure A.15). Second, as shown in Figure A.17e, the effects for patient volumes are largely accounted for by reductions in the number of white beneficiaries, which cannot be driven by race compositional changes alone.

Next, I consider shifts in the FFS share of beneficiaries, which is particularly important given the rapid increase in the popularity over Medicare Advantage over the last decade. As is shown in Appendix Figure A.16a, the share of beneficiaries with FFS Medicare has been trending down in more Republican areas relative to Democratic ones in recent years. However, this shift again appears disconnected from the utilization patterns reported earlier. As the shift toward Medicare Advantage has accelerated in recent years, it has done so in particular in regions with lower baseline MA prevalence, which tended to be more Republican. In Appendix Figure A.16b, including interactions between the 2019 FFS share and year dummies (gold) to control for baseline prevalence in shifts over time reduces the estimated coefficients dramatically. Moreover, take-up of Medicare Advantage is highly age-dependent, with younger beneficiaries driving many of these shifts. Adding controls for the average age of the FFS population in 2019, again interacted with year dummies to control for this measure's influence on trends, wipes out most of the remaining effect. Critically, as is shown in Appendix Figure A.16c and Figure A.16d, adding these same controls to my main analyses on demand for routine care has almost no influence on the estimated coefficients. In other words, Republican areas started my sample period more exposed to many of the predictors of post-2017 Medicare Advantage growth, but these same predictors do not explain the shifting utilization patterns.

I also note that though compositional trends in race and FFS prevalence are apparent when examining more or less Republican areas, they do not explain the heterogeneity documented earlier between high and low restriction areas or providers of different political leanings. In Appendix Figure A.15e and Figure A.16e, I show results when including the pandemic restriction interactions. Though there are some pre-trends, there is no post-pandemic trend break and the patterns are inconsistent with the shifting utilization presented in Figure 3. Meanwhile, the provider politics analysis includes county-year fixed effects, meaning that comparisons are between physicians in the same counties, in effect shutting off the impact of any county-level differential trends in beneficiary compositions. Together, these various results suggest that compositional shifts are an implausible explanation for the changes in utilization post-pandemic.

The third alternative explanation I consider is that these patterns are driven by supply side shifts, either on the extensive margin through moves or retirement or the intensive margin through hours worked or staffing levels. Given that the number of patients per PCP falls in more Republican areas, the patterns cannot be explained fully by extensive margin

shifts. However, it would also be surprising if the supply side of the market did not respond at all to demand. Indeed, in Appendix Figure A.17b, I report estimates for the log number of PCPs per county from the CMS' Doctors and Clinicians files (which begins in 2018 and runs through 2025). In the initial years post-Covid, there is in fact a slight increase in supply contrary to the declining utilization, but over time this reverses and the supply of providers begins declining starkly. These patterns are consistent with a supply response to declining demand rather than an extensive margin supply shift that causes the changes in utilization.

Although the extensive margin of supply is not driving these shifts, it is possible that intensive margin supply has changed post-pandemic. In recent years, there has been increased discussion of burnout among physicians, potentially influenced by stresses induced by the pandemic and rising mistrust by patients. There have also been concerns about staffing shortages among nurses, many of whom bore the brunt of pandemic-related care. If providers in more Republican areas have cut back their hours due to burnout or staffing shortages, it could produce equivalent patterns to a decline in demand. I test for this in three ways. First, in Appendix Figure A.17c, I show that as measured in the American Communities Survey, the number of nurses per capita has, if anything, risen in more Republican areas since the pandemic. Second, in Appendix Figure A.17d, though this measure is not available longitudinally, I show that the share of people in the National Health Interview Study who report delaying or skipping care due to waiting times was much higher in urban than rural areas in 2022. Rural areas are in general far more Republican than urban ones, suggesting that a similar pattern would hold in the cross-section across local politics. Finally, in Appendix Figure A.17e, I show that the relationship between political ideology and patient volume for PCPs is much stronger for white than non-white beneficiaries (albeit the censored data restricts the sample). Given that non-white Americans are much more likely to be Democrats, we would expect politicized trust to disproportionately appear among white beneficiaries. If these patterns were driven by the supply side, meanwhile, we would expect the patterns to appear among both populations.

Taken together, the results from the previous three sections provide strong evidence that the polarization of trust post-pandemic has caused substantial shifts in the utilization of health care. However, the importance of health care is not intrinsic, but rather in its link to outcomes, and whether mistrust and declining demand for care primarily reduced the take-up of high or low value care remains an open question. To provide insight on this, I conclude with an analysis of the health implications of these shifts in trust.

4.4 Trust and Mortality

Examining the health effects of trust in this context is in some ways more difficult than examining the influence on demand for care. First, mistrust can influence health through a range of mechanisms — as highlighted earlier, it can reduce the demand for routine and preventive health care, which may have deleterious health effects, but it may influence other health decisions, such whether patients fill and take prescriptions and the use of non-traditional medicine or supplements, which may impact health outcomes as well. To the extent that declining trust is a bundled treatment, I am constrained in my ability to make broad statements about the specific channels through which health effects run.

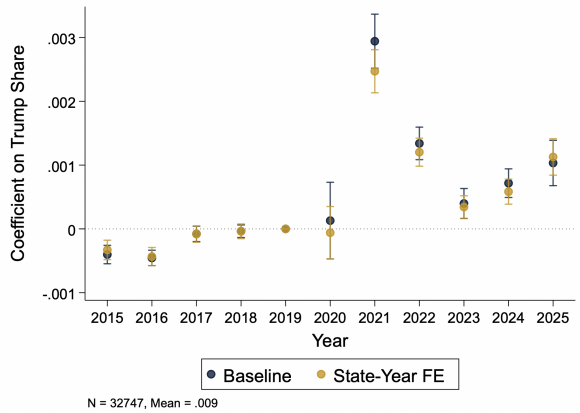
The second difficulty, meanwhile, is that the shock to trust which I have leveraged was also a major public health crisis that lead to the deaths of over one million Americans (Centers for Disease Control and Prevention, 2026). Mistrust, to the extent that it influenced vaccine take-up or precautionary behaviors, will have played a key role in this mortality. At the same time, the direct impact of mistrust during the pandemic on Covid-19 mortality will be less applicable to our understanding of the health consequences of trust in more ordinary times. I thus focus primarily on estimates from more recent years, at which point Covid-19 mortality has become a much smaller share of overall mortality.

Figure 6 reports results, with Figure 6a showing estimates for overall mortality while Figure 6b presents results for infant mortality rates. In each case, rates spiked in more Republican areas during the pandemic, though for infant mortality this occurred in 2020 (where lower stay-at-home adherence likely led to more accidents and non-Covid illness), while for overall mortality it occurred in 2021 and 2022 (when vaccination disparities would have driven differential mortality). Though these mid-pandemic patterns are somewhat distinct from the shifts in care utilization documented earlier, they remain closely connected to trust. Indeed, the high level of excess mortality in Republican areas during the pandemic can in some sense be viewed as the most important effect of declining trust in medicine.

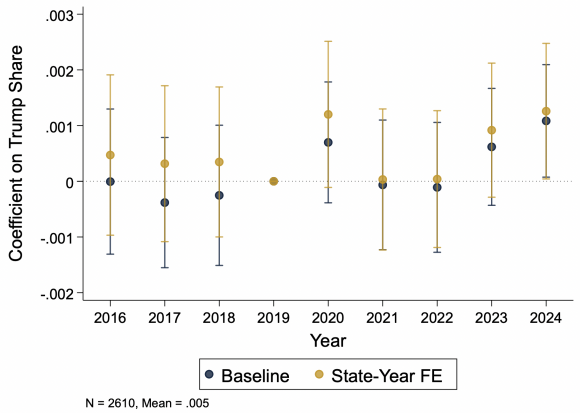
Importantly, though, as with emergency room visits, the relationship between mortality and county politics after the pandemic did not simply return to its prior level and remain flat. Though there was convergence to just above the 2019 relationship by 2023, the trend has since reversed, with mortality increasing steadily in Republican relative to Democratic areas in both 2024 and 2025. By 2025, a 10 percentage point increase in the Trump vote share implied an increase in the overall mortality rate of over 1 death per 10,000 people, an increase of roughly 1% of the mean. For infant mortality (available only through 2024), rates began increasing in more Republican areas in 2023 and were significantly higher by 2024 than in 2019, with each 10 percentage point increase in the Trump vote share implying a similar increase of 1 death per 10,000 births, equivalent to a roughly 2% increase.

Figure 6: Event Study Results - Mortality

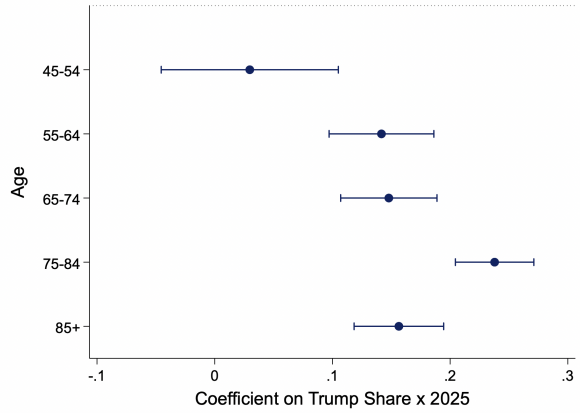
(a) Overall Mortality



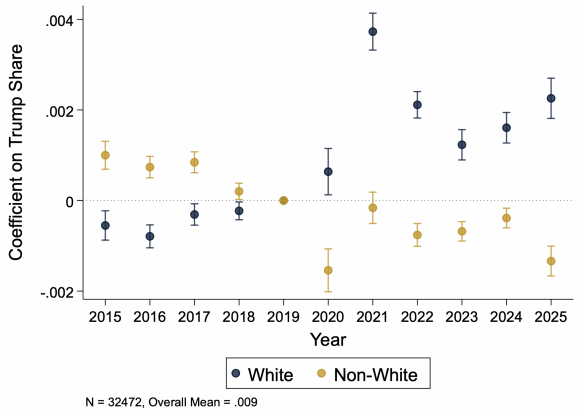
(b) Infant Mortality



(c) 2025 Mortality Coefficients by Age Bin



(d) Overall Mortality - by Race



Notes: Mortality data are from CDC Wonder's multiple cause of death data. Each figure reports coefficients from regressions of mortality rates on the Trump 2020 vote share interacted with year dummies and (gold) state-year fixed effects. Regressions are at the county level, weighting by the 2010 population, with standard errors clustered at the county level.

One issue with examining overall mortality rates is that they are sensitive to shifts in population age composition. In Figure 6c, I examine mortality rates by ten-year age bins, transforming them to logs given the vastly different baseline rates by age and reporting the coefficient on the Trump vote share in 2025 (Figure A.19 reports the full set of years). For all age groups older than 55, the mortality rate increased between 2019 and 2025 in Republican areas. By 2025, a 10% increase in the Trump vote share implies increases in mortality of around 1.5% for those 55-64, 65-74, and 85+ and 2.5% for those 75-84. Thus, age composition changes do not appear to be driving the results. As further evidence of the role

of trust in driving these patterns, in Figure 6d, I report mortality rates by race, estimating separately for white and non-white mortality rates. Consistent with white Americans being far more likely to be Republicans, I show that increases in mortality in Republican areas are concentrated among whites while non-white death rates continued trending down slightly after the pandemic.

The aggregated nature of the outcomes make it difficult to establish a clear mechanism for these increases. Whether these patterns are the result of reduced vaccination rates, fewer routine visits, missed screenings, delays in seeking out care, or some other channel cannot be clearly established, though all of these may play a role. What is clearer, however, is that the way in which Republicans interact with medicine and the health care system has shifted dramatically, with evidence of dire health effects already emerging.

To put these estimates in perspective, it is worth considering a back-of-the-envelope calculation. First, note that the (population-weighted) average county cast 45% of the vote for Trump in the 2020 election. Extrapolating this average to the mortality coefficients (0.00113 for overall 2025 mortality and 0.00126 for 2024 infant mortality), this would imply an increase of around 5.1 deaths per 10,000 for total mortality and 5.7 per 10,000 births for infant mortality. With a 2025 population of 340 million, this implies excess total mortality of around 170,000 people, and with 3.6 million births in 2024, roughly 2,000 excess infant deaths. Though these estimates come with wide standard errors and a several crucial assumptions, they provide suggestive evidence that the shifts in trust have had severe consequences. For put this in perspective, the CDC places an upper bound on mortality during the 2024-2025 flu season at roughly 130,000 flu-related deaths, while 2025 saw around 20,000 recorded deaths from Covid-19 (though incomplete reporting may understate the total).[7] In comparison, the mortality estimates in this paper are sizable and seem unlikely to be fully accounted for by shifting vaccination rates.

5 Conclusion

In this paper, I have studied the impact of declining and increasingly polarized trust in medicine on the demand for care and subsequent patient health. I first highlighted the rapid decline in reported trust in doctors since the pandemic, with views worsening especially among Republicans. In turn, I showed that in the years since 2020, the utilization of routine medical care among Medicare beneficiaries has declined rapidly in more Republican counties. Consistent with patients forgoing care they deem less essential, similar patterns are absent for

[7]Flu Mortality: https://www.cdc.gov/flu-burden/php/data-vis/2024-2025.html
Covid Mortality: https://www.cdc.gov/flu-burden/php/data-vis/2024-2025.html

acute and hospital based care. Trends in two other salient trust-related measures, influenza vaccination rates and intended home births also show sharp changes post-pandemic.

I then considered several sources of trust-relevant heterogeneity to shed light on the role of trust in driving these shifts. First, I showed that declining utilization among Republicans was especially pronounced in places with more stringent Covid-19 restrictions, highlighting the importance of pandemic-era dissatisfaction among Republicans in the subsequent declines in trust. Second, I documented heterogeneity across physician characteristics, showing that among PCPs, declines in patient volumes in more Republican areas disproportionately occurred for Democratic physicians. Amid the polarization of Covid-19 vaccinations and public health post-pandemic, patient trust appears to be a function of the gap in beliefs between patients.

After ruling out several alternative explanations for the patterns presented before, I closed with an examination of the health implications of these shifts. As late as 2024 and 2025, mortality across the age distribution remained elevated and rising in more Republican counties relative to Democratic ones. The scale of these increases is dramatic, suggesting that distrust has resulted in significant harm.

In total, these results highlight the critical importance of trust in driving the utilization of health care, health behaviors, and subsequent health outcomes. However, the question of how to rebuild trust in medicine remains. Research into ways of improving communication between providers and patients with distinct beliefs seems particularly fruitful. Moreover, declining institutional trust extends beyond both the health care sector and the US. Rebuilding institutional confidence in areas ranging from government to education to the media will remain a crucial challenge for the decades to come, with health only one of many areas dependent upon success.

References

Adolph, C., Amano, K., Bang-Jensen, B., Fullman, N., Magistro, B., Reinke, G., Castellano, R., Erickson, M., and Wilkerson, J. (2022). The pandemic policy u-turn: Partisanship, public health, and race in decisions to ease covid-19 social distancing policies in the united states. *Perspectives on Politics*, 20(2):595–617.

Allcott, H., Boxell, L., Conway, J., Gentzkow, M., Thaler, M., and Yang, D. (2020). Polarization and public health: Partisan differences in social distancing during the coronavirus pandemic. *Journal of Public Economics*, 191:104254.

Alsan, M. and Wanamaker, M. (2017). Tuskegee and the Health of Black Men. *The Quarterly Journal of Economics*, 133(1):407–455.

Aron-Dine, A., Einav, L., and Finkelstein, A. (2013). The RAND Health Insurance Experiment, Three Decades Later. *Journal of Economic Perspectives*, 27(1):197–222.

Arrow, K. (1963). Uncertainty and the Welfare Economics of Medical Care. *The American Economic Review*, 53(5):941–973.

Arteaga, C. and Barone, V. (2025). Republican Support and Economic Hardship: The Enduring Effects of the Opioid Epidemic. *The Quarterly Journal of Economics*, 141(1):499–558.

Blewett, L., Rivera Drew, J., Fenelon, A., King, M., Williams, K., Backman, D., Breton, E., Cooper, G., and Richards, S. (2025). IPUMS Health Surveys: National Health Interview Survey, Version 8.1.

Blumenthal, M. (2020). On coronavirus social distancing, Americans not so divided. *Yougov*.

Bonica, A. (2024). Database on Ideology, Money in Politics, and Elections: Public version 4.0.

Boxell, L., Gentzkow, M., and Shapiro, J. (2024). Cross-country trends in affective polarization. *The Review of Economics and Statistics*, 106(2):557–565.

Brot-Goldberg, Z. C., Chandra, A., Handel, B. R., and Kolstad, J. T. (2017). What does a Deductible Do? The Impact of Cost-Sharing on Health Care Prices, Quantities, and Spending Dynamics. *The Quarterly Journal of Economics*, 132(3):1261–1318.

Bursztyn, L., Kolstad, J., Rao, A., Tebaldi, P., and Yuchtman, N. (2025). Polarisation and Public Policy: Political Adverse Selection Under Obamacare. *The Economic Journal*, page ueaf079.

Bursztyn, L., Rao, A., Roth, C., and Yanagizawa-Drott, D. (2022). Opinions as Facts. *The Review of Economic Studies*, 90(4):1832–1864.

Camacho-Garcia, M., Serrano-Macías, M., Ortega-Martin, E., and Alvarez-Galvez, J. (2025). Drivers of health polarization during the COVID-19 pandemic: A systematic review. *Science Advances*, 11(46):eady5064.

Centers for Disease Control and Prevention (2021). U.S. State and Territorial Public Mask Mandates From April 10, 2020 through August 15, 2021 by County by Day.

Centers for Disease Control and Prevention (2025a). Multiple Cause of Death Data.

Centers for Disease Control and Prevention (2025b). Natality Data.

Centers for Disease Control and Prevention (2026). COVID-19 Surveillance Data in the United States.

Centers for Medicare and Medicaid Services (2025a). Doctors and Clinicians National Downloadable File.

Centers for Medicare and Medicaid Services (2025b). Mapping Medicare Disparities by Population.

Centers for Medicare and Medicaid Services (2025c). Medicare Geographic Variation - by National, State and County.

Centers for Medicare and Medicaid Services (2025d). Medicare Physician and Other Practitioners - by Provider and Service.

Currie, J., MacLeod, W. B., and Musen, K. (2024). Doctor Decision Making and Patient Outcomes. Working Paper 32788, National Bureau of Economic Research.

Darden, M. and Macis, M. (2024). Trust and Health Care-Seeking Behavior. Working Paper 32028, National Bureau of Economic Research.

Deane, C., Parker, K., and Gramlich, J. (2021). A Year of U.S. Public Opinion on the Coronavirus Pandemic. *Pew Research Center*.

Fan, H., Zhou, Z., Liu, G., Shen, C., and Zhang, Q. (2025). Politics in Public Health: Growing Partisan Divides in COVID-19 Vaccine Attitudes and Uptake Post-2021 Presidential Inauguration. *International Journal of Public Health*, Volume 70 - 2025.

Finkelstein, A., Taubman, S., Wright, B., Bernstein, M., Gruber, J., Newhouse, J. P., Allen, H., Baicker, K., and Group, O. H. S. (2012). The Oregon Health Insurance Experiment: Evidence from the First Year. *The Quarterly Journal of Economics*, 127(3):1057–1106.

Funk, C., Kennedy, B., and Johnson, C. (2020). Trust in Medical Scientists Has Grown in U.S., but Mainly Among Democrats. *Pew Research Center*.

Gallup (2025). Honesty/Ethics in Professions.

Green, J., Edgerton, J., Naftel, D., Shoub, K., and Cranmer, S. (2020). Elusive consensus: Polarization in elite communication on the covid-19 pandemic. *Science Advances*, 6(28):eabc2717.

Grünebaum, A., McCullough, L., Orosz, B., and Chervenak, F. (2020). Neonatal mortality in the united states is related to location of birth (hospital versus home) rather than the type of birth attendant. *American Journal of Obstetrics and Gynecology*, 223(2):254.e1–254.e8.

Hamel, L., Kearney, A., Kirzinger, A., Lopes, L., Munana, C., and Brodie, M. (2020a). KFF Coronavirus Poll: May 2020. *Kaiser Family Foundation*.

Hamel, L., Lopes, L., Munana, C., Kates, J., Michaud, J., and Brodie, M. (2020b). KFF Coronavirus Poll: March 2020. *Kaiser Family Foundation*.

Hamel, L., Lopes, L., Sparks, G., Kirzinger, A., Kearney, A., Stokes, M., and Brodie, M. (2021). KFF COVID-19 Vaccine Monitor: September 2021. *Kaiser Family Foundation*.

Handel, B. (2013). Adverse selection and inertia in health insurance markets: When nudging hurts. *American Economic Review*, 103(7):2643–82.

Ho, K. (2006). The welfare effects of restricted hospital choice in the us medical care market. *Journal of Applied Econometrics*, 21(7):1039–1079.

Jones, J. (2013). Honesty Ratings of Police, Clergy Differ Most by Party. *Gallup*.

Kaiser Family Foundation (2025). Health Information and Trust Tracking Poll.

Kat, D., Fagan, M., and Connaughton, A. (2021). People in Advanced Economies Say Their Society Is More Divided Than Before Pandemic. *Pew Research Center*.

Kerr, J., Panagopoulos, C., and van der Linden, S. (2021). Political polarization on COVID-19 pandemic response in the United States. *Personality and Individual Differences*, 179:110892.

Kim, W. (2025). Political Polarization in Medicine. Working paper.

Kirzinger, A., Lopes, L., Kearney, A., and Brodie, M. (2020). KFF Health Tracking Poll – October 2020. *Kaiser Family Foundation*.

L2 (2025). Voter Data File.

Lerman, A. E., Sadin, M. L., and Trachtman, S. (2017). Policy Uptake as Political Behavior: Evidence from the Affordable Care Act. *American Political Science Review*, 111(4):755–770.

Levin, J., Bukowski, L., Minson, J., and Kahn, J. (2023). The political polarization of COVID-19 treatments among physicians and laypeople in the United States. *Proceedings of the National Academy of Sciences*, 120(7):e2216179120.

MIT Election Data and Science Lab (2023). U.S. President 1976–2020.

Musa, D., Schulz, R., Harris, R., Silverman, M., and Thomas, S. (2009). Trust in the Health Care System and the Use of Preventive Health Services by Older Black and White Adults. *American Journal of Public Health*, 99(7):1293–1299.

Organisation for Economic Cooperation and Development (2019). Society at a Glance 2019.

O'Brian, N. A. and Kent, T. B. (2025). Partisanship and Trust in Personal Doctors: Causes and Consequences. *British Journal of Political Science*, 55:e34.

O'Brien, S. A. (2026). 'My Family Thought I Was Crazy': More Women Are Choosing to Give Birth at Home. *The Wall Street Journal*.

Perlis, R. H., Ognyanova, K., Uslu, A., Lunz Trujillo, K., Santillana, M., Druckman, J. N., Baum, M. A., and Lazer, D. (2024). Trust in Physicians and Hospitals During the COVID-19 Pandemic in a 50-State Survey of US Adults. *JAMA Network Open*, 7(7):e2424984–e2424984.

Ruggles, S., Flood, S., Sobek, M., et al. (2025). IPUMS USA: Version 16.0 American Communities Survey.

Sehgal, N. J., Yue, D., Pope, E., Wang, R. H., and Roby, D. H. (2022). The Association Between COVID-19 Mortality And The County-Level Partisan Divide In The United States. *Health Affairs*, 41(6):853–863.

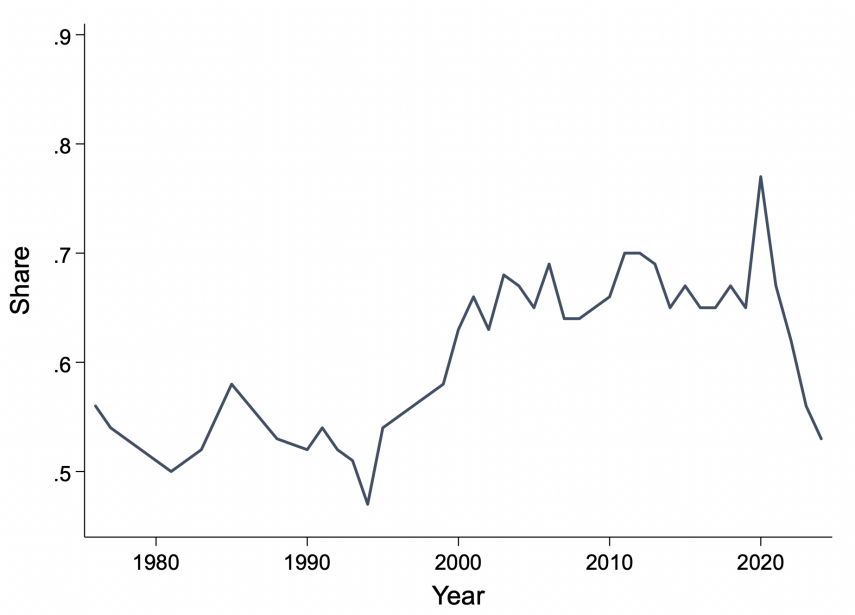
Tyson, A. and Pasquini, G. (2024). 60% of Americans say they probably won't get an updated COVID-19 vaccine. *Pew Research Center*.

U.S. Bureau of Labor Statistics (2025). Local Area Unemployment Statistics.

Appendix

Figures

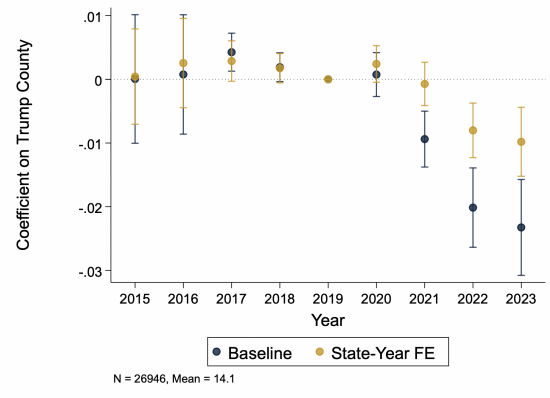
Figure A.1: Share Describing Doctors as Honest or Ethical — Full Time Series



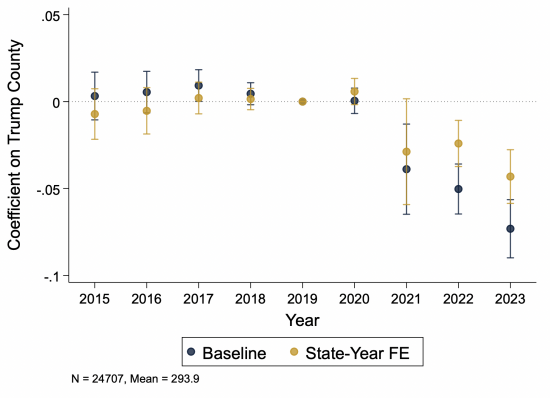
Notes: Data from Gallup.

Figure A.2: Event Study Results — Routine Care by Trump County

(a) Log E&M Visits per Beneficiary



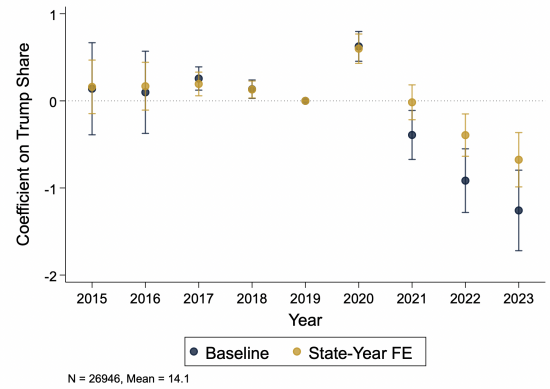
(b) Log Beneficiaries per PCP



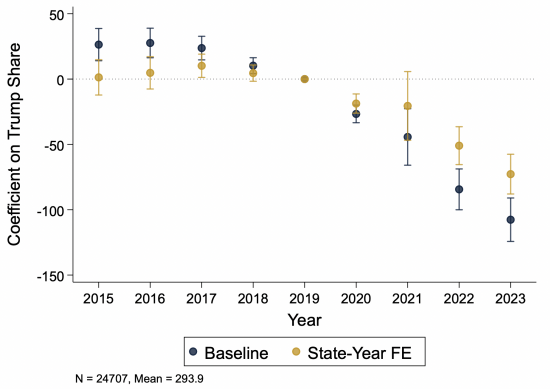
Notes: Figures report coefficients on a dummy for whether Trump won over 50% of the 2020 vote interacted with year dummies for either the baseline specification (blue) or the specification with state-year fixed effects included (gold).

Figure A.3: Event Study Results — Utilization of Routine Care in Levels

(a) E&M Visits per Beneficiary



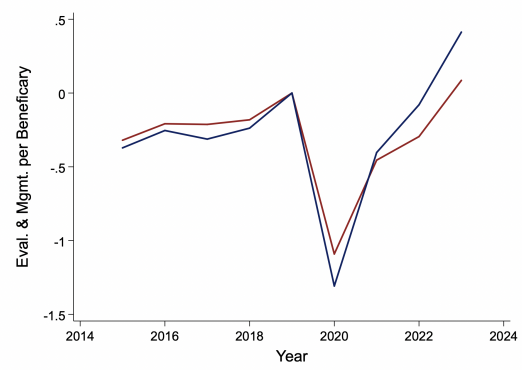
(b) Beneficiaries per PCP



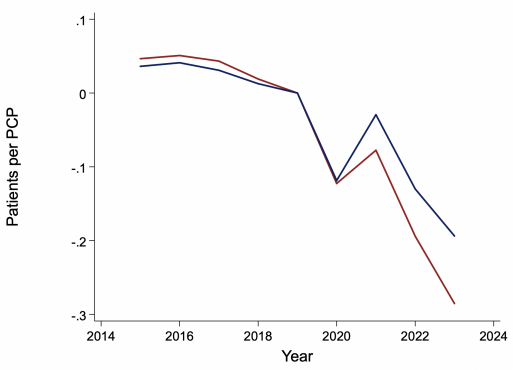
Notes: Figures report coefficients on the 2020 Trump vote share interacted with year dummies for either the baseline specification (blue) or the specification with state-year fixed effects included (gold).

Figure A.4: Raw and Residualized Trends — Routine Care

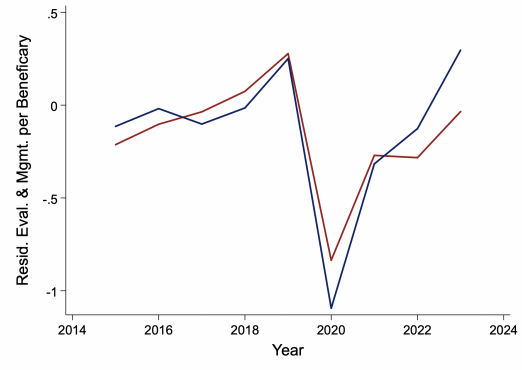
(a) E&M Visits per Beneficiary - Raw



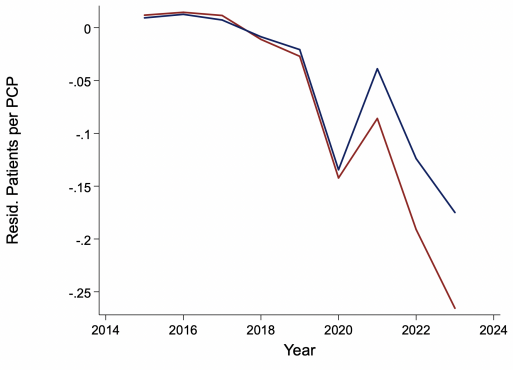
(b) Beneficiaries per PCP - Raw



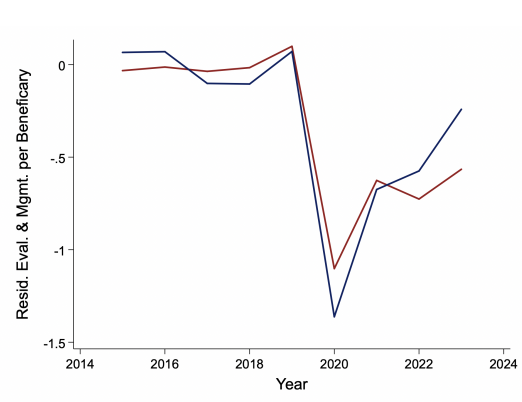
(c) E&M Visits per Beneficiary - Resid.



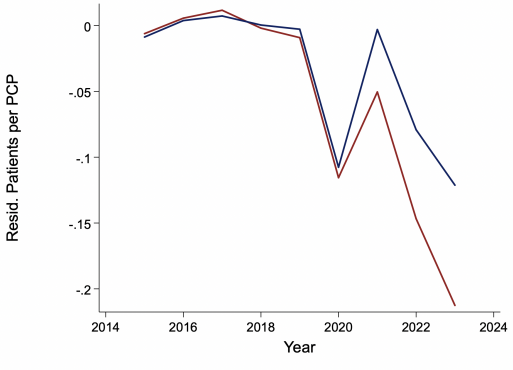
(d) Beneficiaries per PCP - Resid.



(e) E&M Visits per Beneficiary - Resid. + Detr.

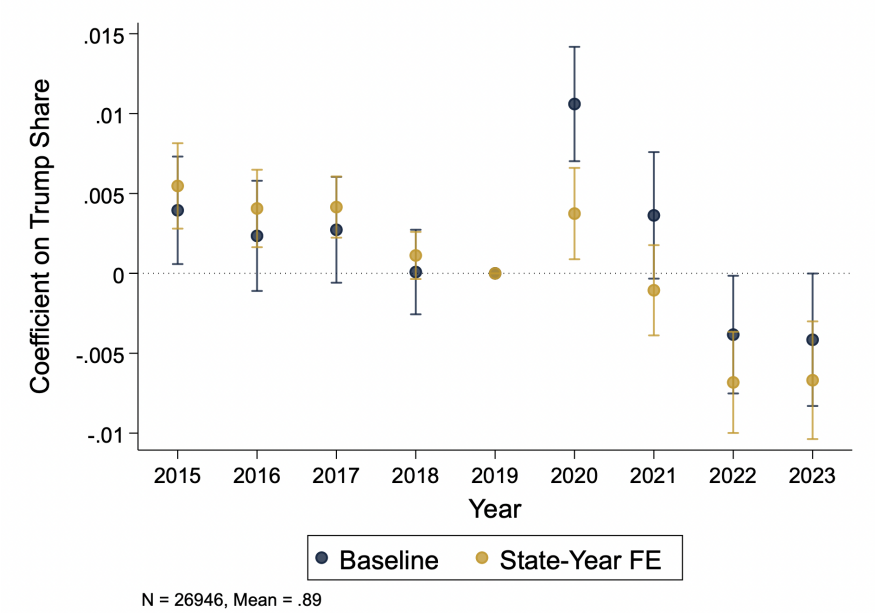


(f) Beneficiaries per PCP - Resid. + Detr.



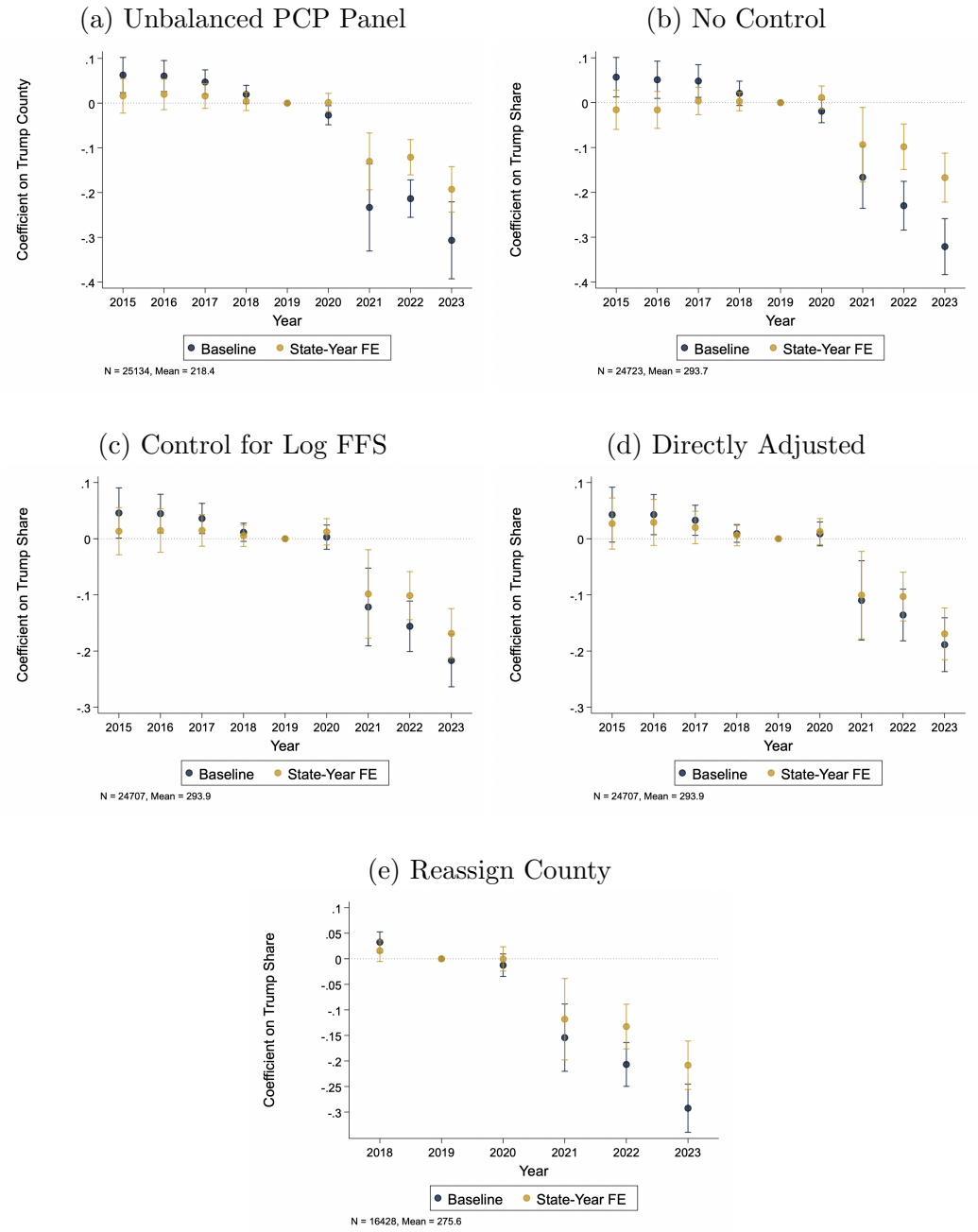
Notes: Figures report trends for E&M and beneficiaries per PCP, split by counties in which Trump won more (red) or less (blue) than 50% of the vote in 2020. (a) and (b) report raw trends, (c) and (d) residualize on beneficiary average age, average age quintile, female share, and dual share, and (e) and (f) residualize on these plus a time trend. These regressions are run in the pre-2020 data and coefficients are applied to the post-2020 data when residualizing.

Figure A.5: Event Study Results — Share with Any E&M



Notes: Figure reports coefficients on a dummy for whether Trump won over 50% of the 2020 vote interacted with year dummies for either the baseline specification (blue) or the specification with state-year fixed effects included (gold).

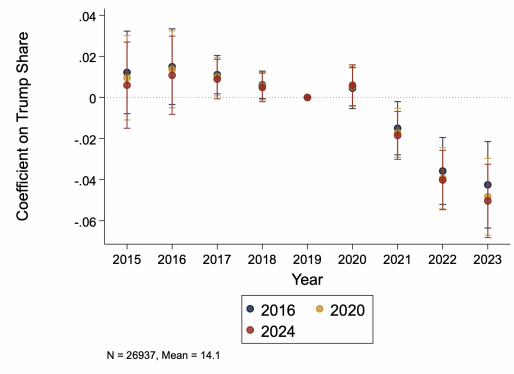
Figure A.6: Robustness — PCP Patient Volumes



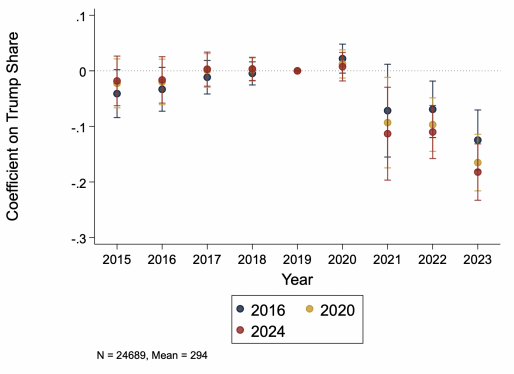
Notes: Figures report coefficients on the 2020 Trump vote share interacted with year dummies for either the baseline specification (blue) or the specification with state-year fixed effects included (gold). Part (a) includes all PCPs when calculating average patient volume while part (b)-(d) restrict to a balanced panel of physicians. (b) includes no controls for the local FFS population, (c) controls for the log FFS population in the county, (d) adjusts average patient volumes by the ratio of the county's FFS population in each year divided by the 2019 FFS population, and (e) replaces physician counties with those from the Doctors and Clinicians files.

Figure A.7: Robustness — Election Year, Weights, and Controls

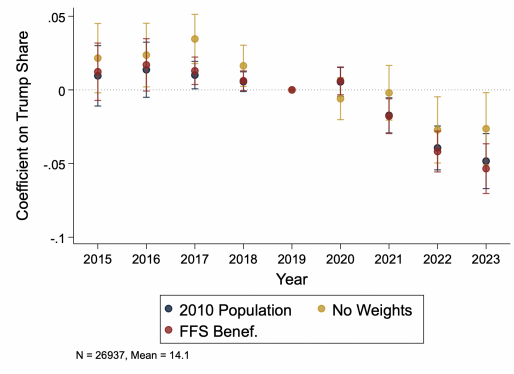
(a) E&M — By Election Year



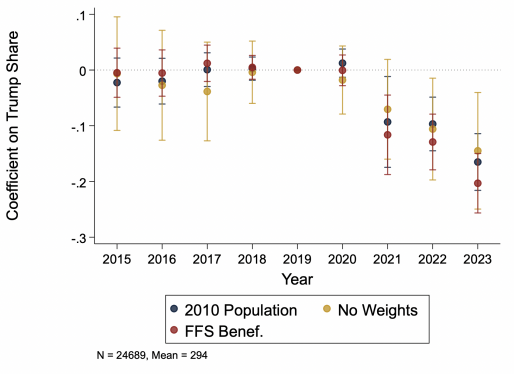
(b) PCP Benef. — By Election Year



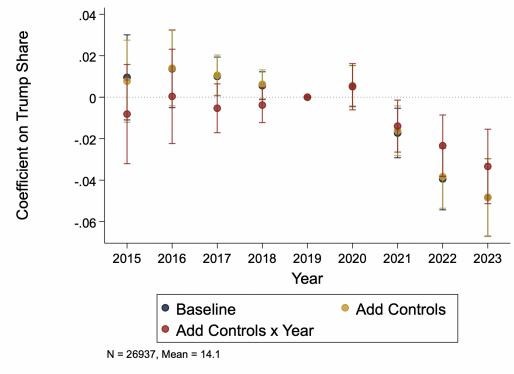
(c) E&M — Weighting



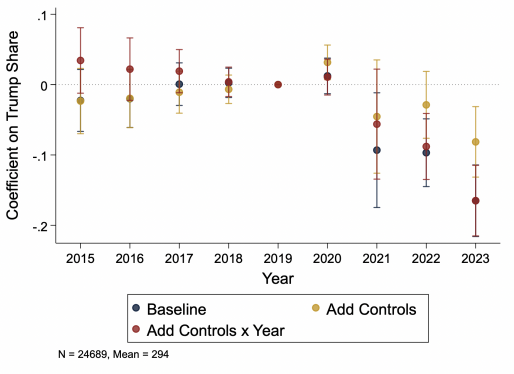
(d) PCP Benef. — Weighting



(e) E&M — Controls



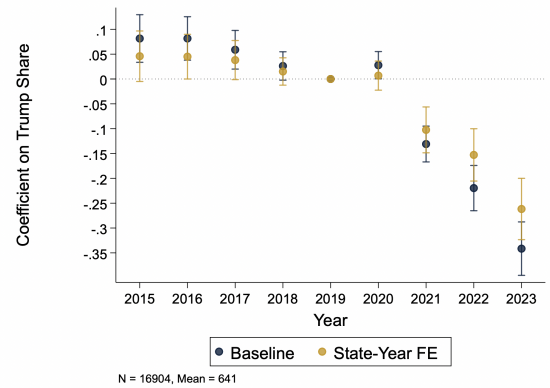
(f) PCP Benef. — Controls



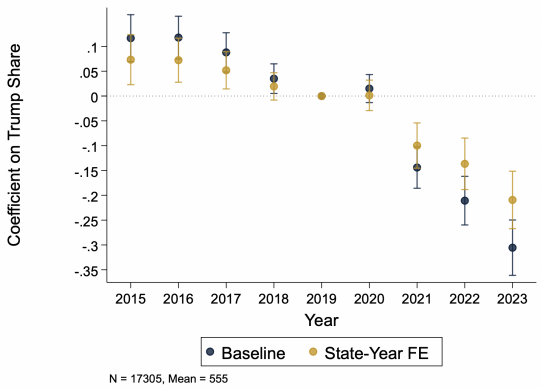
Notes: Figures report coefficients on the Trump vote share interacted with year dummies for log E&M per beneficiary (left) and log PCP patient volumes (right). Parts (a) and (b) vary the election year, (c) and (d) report results without weights or when using the number of FFS beneficiaries, and (e) and (f) add controls for the county-level FFS, female, and dual-eligible share of beneficiaries as well as the average age of FFS beneficiaries, either on their own (gold) or interacted with year dummies (red).

Figure A.8: Specialist Patient Volumes

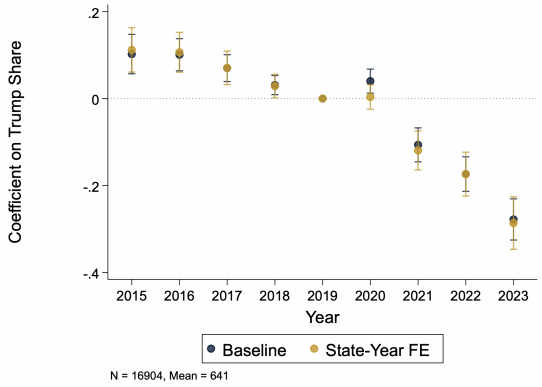
(a) Main Specification



(b) Unbalanced



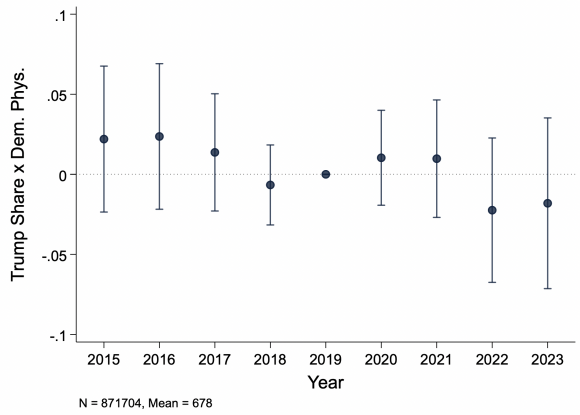
(c) Directly Adjusted



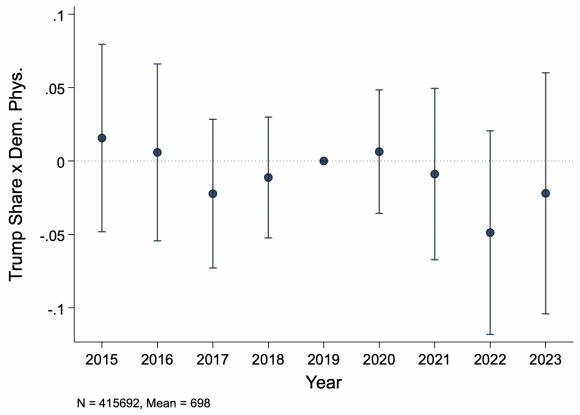
Notes: Figures report coefficients on the 2020 Trump vote share interacted with year dummies for either the baseline specification (blue) or the specification with state-year fixed effects included (gold). Part (a) restricts to a balanced panel of specialists while part (b) includes all specialists when calculating average patient volume; both control for the log of the ratio of patient volumes to specialists. Part (d) adjusts average patient volumes by the ratio of the county's FFS population in each year divided by the 2019 FFS population. All regressions are run at the county level weighting by the 2020 population and with standard errors clustered at the county level.

Figure A.9: Provider-Patient Political Concordance — Specialists

(a) All Specialists



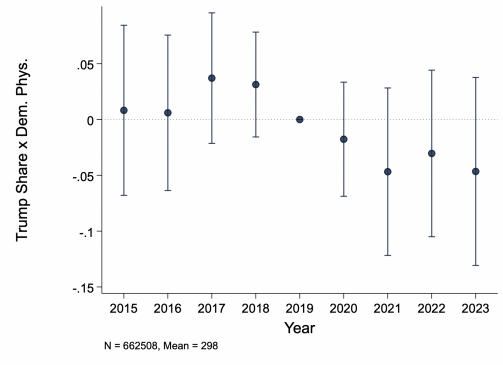
(b) Specialist Donors



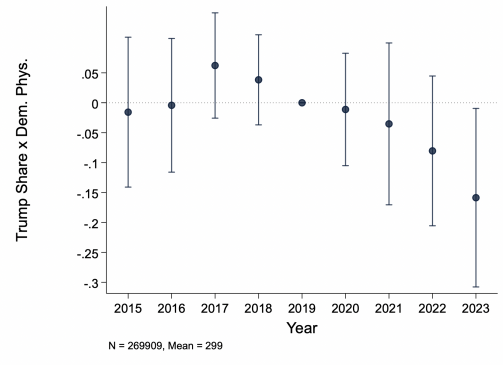
Notes: Figures report coefficients from physician-level regressions restricted to specialists of log Medicare patient volumes on the 2020 Trump vote share interacted with a whether the physician is a Democrat and year dummies. Standard errors clustered at the county level and regressions include county-year fixed effects to restrict comparisons to physicians in the same market. The measure of political affiliation is from L2+DIME donations data in part (a) and DIME donations alone in (b).

Figure A.10: PCP-Patient Political Concordance — Robustness

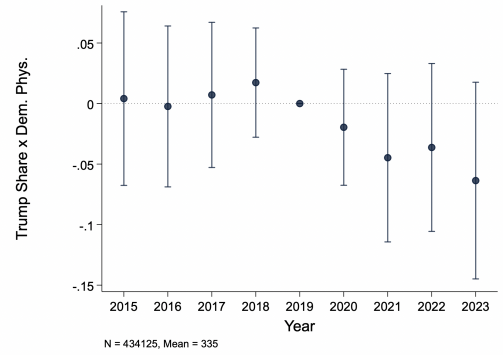
(a) By Party — Unbalanced Panel



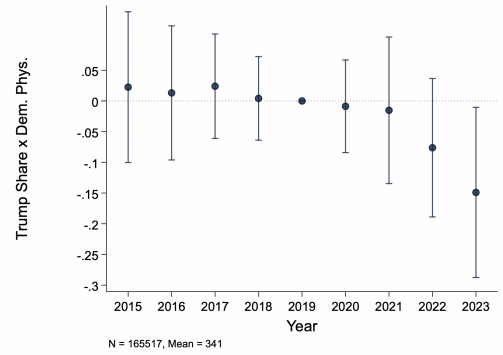
(b) By Donations — Unbalanced Panel



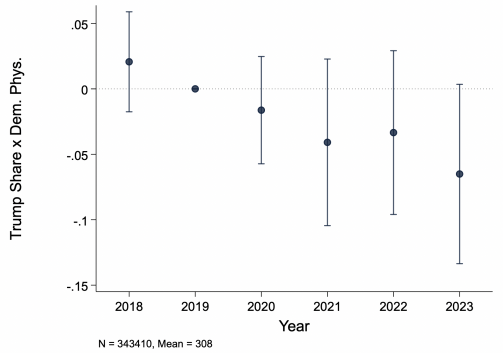
(c) By Party — with Moves



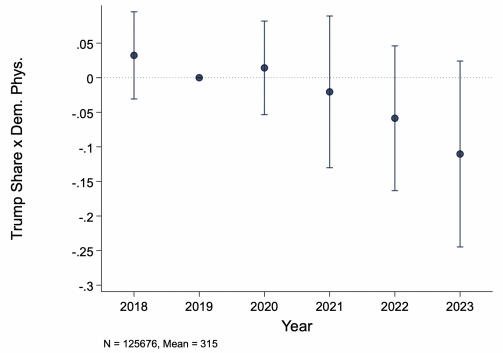
(d) By Donations — with Moves



(e) By Party — Reassign Location



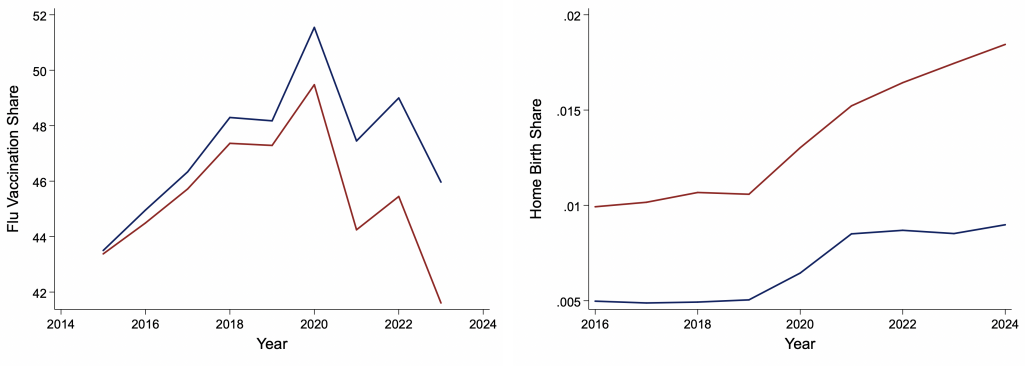
(f) By Donations — Reassign Location



Notes: Figures report coefficients from physician-level regressions of log Medicare patient volumes on the 2020 Trump vote share interacted with a whether the physician is a Democrat and year dummies. Standard errors clustered at the county level and regressions include county-year fixed effects to restrict comparisons to physicians in the same market. The measure of political affiliation is from either a combination of L2 and DIME donations data (a), (c), and (e) or DIME data alone (b), (d), and (f). Parts (a) and (b) includes an unbalanced panel of primary care physicians who see 10+ Medicare patients and are linked to a political affiliation, Parts (c) and (d) restrict to a balanced panel of primary care physicians but does not remove those who move during the sample frame, while Parts (e) and (f) replace physician location from the NPPES-derived CMS Physicians & Other Practitioners files with those from the CMS' Doctors and Clinicians files.

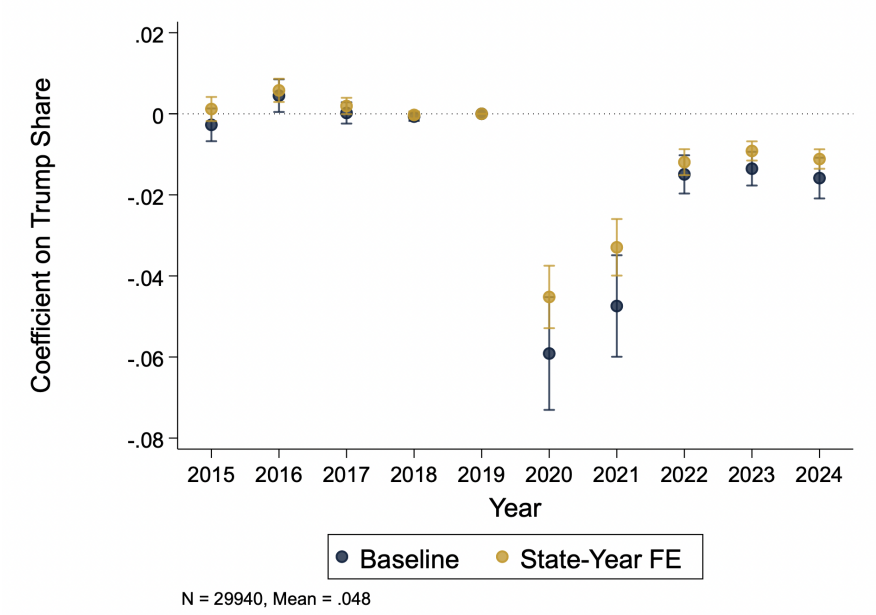
Figure A.11: Trust-Related Care — Raw Trends

(a) Flu Vaccinations (b) Home Births



Notes: Figures report raw trends in my measures, split by whether Trump received over (red) or under (blue) 50% of the 2020 vote.

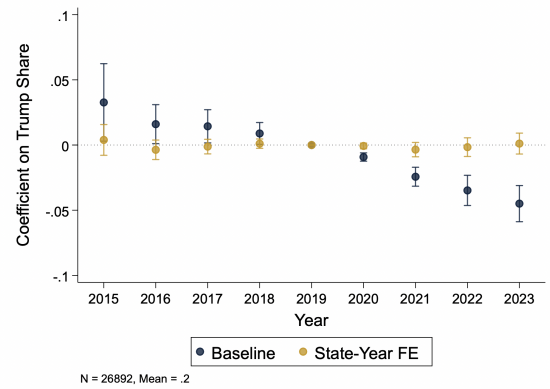
Figure A.12: Event Study Results — Unemployment Rate



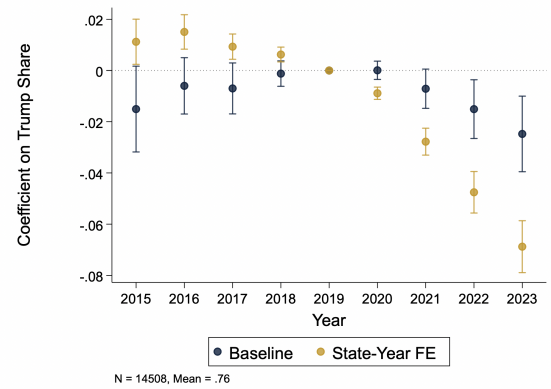
Notes: Figure reports coefficients on a dummy for whether Trump won over 50% of the 2020 vote interacted with year dummies for either the baseline specification (blue) or the specification with state-year fixed effects included (gold).

Figure A.13: Beneficiary Composition

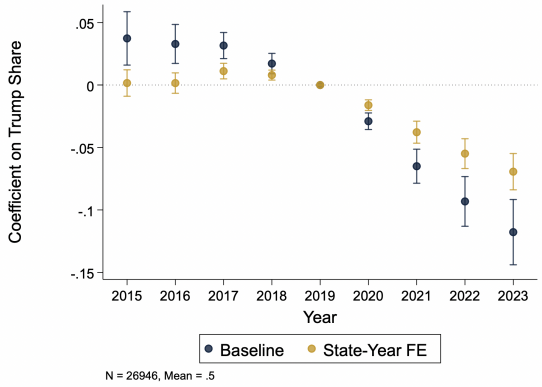
(a) Share Dual-Eligible



(b) Share White



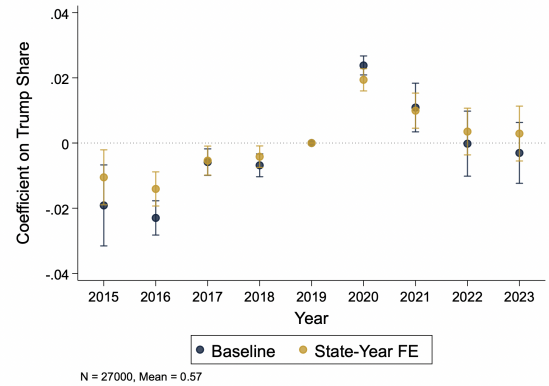
(c) Share Fee-For-Service



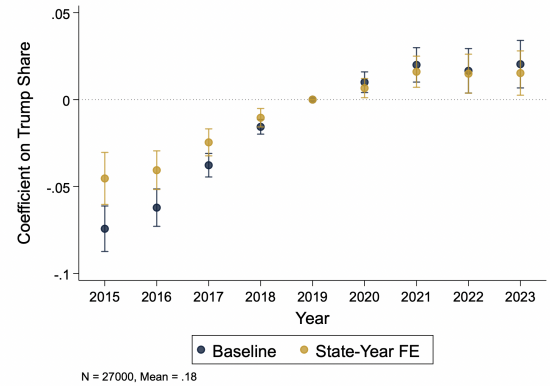
Notes: Figures report coefficients on the 2020 Trump vote share interacted with year dummies for either the baseline specification (blue) or the specification with state-year fixed effects included (gold). All regressions are run at the county level weighting by the 2020 population and with standard errors clustered at the county level.

Figure A.14: Beneficiary Health and Age

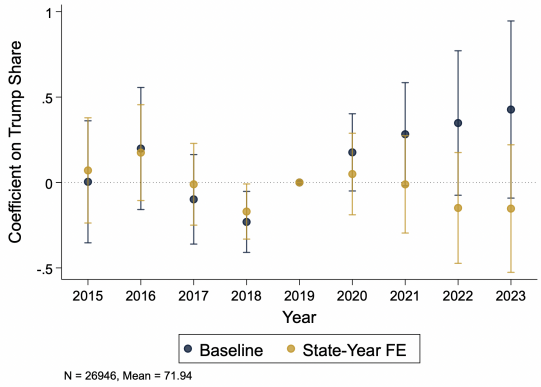
(a) Share with 3+ Chronic Conditions



(b) Obesity Rate



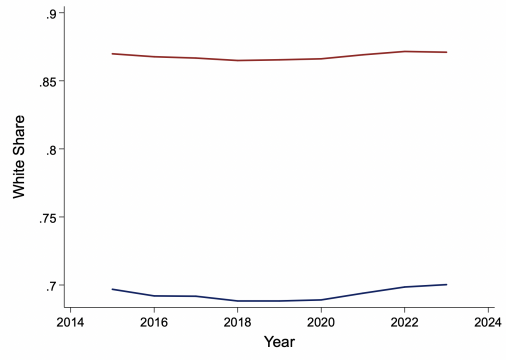
(c) Average Age



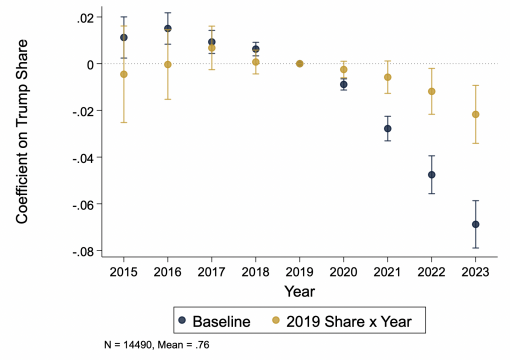
Notes: Figures report coefficients on the 2020 Trump vote share interacted with year dummies for either the baseline specification (blue) or the specification with state-year fixed effects included (gold). All regressions are run at the county level weighting by the 2020 population and with standard errors clustered at the county level.

Figure A.15: Beneficiary White Share — Robustness

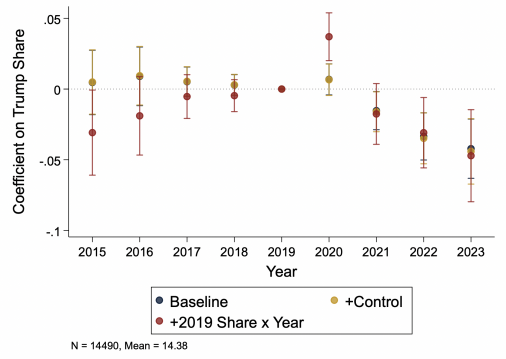
(a) Raw Trends



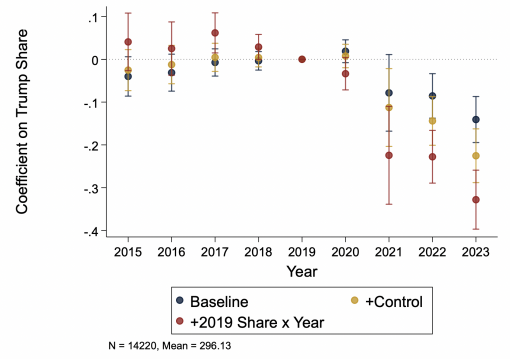
(b) Share White — Controls



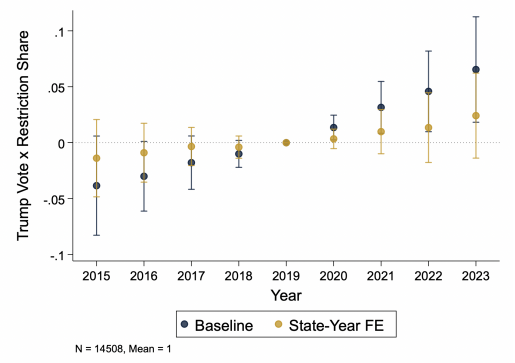
(c) Log E&M — Controls



(d) PCP Patient Vol. — Controls



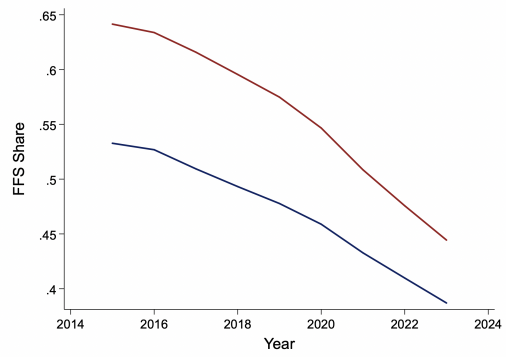
(e) White Share — Restriction Interaction



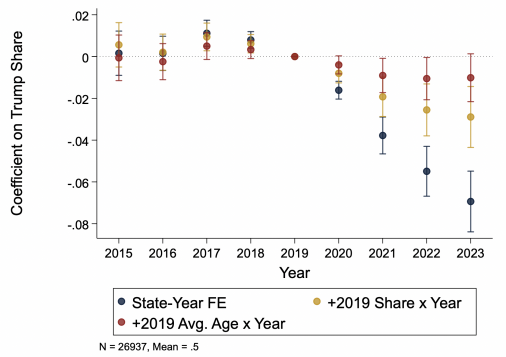
Notes: Part (a) reports raw trends for the white share of beneficiaries, splitting by counties where Trump got over (red) and under (blue) 50% of the 2020 vote. Parts (b) to (d) report coefficients on the 2020 Trump vote share interacted with year dummies for either the state-year fixed effect specification (blue), one adding a control for the white share of beneficiaries (gold), and one that adds controls for the 2019 share interacted with year dummies. Part (e) reports coefficients on the Covid restriction share of days interacted with the Trump vote share and year dumies.

Figure A.16: Beneficiary FFS Share — Robustness

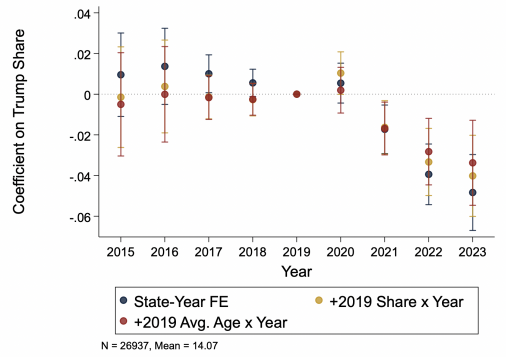
(a) Raw Trends



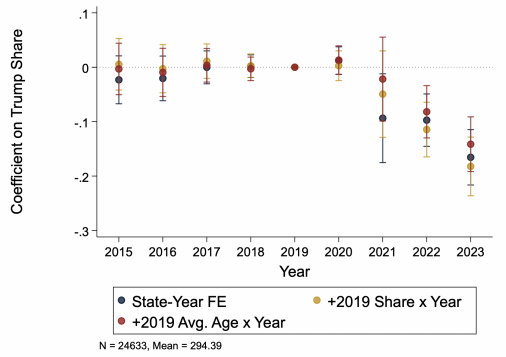
(b) Share White — Controls



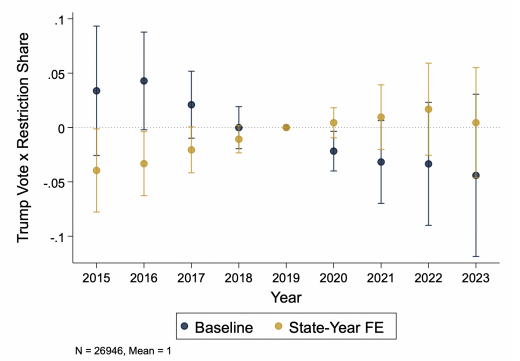
(c) Log E&M — Controls



(d) PCP Patient Vol. — Controls



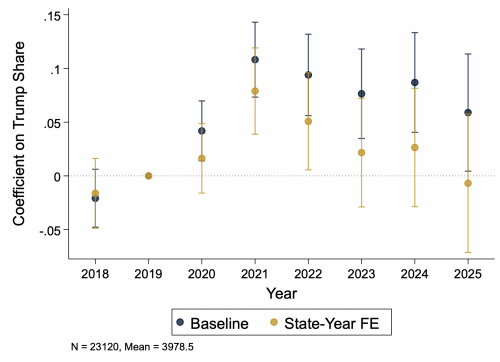
(e) White Share — Restriction Interaction



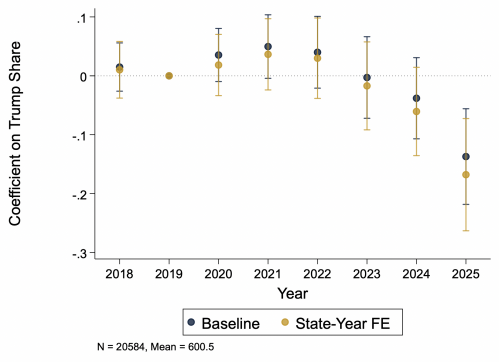
Notes: Part (a) reports raw trends for the FFS share of beneficiaries, splitting by counties where Trump got over (red) and under (blue) 50% of the 2020 vote. Parts (b) to (d) report coefficients on the 2020 Trump vote share interacted with year dummies for either the state-year fixed effect specification (blue), first adding controls for the 2019 share interacted with year dummies (gold), and then adding controls for the 2019 average age of beneficiaries interacted with year dummies (red). Part (e) reports coefficients on the Covid restriction share of days interacted with the Trump vote share and year dummies.

Figure A.17: Supply Side

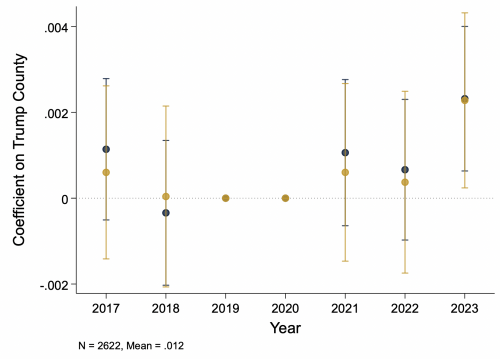
(a) Event Study - Log Providers



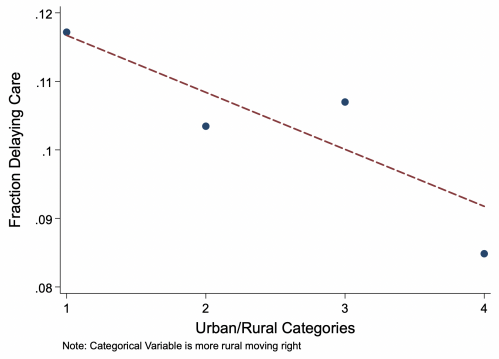
(b) Event Study - Log PCPs



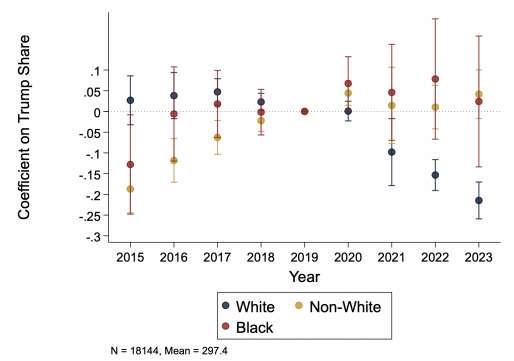
(c) Nurses per Capita



(d) Delay Care — by Rurality



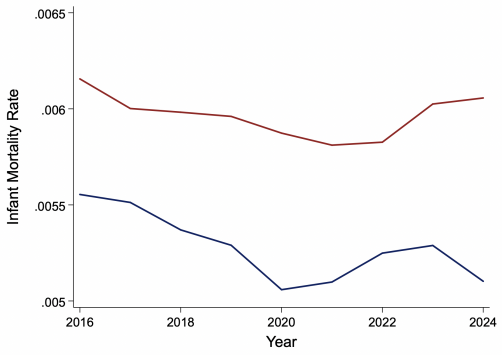
(e) PCP Patient Volume - by Benef. Race



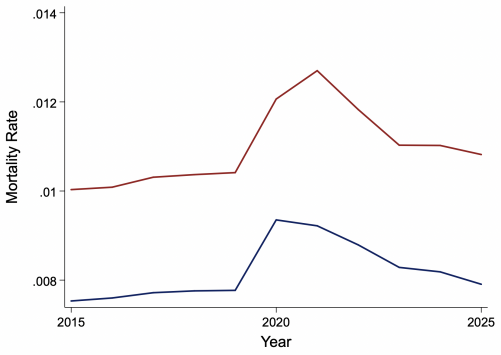
Notes: Parts (a)-(c) report coefficients on the 2020 Trump vote share interacted with year dummies for either the baseline specification (blue) or the specification with state-year fixed effects included (gold), while (e) reports coefficients by race of beneficiaries with state-year fixed effects included. All regressions are run at the county level weighting by the 2020 population and with standard errors clustered at the county level. Part (d) reports the share of 2022 NHIS respondents who report delaying care due to wait times/availability, by rurality categories, with movement right indicating more rural areas.

Figure A.18: Mortality — Raw Trends

(a) Infant Mortality

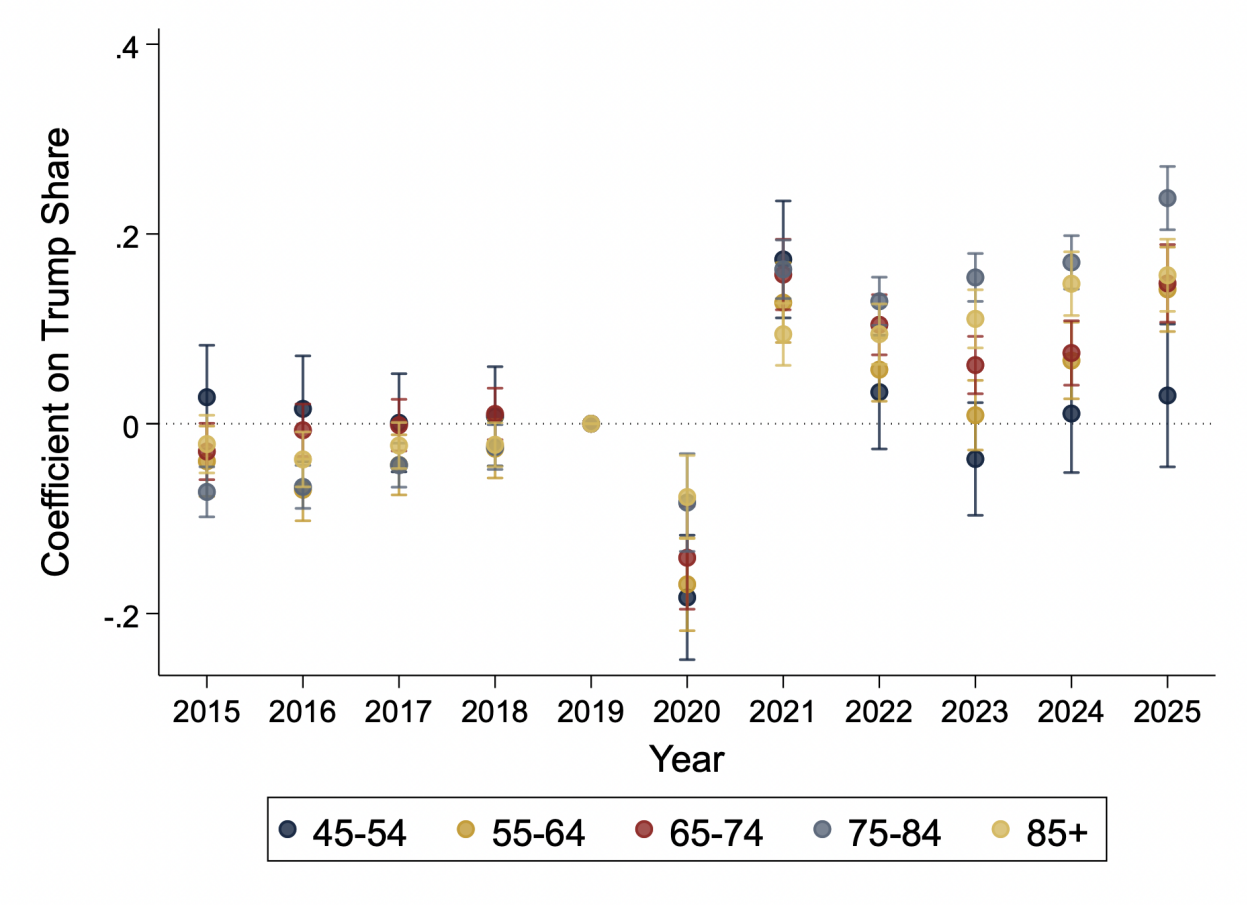


(b) Overall Mortality



Notes: Figures report raw trends in my mortality measures, split by whether Trump received over (red) or under (blue) 50% of the 2020 vote.

Figure A.19: Mortality — By Age Bins



Notes: Figures report coefficients on the 2020 Trump vote share interacted with year dummies for either the baseline specification (blue) or the specification with state-year fixed effects included (gold). All regressions are run at the county level weighting by the 2020 population and with standard errors clustered at the county level.

Tables

Table A1: Log E&M Events

Year x Share Trump	(1) Baseline	(2) State-Year FE
2015	0.00203	0.00956
	(0.0148)	(0.0105)
2016	0.00290	0.0137
	(0.0133)	(0.00955)
2017	0.0128***	0.0100**
	(0.00420)	(0.00475)
2018	0.00464	0.00556
	(0.00323)	(0.00342)
2020	0.00535	0.00543
	(0.00542)	(0.00500)
2021	-0.0420***	-0.0173***
	(0.00800)	(0.00608)
2022	-0.0711***	-0.0394***
	(0.0103)	(0.00760)
2023	-0.0810***	-0.0483***
	(0.0119)	(0.00952)
Observations	26,946	26,937

Notes: Table reports coefficients corresponding to **??**.

Table A2: Log Beneficiaries per PCP

Year x Share Trump	(1) Baseline	(2) State-Year FE
2015	0.0254	-0.0225
	(0.0215)	(0.0224)
2016	0.0258	-0.0200
	(0.0191)	(0.0209)
2017	0.0309**	0.000640
	(0.0154)	(0.0154)
2018	0.0139	0.00247
	(0.0106)	(0.0106)
2020	-0.00413	0.0124
	(0.0126)	(0.0129)
2021	-0.136***	-0.0932**
	(0.0354)	(0.0416)
2022	-0.184***	-0.0968***
	(0.0246)	(0.0245)
2023	-0.258***	-0.165***
	(0.0261)	(0.0260)
Observations	24,707	24,689

Notes: Table reports coefficients corresponding to **??**.

Table A3: Log Utilization by Category

Year x Share Trump	(1) ER	(2) IP	(3) OP	(4) Prcdr	(5) Tests	(6) Imgng	(7) Trtmt
2015	0.0258*	-0.000937	-0.0106	-0.0364***	0.00396	-0.00712	0.126***
	(0.0149)	(0.0110)	(0.0195)	(0.00824)	(0.0156)	(0.00797)	(0.0171)
2016	0.0108	0.00382	-0.0233	-0.0155**	0.00432	-0.00158	0.116***
	(0.0115)	(0.0104)	(0.0170)	(0.00716)	(0.0127)	(0.00751)	(0.0146)
2017	0.0195**	0.00948	-0.0201*	-0.00762	0.0115	0.00446	0.108***
	(0.00791)	(0.00857)	(0.0121)	(0.00529)	(0.0106)	(0.00561)	(0.0121)
2018	0.0179***	0.00602	-0.0144	-0.00294	0.00354	0.00501	0.0603***
	(0.00588)	(0.00631)	(0.00877)	(0.00356)	(0.00679)	(0.00400)	(0.00858)
2020	0.0874***	-0.00524	0.135***	0.0937***	0.0674***	0.0609***	0.0625***
	(0.00827)	(0.00943)	(0.0118)	(0.00971)	(0.0103)	(0.00609)	(0.0129)
2021	0.101***	-0.0158	-0.0324*	0.00640	-0.0299**	-0.00695	-0.00372
	(0.0123)	(0.0115)	(0.0187)	(0.00875)	(0.0142)	(0.00673)	(0.0233)
2022	0.0989***	-0.0214	0.00483	0.00477	-0.0691***	-0.0230***	-0.182***
	(0.0142)	(0.0133)	(0.0169)	(0.0101)	(0.0168)	(0.00790)	(0.0212)
2023	0.0786***	-0.00984	0.0235	-0.00662	-0.0465***	-0.0406***	-0.239***
	(0.0147)	(0.0148)	(0.0201)	(0.0160)	(0.0170)	(0.0103)	(0.0221)
Observations	26,928	26,901	26,937	26,937	26,937	26,937	26,937

Notes: Table reports coefficients corresponding to **??** and **??**.

Table A4: Log E&M per Benef. - Restriction Interaction

Year x Share x Restr.	(1) Baseline	(2) State-Year FE
2015	0.0164	0.0254
	(0.0397)	(0.0346)
2016	0.00166	0.0155
	(0.0366)	(0.0340)
2017	-0.0394**	-0.0279
	(0.0165)	(0.0200)
2018	-0.0238*	-0.0288*
	(0.0124)	(0.0155)
2020	0.00291	0.00365
	(0.0174)	(0.0172)
2021	-0.0571**	-0.0383*
	(0.0241)	(0.0207)
2022	-0.0472	-0.0243
	(0.0305)	(0.0262)
2023	-0.0899**	-0.0726**
	(0.0350)	(0.0322)
Observations	26,946	26,937

Notes: Table reports coefficients corresponding to **??**.

Table A5: Log Beneficiaries per PCP - Restriction Interaction

Year x Share x Restr.	(1) Baseline	(2) State-Year FE
2015	0.0449	-0.0380
	(0.0839)	(0.0723)
2016	0.0210	-0.0530
	(0.0733)	(0.0659)
2017	-0.0132	-0.0686
	(0.0501)	(0.0530)
2018	-0.0499	-0.0680*
	(0.0353)	(0.0396)
2020	-0.0642	-0.0641
	(0.0437)	(0.0441)
2021	-0.147	-0.130
	(0.155)	(0.132)
2022	-0.272***	-0.167**
	(0.0756)	(0.0846)
2023	-0.232***	-0.139
	(0.0781)	(0.0883)
Observations	24,707	24,689

Notes: Table reports coefficients corresponding to **??**.

Table A6: Log Beneficiaries per Provider - by Party

VARIABLES	(1) All Phys.	(2) PCPs	(3) Specialists	(4) PCP Donors
2015	0.0187	0.00604	0.0220	0.0118
	(0.0197)	(0.0357)	(0.0232)	(0.0566)
2016	0.0188	-0.00146	0.0236	0.00716
	(0.0183)	(0.0316)	(0.0232)	(0.0514)
2017	0.0155	0.00499	0.0137	0.0110
	(0.0147)	(0.0284)	(0.0187)	(0.0394)
2018	0.00131	0.0103	-0.00665	0.0140
	(0.0107)	(0.0216)	(0.0127)	(0.0313)
2020	-0.00442	-0.00729	0.0103	-0.00759
	(0.0131)	(0.0243)	(0.0151)	(0.0383)
2021	-0.0214	-0.0521	0.00976	-0.0567
	(0.0169)	(0.0353)	(0.0187)	(0.0554)
2022	-0.0387**	-0.0564*	-0.0224	-0.102*
	(0.0192)	(0.0336)	(0.0230)	(0.0546)
2023	-0.0511**	-0.0946**	-0.0181	-0.198***
	(0.0233)	(0.0402)	(0.0272)	(0.0696)
Observations	1,266,624	391,428	871,704	149,796

Notes: Table reports coefficients corresponding to **??**.

Table A7: Log Beneficiaries per Provider - Concordance

VARIABLES	(1) Fem.	(2) Male	(3) White	(4) Non-White
2015	0.00440	0.0312	0.0148	0.0182
	(0.0253)	(0.0290)	(0.0384)	(0.0466)
2016	-0.00274	0.0362	0.0242	0.0233
	(0.0207)	(0.0226)	(0.0338)	(0.0408)
2017	-0.00600	0.0334*	-0.000340	0.0306
	(0.0175)	(0.0190)	(0.0285)	(0.0330)
2018	-0.0120	0.0182	0.00703	0.00224
	(0.0138)	(0.0149)	(0.0200)	(0.0239)
2020	-0.0143	0.0109	0.0266	-0.0150
	(0.0162)	(0.0168)	(0.0208)	(0.0234)
2021	0.00910	-0.0277	0.0139	0.00664
	(0.0241)	(0.0269)	(0.0382)	(0.0422)
2022	0.0277	-0.00796	0.0511	-0.0313
	(0.0234)	(0.0266)	(0.0378)	(0.0423)
2023	0.0413	-0.0213	0.0659	-0.0571
	(0.0252)	(0.0263)	(0.0437)	(0.0461)
Observations	598,059	598,059	233,442	233,199

Notes: Table reports coefficients corresponding to **??**.

Table A8: Health Outcomes

Year x Share Trump	(1) Home Births	(2) Inf. Mort	(3) Flu Vax	(4) Mort Rate
2015			0.0359***	-0.000329***
			(0.00495)	(7.74e-05)
2016	-0.00285***	0.000471	0.0227***	-0.000433***
	(0.000738)	(0.000731)	(0.00439)	(7.23e-05)
2017	-0.00138**	0.000316	0.0131***	-8.13e-05
	(0.000589)	(0.000711)	(0.00348)	(6.54e-05)
2018	0.000218	0.000347	0.000964	-3.77e-05
	(0.000575)	(0.000684)	(0.00284)	(5.88e-05)
2020	0.00243***	0.00120*	-0.0336***	-5.97e-05
	(0.000790)	(0.000666)	(0.00383)	(0.000209)
2021	0.00648***	3.28e-05	-0.0742***	0.00247***
	(0.00129)	(0.000643)	(0.00426)	(0.000172)
2022	0.0101***	3.95e-05	-0.0895***	0.00120***
	(0.00143)	(0.000624)	(0.00541)	(0.000112)
2023	0.0131***	0.000917	-0.119***	0.000343***
	(0.00158)	(0.000611)	(0.00550)	(9.01e-05)
2024	0.0155***	0.00126**		0.000583***
	(0.00174)	(0.000618)		(9.99e-05)
2025				0.00113***
				(0.000146)
Observations	5,553	2,529	26,982	32,736

Notes: Table reports coefficients corresponding to **??** and **??**.