Trust in Medicine and the Demand for Health Care*

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Abstract

This paper studies how trust in medicine shapes health care utilization and health outcomes. I leverage the sharp partisan divergence in views of the medical profession following the Covid-19 pandemic as a shock to trust that differentially affected local areas by political orientation. I first document that since 2019, routine care utilization among Medicare beneficiaries has declined sharply in more Republican areas. By 2023, a 10 percentage point increase in a county's 2020 Republican presidential vote share implies a 0.8% reduction in routine visits per beneficiary and around a 2.5% drop in the number of beneficiaries per primary care provider. Consistent with pandemic-related dissatisfaction driving changes in trust, I show that these declines are larger in places with more stringent Covid-19 restrictions. I also find that patient volume reductions in Republican areas are substantially larger for Democratic physicians, underscoring the importance of belief concordance in sustaining trust. Finally, I link declining trust to worse health, documenting sizable 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 1% increase in mortality, with even larger percent increases for infant and elderly mortality. These results highlight the central role of trust in shaping both care utilization and health outcomes and suggest that rebuilding trust will be critical going forward.

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1 Introduction

Across a range of settings, trust in institutions and expertise has declined sharply in the United States over recent decades.[1] Until the Covid-19 pandemic, the medical profession had largely avoided this trend, but since 2019, the share describing doctors positively has fallen sharply, particularly among Republicans (Gallup, 2025). Though this decline has coincided with a well-publicized rise in vaccine skepticism, the effect of (dis)trust on demand for health care more broadly has received less scrutiny.[2] More generally, 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, because trust is multifaceted and correlates with a range of individual characteristics, quasi-experimental evidence on its role in medicine remains limited.[3]

This paper exploits the pandemic-induced shock to trust — and its starkly partisan nature — to study how trust affects care utilization and health outcomes. In the years since the Covid-19 pandemic, Republicans and Democrats have diverged sharply in their views of the medical sector. Consistent with a distrust-driven decline in demand, I document large, concurrent reductions in the use of routine health care in more Republican counties as measured by 2020 presidential vote shares. Motivated by prior work linking Republican declines in trust to backlash against pandemic-era public health (O'Brian and Kent, 2025), I show that these reductions in routine care use are concentrated in counties that had more stringent pandemic policies. 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 may exacerbate distrust. I document large shifts in other trust-related care, with influenza vaccination rates decreasing and home births increasing sharply in Republican counties. However, I do not find corresponding reductions in less discretionary hospital-based care and 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 ER visits and mortality in Republican areas. 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.

[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).

[2] For example, Kaiser Family Foundation's polling has reported rising rates of vaccine hesitancy alongside coverage by major news outlets (Kaiser Family Foundation, 2025; Paris, 2025).

[3] Darden and Macis (2024) show that trust is highly (positively) correlated with education and age.

The paper begins by documenting the evolution of views toward the medical profession in recent years. At the onset of the Covid-19 pandemic, roughly 75% of both Republicans and Democrats expressed positive views of medical doctors (Funk et al., 2020). In the years since, these views have diverged sharply. By 2024, under half of Republicans viewed doctors as honest or ethical compared with nearly 70% of Democrats, and 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).

I next develop a model that formalizes the patient care-seeking decision to consider the meaning and potential implications of (dis)trust in medicine. I model the decision to access care as a function of the patient's expected benefit of medical care, with their subjective expectation influenced by trust. The benefit of care in turn depends on the treatment choice their provider makes, which may not be patient-optimal given the provider's private incentives and potentially biased beliefs. The model yields two important conclusions. First, utilization of medical care should fall as trust declines, especially for more discretionary, routine care. Second, given the potential for sub-optimal treatment choices, lower trust is not inherently incorrect. Whether declining trust is rational on the part of patients ultimately depends on the downstream health effects of distrust.

To test the model's predictions empirically, my baseline specification is an event study design with a continuous treatment, where the event is the Covid-19 pandemic and the treatment is a county's 2020 Republican presidential vote share. The specification is designed to capture the effect of heterogeneous shifts in views of medicine, as more Republican counties 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, 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 Trump implies a 0.8% decrease in the number of evaluation and management visits per beneficiary and a 2.5% decrease in the average number of unique beneficiaries seen by primary care providers (PCPs) in the county. These decreases begin in 2021 but grow through 2023, in line with the continued decline in reported trust by Republicans over these years.

To build support for the role of distrust in driving reduced utilization, I next adopt a triple differences approach to examine two dimensions that have been shown to influence the extent of political polarization in trust. Recent experimental survey work by O'Brian and Kent (2025) has linked Republican distrust in personal doctors to dissatisfaction with public health authorities while also documenting patient preferences for political concordance

with their providers post-pandemic.[4] I therefore modify my specification by interacting vote shares with either the stringency of local pandemic restrictions or the political affiliation of providers, examining whether declining Republican utilization is concentrated where distrust would have risen most.

First, I exploit the wide heterogeneity across local areas in gathering and mask restrictions during the pandemic. Since these policies were often implemented at the state level, many Republican counties had strict restrictions while many Democratic ones did not. Using data from the CDC on the share of days in each county between April 2020 and August 2021 with a gathering restriction or mask mandate, I find that routine care declines are concentrated in Republican areas with more stringent pandemic policies. Moving from the 25th to the 75th percentile of the restriction measure implies an increase (in absolute terms) in the coefficient on the 2020 Republican vote share of 40-60% for evaluation and management visits and about a third for PCP patient volumes by 2023.

Second, I consider the match in beliefs between patients and providers. In addition to experimental evidence on demand for political concordance, 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 Republican patients or may have views on Covid-19 and vaccines that are more closely aligned with them, helping to mitigate distrust. After identifying physician partisan affiliation from a combination of political donations and voter registration data, I find that declines in 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.

These results are robust to a range of alternative empirical choices, including differences in the construction of outcomes (e.g. in levels versus logs), the use of the 2016 or 2024 election to calculate vote shares, and the inclusion of controls for beneficiary characteristics. One concern is that comparing counties across states may mix effects from shifting trust with those of other state health policies.[5] In specifications that include state-year fixed effects to restrict to within-state, cross-county comparisons, I find qualitatively similar results throughout.

[4] A random set of respondents were shown a quote by President Trump about Dr. Anthony Fauci, with treated Republicans (Democrats) reporting lower (higher) trust in their personal doctor. Meanwhile, in hypothetical choice experiments, patients preferred dermatologists from their own political party.

[5] For example, Medicaid expansions vary by state and could influence the local supply of care.

The key assumption underlying interpretation of the coefficients as the effect of distrust 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, I note a general lack of pre-trends in the various specifications before a clear trend-break coinciding with the onset of the pandemic and subsequent polarization of trust.

Second, I examine patterns in Medicare utilization per beneficiary across a broader set of care categories ranging from hospital-based care (emergency room visits and inpatient stays) to several more discretionary and routine categories (testing and imaging services and influenza vaccinations). Whereas general improvements in health should influence utilization across all types of care, the short-run effect of distrust on demand should be concentrated in discretionary categories. Consistent with this prediction, I find declining post-pandemic utilization in more Republican areas for testing and imaging services and flu shots, while inpatient stays remained 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 use data from the CDC's natality files on planned home births, which have been growing in prevalence in recent years and may signal low patient trust in traditional medicine.[6] I find that more Republican areas have seen sharp increases in home birth prevalence post-pandemic, consistent with growing distrust. 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 consider several potential alternative explanations for these shifting utilization patterns — including changes in the local economic environment, Medicare beneficiary characteristics, and the supply of care — and find that each is inconsistent with the documented changes in care use. The first explanation is that changing economic conditions during the pandemic may have altered demand for care. However, I find that local unemployment rates were lower in the years following 2020 in more Republican areas, inconsistent with lower demand. The second possibility is that differential shifts in the composition of beneficiaries, potentially due to migration or Covid-19 mortality, has changed aggregate utilization without changing individual demand. However, beneficiary trends in obesity rates, chronic

[6]The medical establishment also encourages hospital births, meaning home birth rates are to some extent a measure of adherence to expert advice (American College of Obstetricians and Gynecologists, 2017).

conditions, average age, and the share dually eligible for Medicaid have been relatively stable across vote shares. Moreover, though the white share of beneficiaries has increased somewhat post-pandemic in Democratic areas, I show that utilization declines in Republican counties occur specifically for white beneficiaries, inconsistent with a racial composition shift but in line with non-white voters being relatively unlikely to vote Republican regardless of local politics.[7] The final alternative I consider is that reduced supply rather than demand has driven changing utilization. However, I show that the supply of providers increased somewhat in more Republican areas immediately after the pandemic, inconsistent with the reduced utilization I find.[8]

Having considered alternative explanations, I close by examining whether declining trust has affected health outcomes. As highlighted by the 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 post-pandemic increases in 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 2025 or roughly 1% relative to the mean. Importantly, as for care utilization, these patterns are only apparent among white Americans, and they appear throughout the age distribution, with the largest percent changes occurring specifically for infant and elderly mortality, assuaging concerns that they are driven by compositional shifts or population aging.

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 routine care utilization but increased acute care use and mortality (Alsan and Wanamaker, 2017). In a more recent setting, Darden and Macis (2024) conducted a detailed survey on trust, health care utilization, and other characteristics to highlight the robust correlation between reported trust in medicine and

[7] In the 2020 Cooperative Election Study, a 10 percentage point increase in the state Republican vote share implies a 9 percentage point increase in a white voter's probability of voting for Trump versus a 1 percentage point increase in that of non-white voters (Schaffner et al., 2021).

[8] Interestingly, the supply side does contract between 2023 and 2025 in Republican counties, potentially indicating a supply response to reduced demand.

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, its composition, 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 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 (Jena et al., 2018; 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 in beliefs 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 (e.g. 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 an 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, though 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

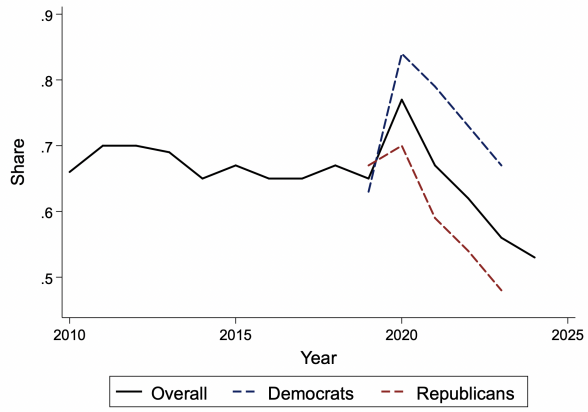
were around twice as likely as Republicans to report wearing a mask every time they left the house. And by July-August of 2020, whereas 94% of Democrats supported reducing infections first before opening businesses, Republicans were split evenly between prioritizing infections and the economy (Deane 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 theories. First, it is not necessarily surprising that conservatives, with a greater emphasis on individual liberty, would be more opposed to government mandated business closures, mask requirements, or compulsory 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.

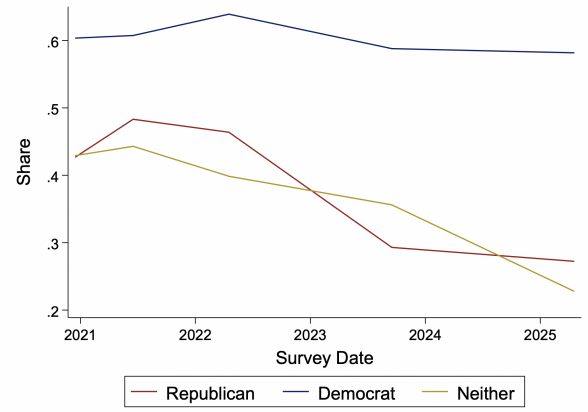
Prior work has highlighted several key distinguishing features of the United States in this context. First, in most other developed countries, mainstream political parties regardless of ideology maintained support for public health measures through the pandemic. By contrast, President Trump's views on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

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.

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. Moreover, 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 personal 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. It produces three key implications: declining trust should reduce demand for care, these reductions will likely be concentrated in routine and preventive care, and whether lower trust is rational is ambiguous without an examination of health outcomes.

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, 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:

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

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 expected patient benefit (i.e. the expected returns to treatment intensity diminish) and decreasing marginal private benefits (i.e. financial returns diminish while marginal opportunity and psychic costs increase), the physician will choose τ_i^* such that $\frac{\partial}{\partial \tau}\hat{E}_j[v(\alpha_{2i}) \mid \alpha_{1i}, \tau_i^*)] = -\pi_j'(\tau_i^*)$.

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 a hassle or 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 care depends on their health state in period 1, α_{1i}, and the treatment received if they choose to obtain care. This treatment in turn depends on 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 $E[v(\alpha_{2i}) \mid \alpha_{1i}, m_i]$ 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 $\tilde{E}_i[v(\alpha_{2i}) \mid \alpha_{1i}, m_i]$ as the individual's analogous, potentially incorrect, subjective expected utility. Then, the objective function for person i is:

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

The individual will choose to access medical care if

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

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, $\Delta(\alpha_{1i}) := E[v(\alpha_{2i}) \mid \alpha_{1i}, m_i = 1] - E[v(\alpha_{2i}) \mid \alpha_{1i}, m_i = 0]$, 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.[9] 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 healthy 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, at least before any health effects of foregone care emerge.[10]

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 Centers for Disease Control and Prevention (CDC) birth and death data. The Medicare data consists of two sets of files: Geographic Variation public data (Centers for Medicare and Medicaid Services, 2025c), running from 2014 to 2023, and 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 local areas.

The Geographic Variation files include county-year-level information on the general characteristics of Medicare's fee-for-service beneficiaries, including average age, racial composition, and the share dually eligible for Medicaid, as well as summary utilization measures for

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

[10]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.

a series of care categories. The categories used in this paper include three location-of-care based measures — emergency room visits, inpatient stays, and hospital outpatient visits — as well as service-based measures using the Restructured BETOS Classification System for Part B services — evaluation and management visits, treatments, procedures, tests, and imaging services. For each 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 many 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. In part due to these limitations, I also examine outcomes derived from provider-level data.

My main source of provider data, CMS' Physicians and Other Practitioners file, 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 by provider type (PCPs and specialists).

These provider measures have their own limitations 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 retirements and entry. To address this, I report 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 at times 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 in 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 only a minority were kept 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 with patients 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 (as long as they are billing under their own NPI).

Finally, in my analysis of health outcomes, I 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 these analyses. It is important to note that 2025 data are provisional while earlier years have been finalized.[11] To remove cases in which reporting may still be incomplete, I drop counties in which there was a greater than 10% change in mortality between 2024 and the provisional

[11]However, the finalization of 2024 data made little difference for results.

2025 data.

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 average age is relatively balanced, beneficiaries in 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. 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 shifts in utilization across local vote shares reflect shifts across individual politics. In other words, if more Republican areas see lower utilization post-Covid, I interpret this as reflecting reduced utilization *among Republicans*, rather than the effect of the local political environment more generally. Though this is not directly testable, I provide evidence looking at demographic heterogeneity to suggest this is reasonable.

When I examine the role of 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 $Restr_c$:

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

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:

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

In these analyses, I include county-year fixed effects, both to remove the influence of shifts in the local FFS population and because there is a high degree of sorting by physicians across political geography (or, local politics may influence those of providers directly). Now, β_k represents the extent to which changing utilization across local political affiliation is exacerbated or mitigated by the political beliefs 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 most specifications weight 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. Though these assumptions cannot be tested directly, I consider a range of alternative explanations that would represent violations of them in Section 4.3.

4 Results

4.1 Trust and the Demand for Routine Care

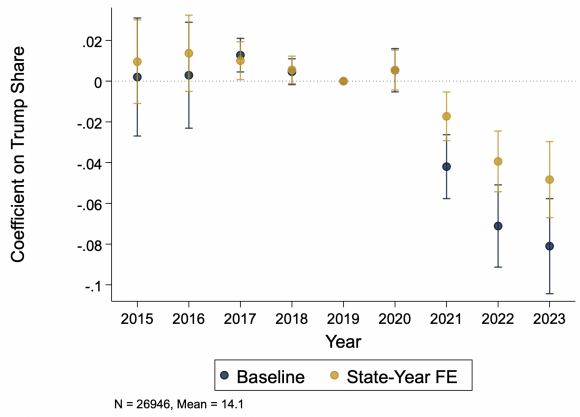
I now turn to my main results for the effect of declining trust on the demand for care. Throughout, I report event study figures, but tables with all corresponding coefficients are reported in the Appendix. I begin by examining patterns in the use of routine care across the political orientation of counties. 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

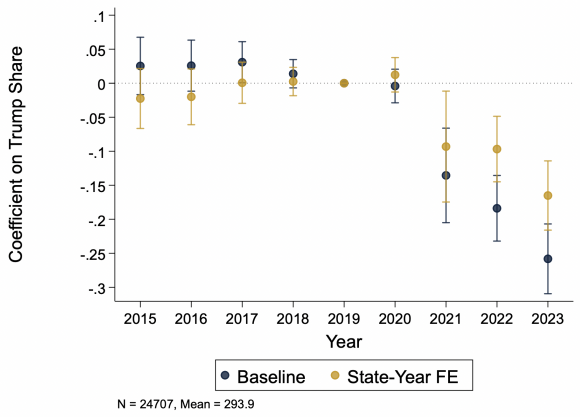
2019. The figure reports versions both without (blue) and with (gold) state-year fixed effects included. In the pre-period, the influence of county-level political affiliation was relatively stable, with Republican counties trending similarly to Democratic ones. Beginning in 2021 and continuing through 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.

Appendix Figure A.2 reports binned and raw scatter plots of 2019 to 2023 log changes in visits per beneficiary and PCP patient volumes against the 2020 Trump vote share, with the relatively linear relationship suggesting the continuous vote share specification is reasonable. Nonetheless, in Appendix Figure A.3, I show that these patterns are robust to simply considering whether a county voted for Trump. Appendix Figure A.4 also confirms that these results are replicated when using levels rather than logs. Moreover, though an aging Medicare population means utilization has been rising over time, Appendix Figure A.5 shows that in Republican counties, the number of E&M visits has not returned to the long-run trend and that conditional on beneficiary population characteristics, has fallen in Republican counties post-pandemic. Meanwhile, patient volumes for PCPs have declined overall, especially 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 Appendix Figure A.6, with a decline in the share post-Covid in more Republican areas following an increase during the pandemic. 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.

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.7a, 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.7, 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.8, 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 Republican 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.

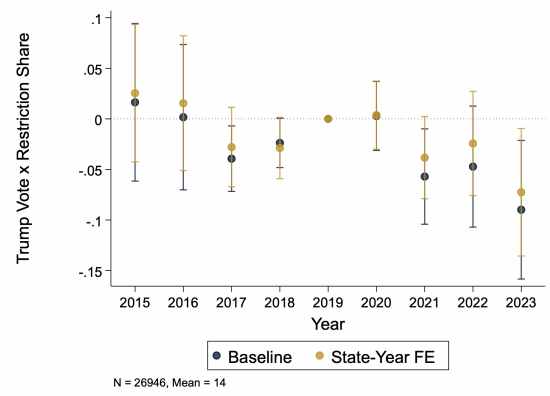
I begin by analyzing the influence of Covid-19 policies in driving changes in the utilization of routine care. Importantly, because many policies were implemented at the state-level, a substantial number of Republican counties had stringent restrictions while many Democratic counties had lax ones. Given 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 around 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 0.05-0.09, or about 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

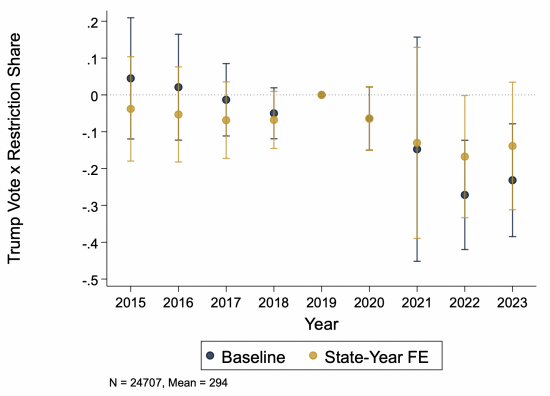
provide further evidence to support the conclusion that declining trust has reduced routine care use.

Figure 3: Triple Difference Regressions — Demand for Routine Care

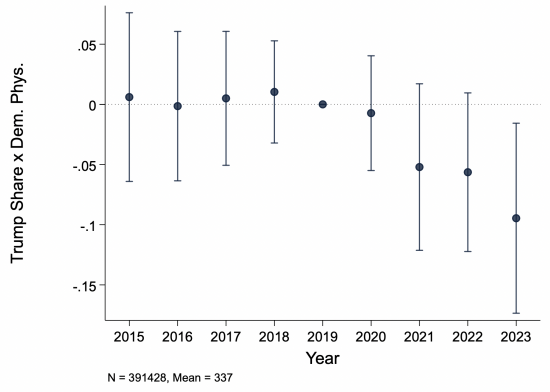
(a) Log E&M Visits by Covid-19 Policies



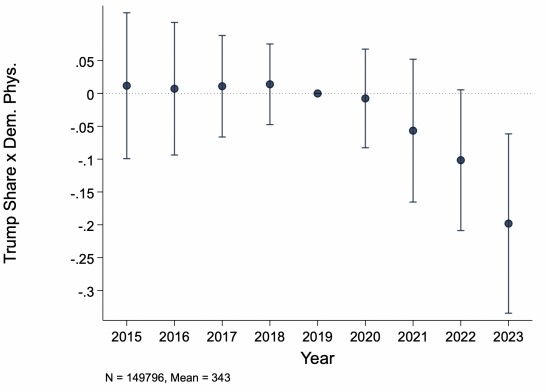
(b) Log PCP Patients by Covid Policies



(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) 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 the 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 percentage point 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 twice as large, though with large standard errors, I cannot reject the null hypothesis of no difference between the coefficients.

Importantly, as shown in Appendix 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 are several important things to note for these results. 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 result 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 physician politics 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 broader composition of care received.

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 thus examine a wider set of care measures, ranging from hospital based care to other more routine categories. Before discussing the results, several important points are necessary.

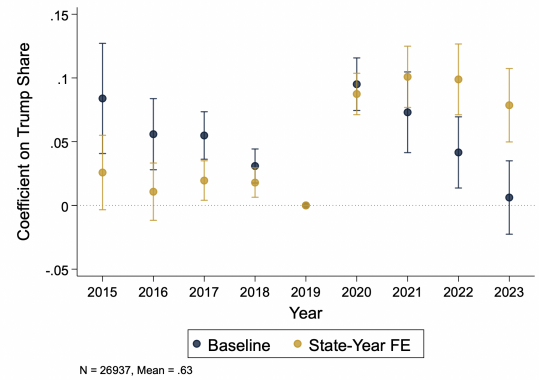
First, these outcomes exhibit more substantial pre-trends than had been the case for the routine care measures, though they generally improve when considering within-state variation, particularly for the hospital-based measures. One potential reason for this is that state policy may be especially important for hospital care, given that policies such as 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, a pattern also documented in (Alsan and Wanamaker, 2017). Yet 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 of 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.

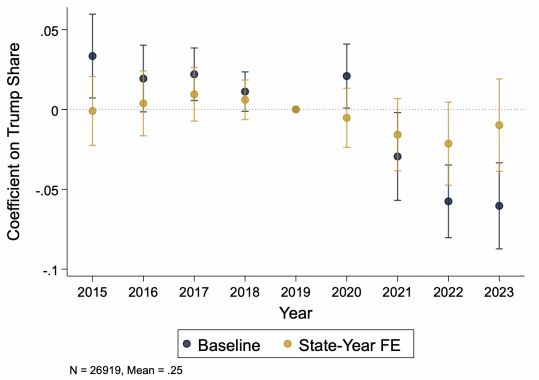
Next, in Figure 4b and Figure 4c, I show results for the log number of inpatient stays and hospital outpatient visits per person. As with emergency room visits, inpatient stays were declining prior to 2020 in more Republican areas, though in this case they continued to do so after 2020. And again, the 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 hospital outpatient visits, the inclusion of state-year fixed effects again attenuates both

Figure 4: Event Study Results — Other Care Categories

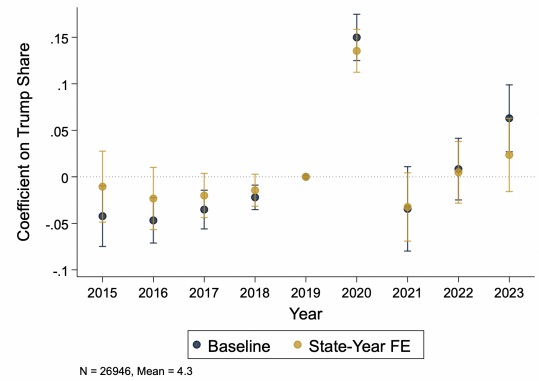
(a) Log ER Visits per Beneficiary



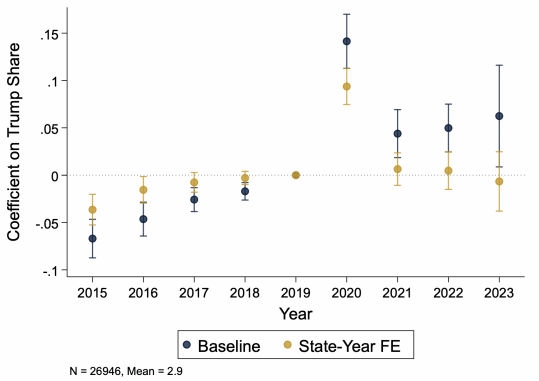
(b) Log Inpatient Stays per Beneficiary



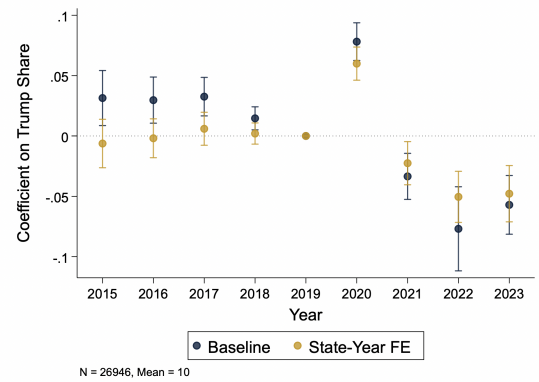
(c) Log Outpatient Visits per Beneficiary



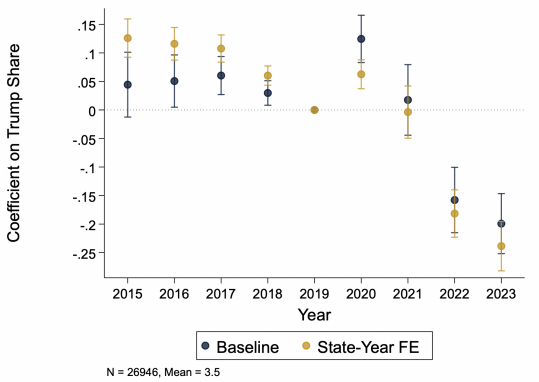
(d) Log Procedures per Beneficiary



(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.

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+Imaging services, and Treatments.[12] 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 imaging services. Additionally, given that vaccinations fall under the treatments category, lower utilization in more Republican areas is unsurprising. Importantly, these reductions in tests, images, 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 mortality, 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.

In Appendix Figure A.11, 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. In any case, these results show 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

[12]Note that procedures are defined as services designed to be performed at a single time and place, while treatments are designed to be a series over time and also include vaccinations.

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.[13]

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.13a, in the years running up to the pandemic, annual influenza vaccination rates were rising in 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.

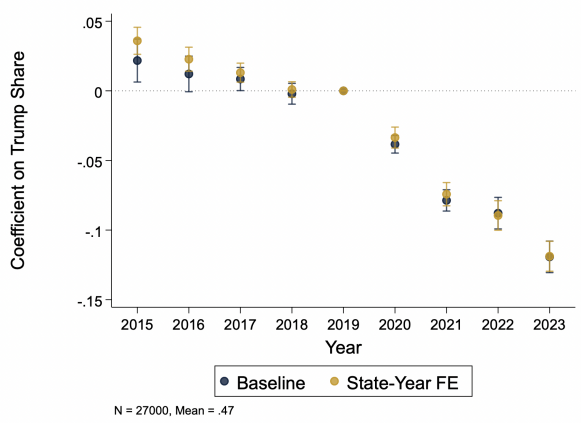
Next, in Figure 5b, I report equivalent results for the fraction of births occurring at home intentionally, which past work has found to be associated with much higher rates of complications and mortality (Grünebaum et al., 2020). Importantly, data censoring required that many smaller counties be combined 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.13b. Notably, much of this increase has been driven by 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 the

[13]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" (American Medical Association, 2025). On home births, the American College of Obstetricians and Gynecologists is somewhat 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" (American College of Obstetricians and Gynecologists, 2017).

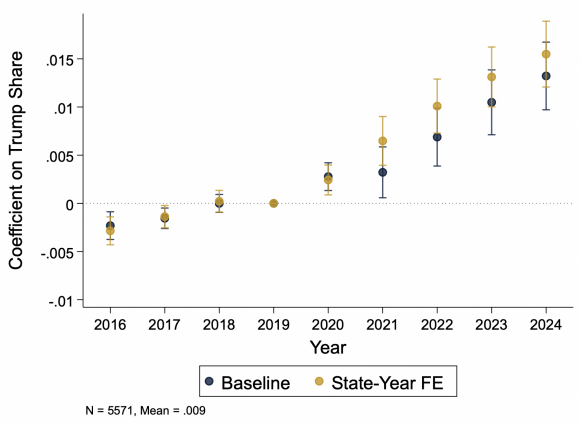
still-low home birth share of a little over 1% post-pandemic, this implies a more than 10% increase relative to the mean.

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/home birth 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.

In Appendix Figure A.12, I again report scatter plots of the relationship between changes in flu vaccination rates (from 2019 to 2023) and home birth rates (from 2019 to 2024) and the Trump 2020 vote share. The relationships are remarkably linear, further supporting the use of a continuous specification. Moreover, given the close link between these outcomes and trust, the linearity provides some indication that the vote share measure is a reasonable proxy for changes in trust.

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. And persistent increases in ER visits provide suggestive evidence of negative health effects, which will be explored further in Section 4.4. 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 other factors that could drive changing utilization across different geographic areas.

4.3 Alternative Explanations

In this section, I examine three main alternatives: changes in economic conditions, the composition of beneficiaries, and the local supply of care. 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. However, as shown in Appendix Figure A.14, 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.15a, 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.16a and Figure A.16b, 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.[14] In neither case is there evidence of health improvements among the FFS Medicare population. In Appendix Figure A.16c, 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.15, 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

[14]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.

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.17a). 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 trends, the magnitude of coefficients falls substantially, without meaningfully altering the routine care estimates (Appendix Figure A.17). Second, as shown in Appendix Figure A.19e, the effects for patient volumes are largely accounted for by reductions in the number of white beneficiaries, which cannot be driven by racial composition changes alone.

Next, I consider shifts in the FFS share of all Medicare 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.18a, 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.18b, 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.18c and Figure A.18d, 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.17e and Figure A.18e, 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 Fig-

ure 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 changes. 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.19b, 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 the results, 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 distrust 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.19c, 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.19d, 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.19e, 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, even in Republican areas, 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 distrust 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 declining trust in this context is in some ways more difficult than examining its influence on demand for care. First, distrust 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 as whether patients fill and take prescriptions or the use of non-traditional medicine and 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 led to the deaths of over one million Americans (Centers for Disease Control and Prevention, 2026). Distrust, 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 distrust 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.

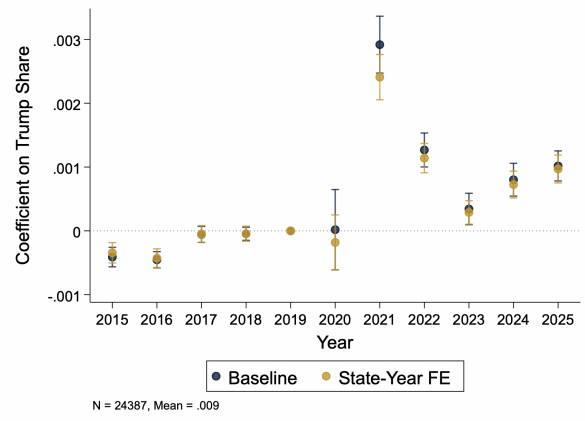
Figure 6 reports results, with Figure 6a showing estimates for overall mortality while Figure 6b presents results for infant mortality rates. In each case, rates spiked in more Republican areas during the pandemic, though for infant mortality this occurred in 2020 (where lower stay-at-home adherence 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

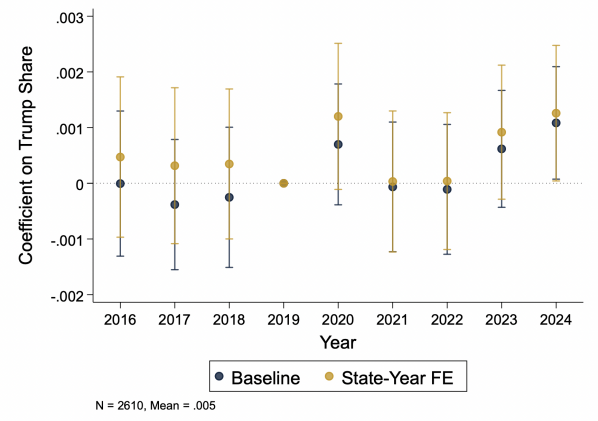
flat. Though there was convergence to just above the 2019 relationship by 2023, the trend has since reversed, with mortality increasing steadily in Republican relative to Democratic areas in both 2024 and 2025. By 2025, a 10 percentage point increase in the Trump vote share implied an increase in the overall mortality rate of over 1 death per 10,000 people, an increase of over 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

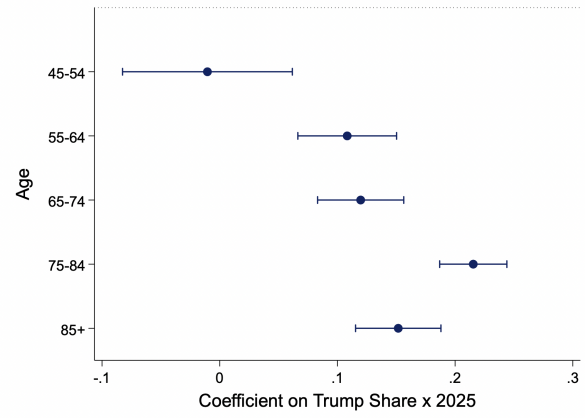
(a) Overall Mortality



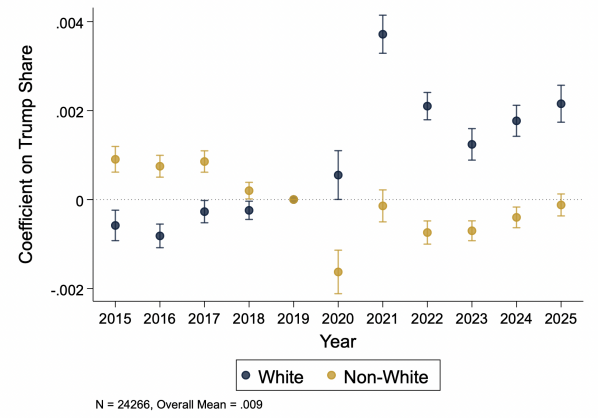
(b) Infant Mortality



(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 (Appendix Figure A.22 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 percentage point increase in the Trump vote share implies increases in mortality of around 1% for those 55-74, 1.5% for those 85+, and 2.5% for those 75-84, suggesting age composition changes not 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 non-white Americans being much less likely to be Republican even in Republican areas, I show that increases in mortality in Republican areas are concentrated among white individuals.

Appendix Figure A.20 reports scatter plots of overall and infant mortality rates against the 2020 Trump share. In this case, the infant mortality patterns are noisier (potentially due to the smaller sample sizes), but still suggests a positive relationship. Interestingly, the overall mortality rate shows some evidence of convexity over the vote share.[15] Given the potential externality of foregone vaccinations, this pattern may indicate a community feedback element in which the health care decisions of some have had negative impacts on others.

Recent work has also highlighted the inverse relationship between unemployment and mortality rates, which is relevant in this case given the persistent divergence in unemployment between Republican and Democratic counties post-pandemic. However, the mortality estimates in this paper cannot be fully explained by the relatively lower unemployment in Republican areas. A 10 percentage point increase in the Trump vote share implies a slightly over 0.1 percentage point decrease in the unemployment rate. Extrapolating the estimates from Finkelstein et al. (2025), this would imply a roughly 0.05% increase in mortality rates, far shy of the 1% increase documented here.

The aggregated nature of the outcomes makes 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 cal-

[15]Indeed, in a regression of the 2019 to 2025 change in mortality rates on the Trump vote share and the vote share squared, the latter is positive and significant at the 1% level.

culation. First, note that the (population-weighted) average county cast 47% of the vote for Trump in the 2020 election. Extrapolating this average to the mortality coefficients (0.000969 for overall 2025 mortality and 0.00126 for 2024 infant mortality), this would imply an increase of around 4.6 deaths per 10,000 for total mortality and 5.9 per 10,000 births for infant mortality. With a 2025 population of 340 million, this implies excess total mortality of around 150,000 people, and with 3.6 million births in 2024, roughly 2,000 excess infant deaths. Though these estimates come with wide standard errors and several crucial assumptions, they provide suggestive evidence that the shifts in trust have had severe consequences. For comparison, 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 (Centers for Disease Control and Prevention, 2025c; Ahmad and Cisewski, 2026). 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 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 also 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 recent as 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.

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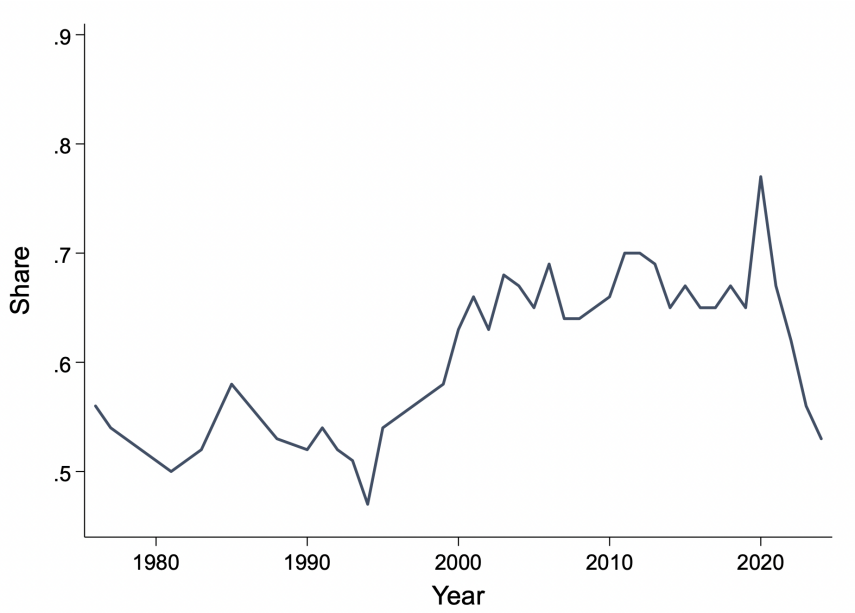
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Appendix

Figures

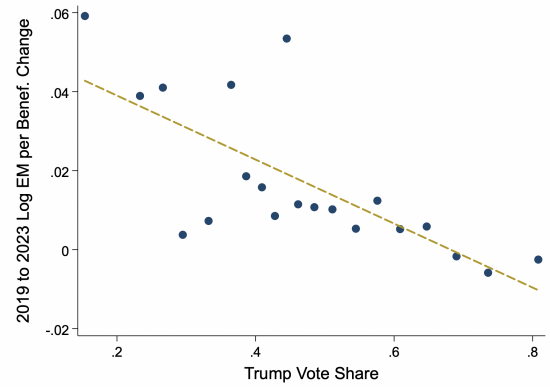
Figure A.1: Share Describing Doctors as Honest or Ethical — Full Time Series



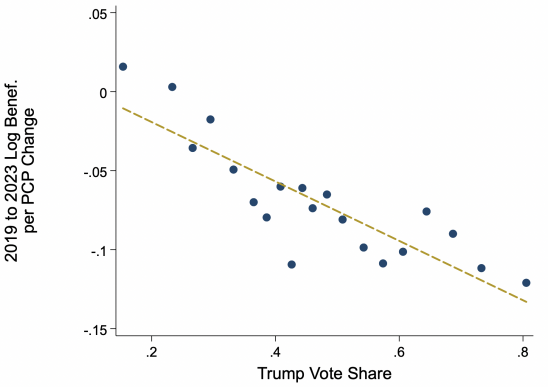
Notes: Data from Gallup.

Figure A.2: Routine Care Changes by Trump Vote

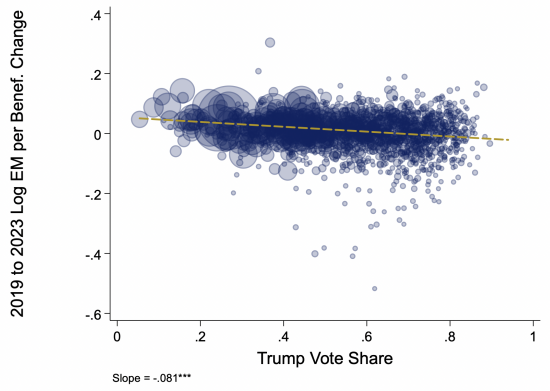
(a) Binned Log E&M Visits per Beneficiary



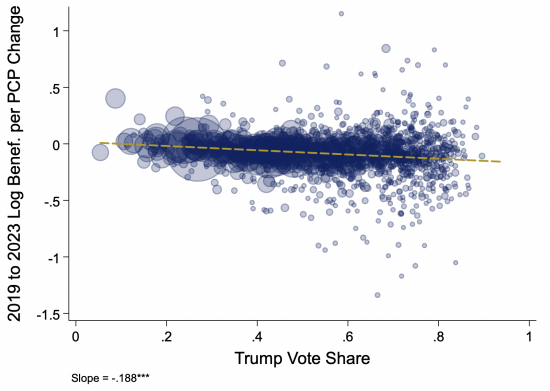
(b) Binned Log Beneficiaries per PCP



(c) Log E&M Visits per Beneficiary



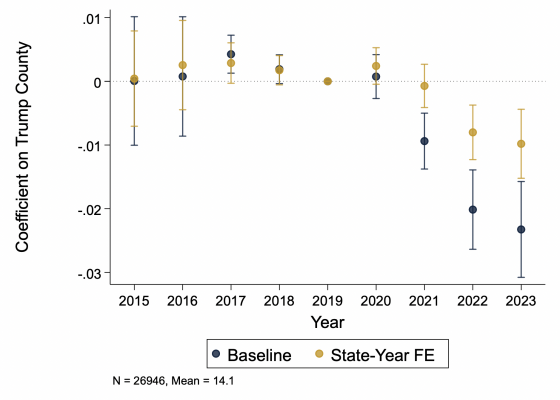
(d) Log Beneficiaries per PCP



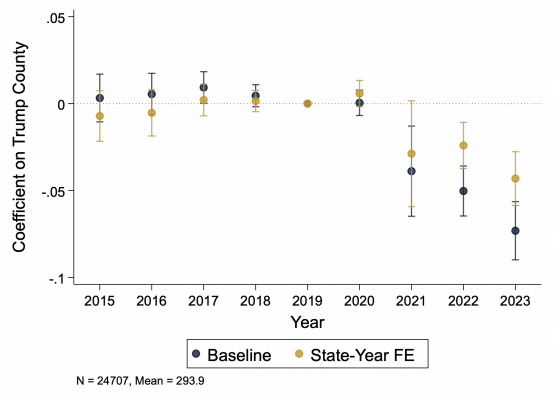
Notes: Figures report binned and raw scatter plots of the log change from 2019 to 2023 in utilization measures against the 2020 Trump county vote share. The PCP beneficiaries versions use 2023 patient volumes that are rescaled by the ratio of the county-level 2019 FFS population to the 2023 FFS population. The raw scatter plots restrict to counties with greater than 25,000 residents to reduce noise.

Figure A.3: Event Study Results — Routine Care by Trump County

(a) Log E&M Visits per Beneficiary



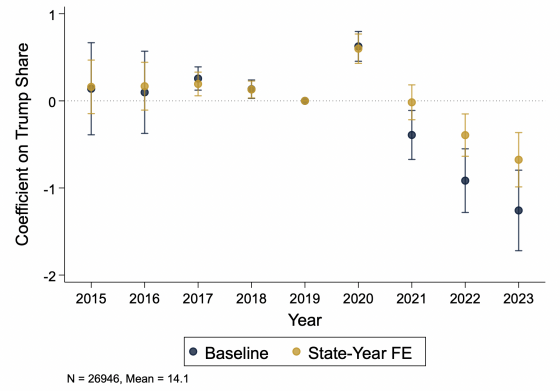
(b) Log Beneficiaries per PCP



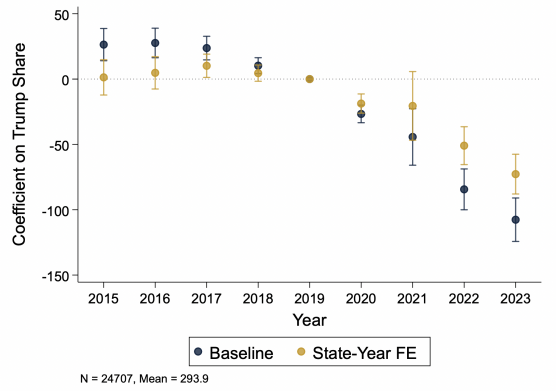
Notes: Figures report coefficients on a dummy for whether Trump won over 50% of the 2020 vote interacted with year dummies for either the baseline specification (blue) or the specification with state-year fixed effects included (gold).

Figure A.4: Event Study Results — Utilization of Routine Care in Levels

(a) E&M Visits per Beneficiary



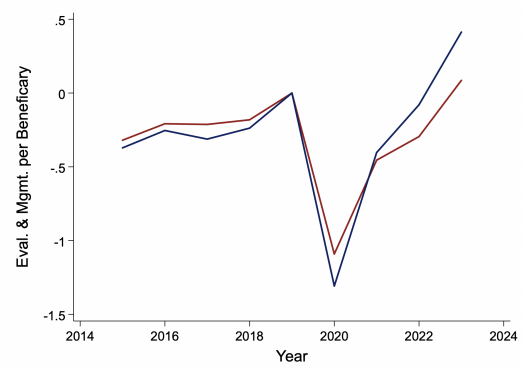
(b) Beneficiaries per PCP



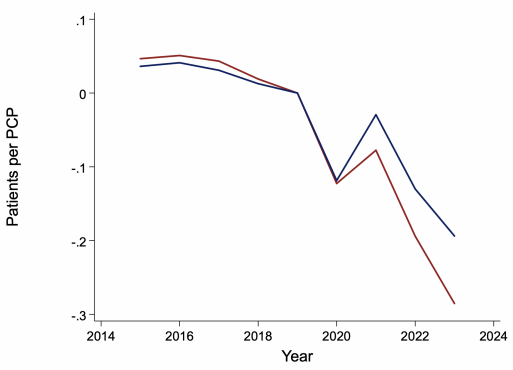
Notes: Figures report coefficients on the 2020 Trump vote share interacted with year dummies for either the baseline specification (blue) or the specification with state-year fixed effects included (gold).

Figure A.5: Raw and Residualized Trends — Routine Care

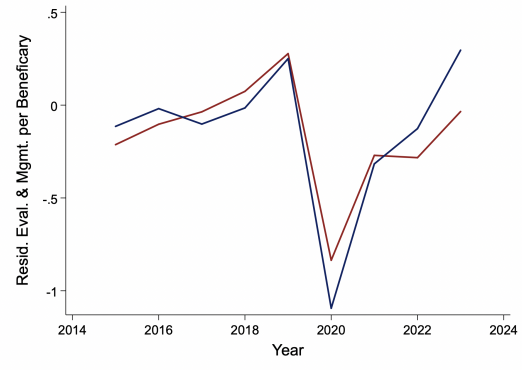
(a) E&M per Beneficiary - Raw



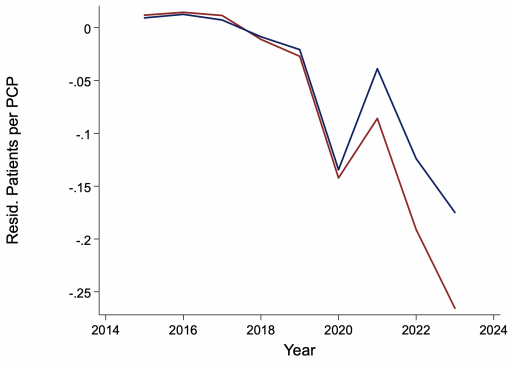
(b) Beneficiaries per PCP - Raw



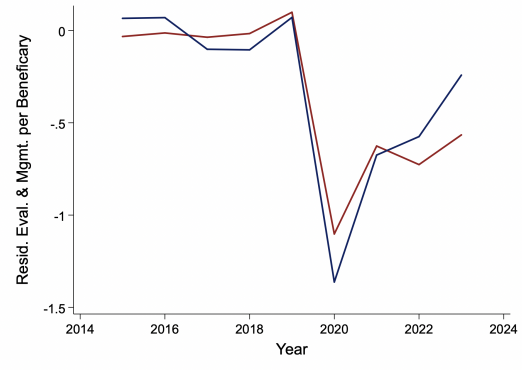
(c) E&M per Beneficiary - Resid.



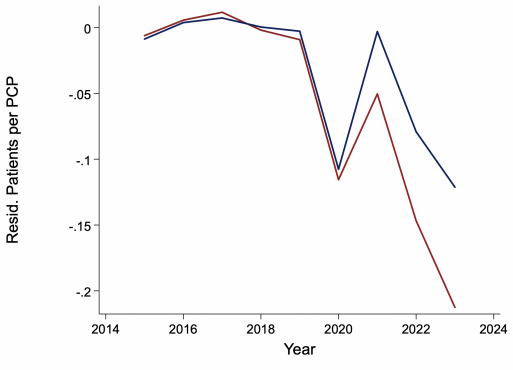
(d) Beneficiaries per PCP - Resid.



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

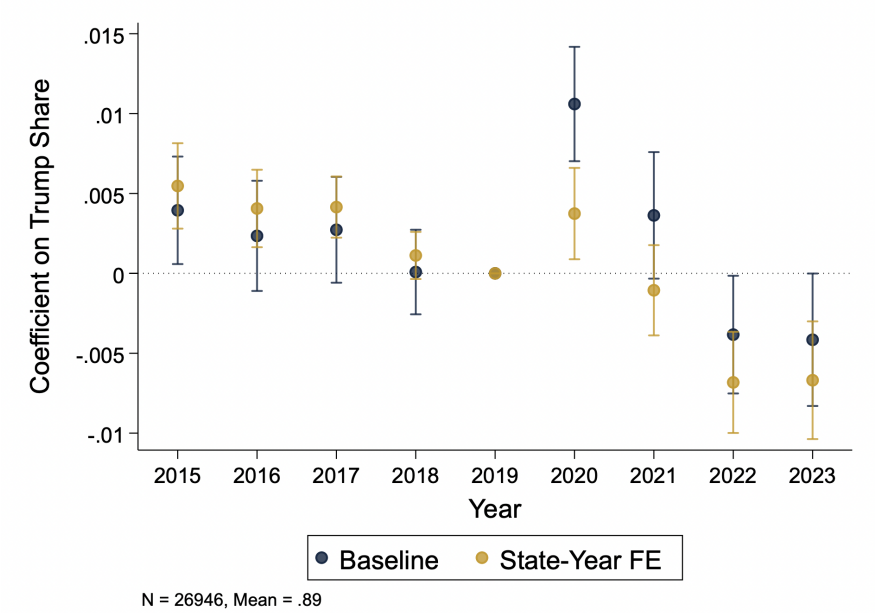


(f) Beneficiaries per PCP - Resid. + Detr.



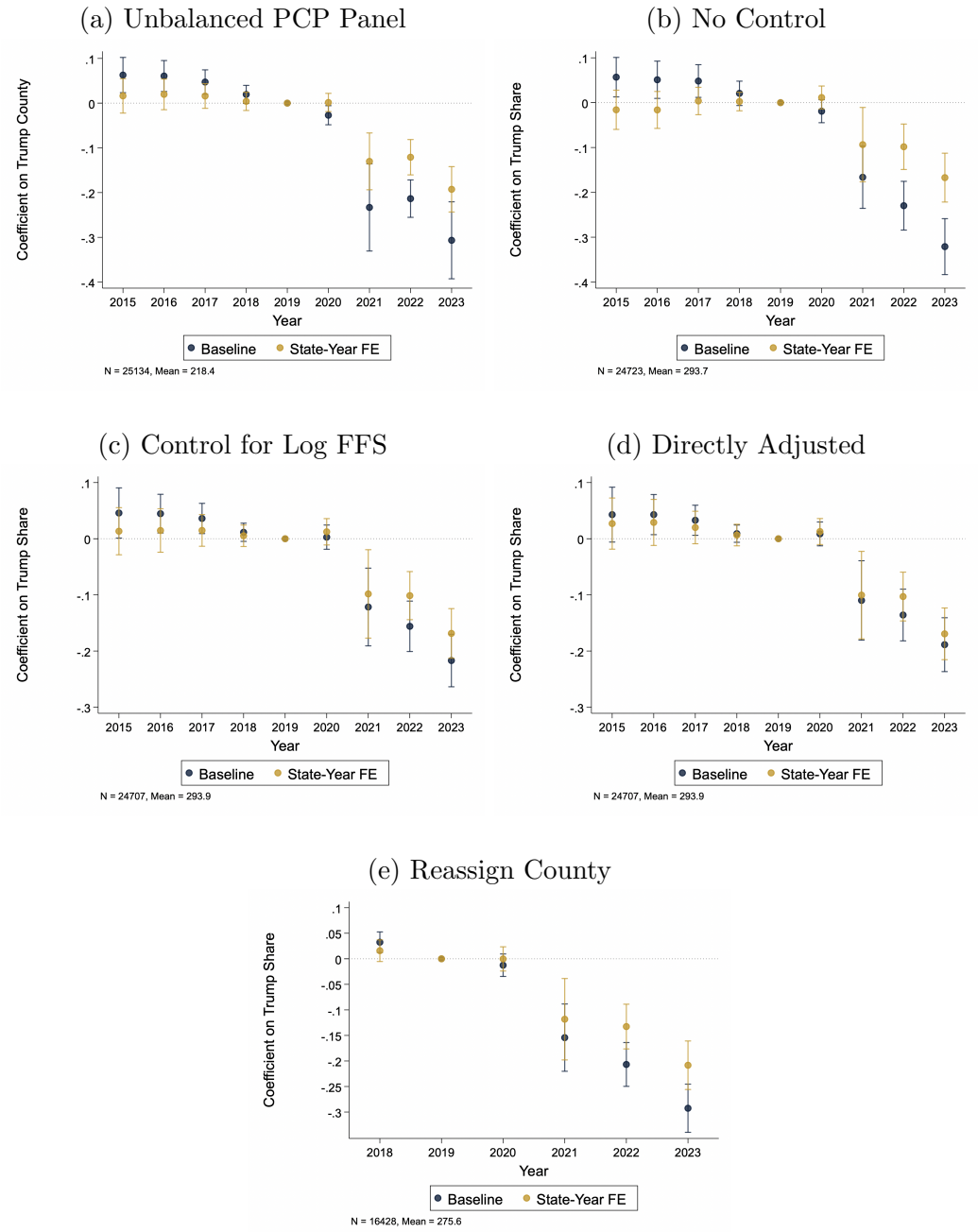
Notes: Figures report trends for E&M and beneficiaries per PCP, split by counties in which Trump won more (red) or less (blue) than 50% of the vote in 2020. (a) and (b) report raw trends, (c) and (d) residualize on beneficiary average age, average age quintile, female share, and dual share, and (e) and (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.6: Event Study Results — Share with Any E&M



Notes: Figure reports 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).

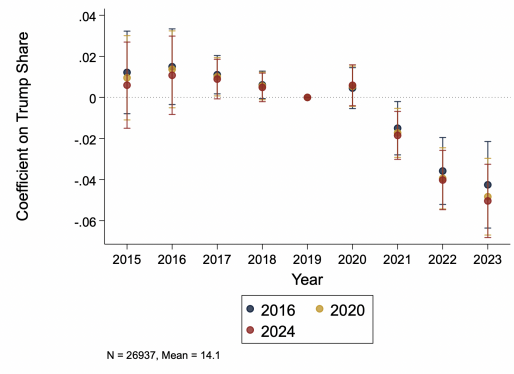
Figure A.7: Robustness — PCP Patient Volumes



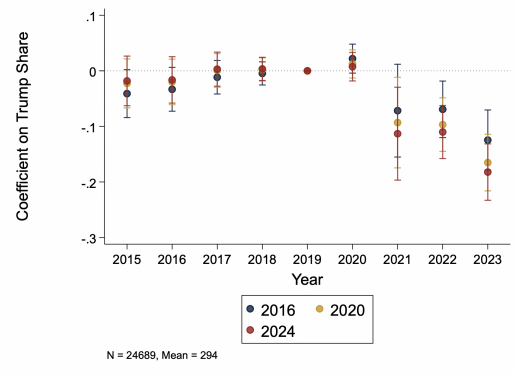
Notes: Figures report coefficients on the 2020 Trump vote share interacted with year dummies for either the baseline specification (blue) or the specification with state-year fixed effects included (gold). Part (a) includes all PCPs when calculating average patient volume while part (b)-(d) restrict 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.8: Robustness — Election Year, Weights, and Controls

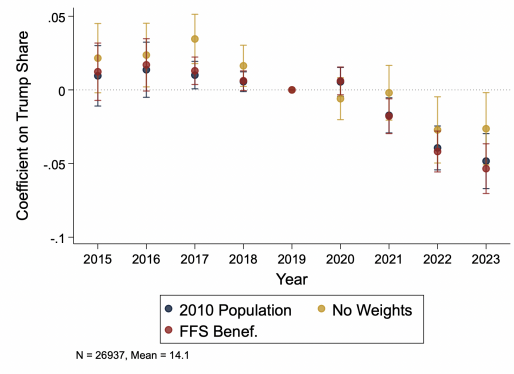
(a) E&M — By Election Year



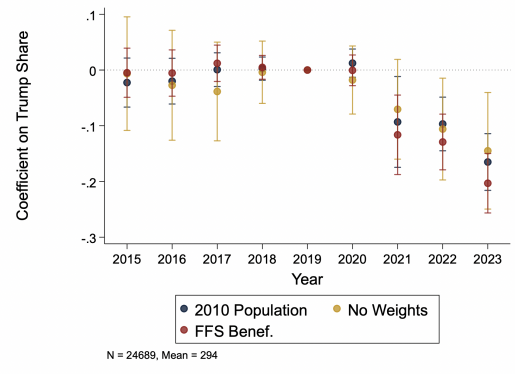
(b) PCP Benef. — By Election Year



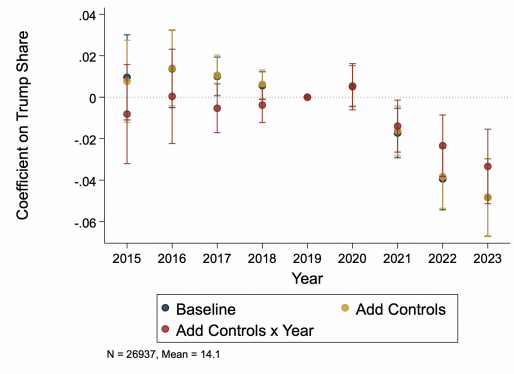
(c) E&M — Weighting



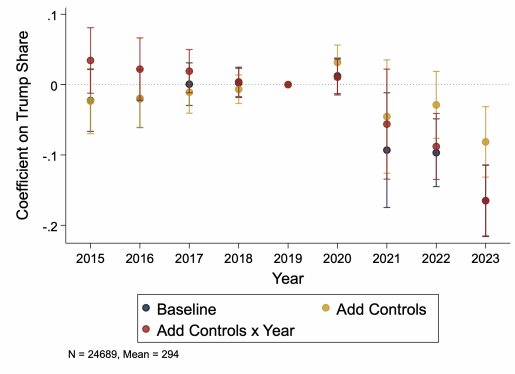
(d) PCP Benef. — Weighting



(e) E&M — Controls



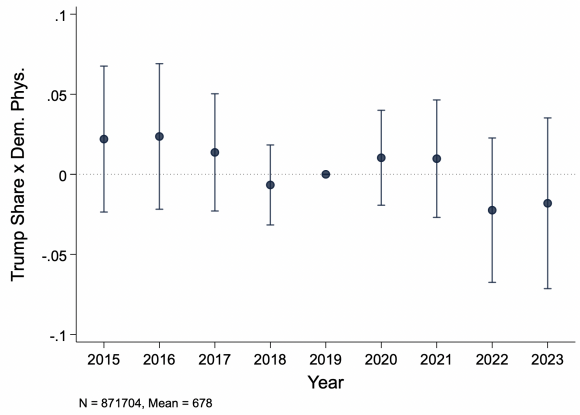
(f) PCP Benef. — Controls



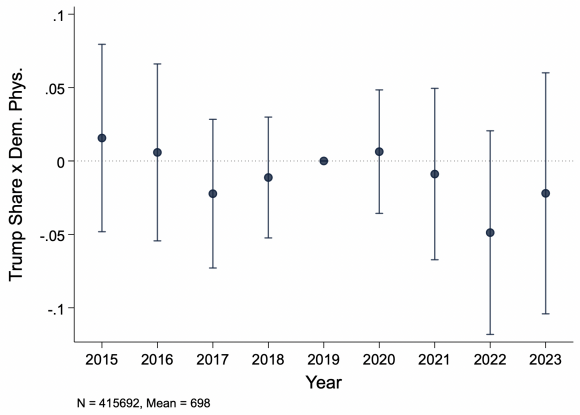
Notes: Figures report coefficients on the Trump vote share interacted with year dummies for log E&M per beneficiary (left) and log PCP patient volumes (right). Parts (a) and (b) vary the election year, (c) and (d) report results without weights or when using the number of FFS beneficiaries, and (e) and (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.9: Provider-Patient Political Concordance — Specialists

(a) All Specialists



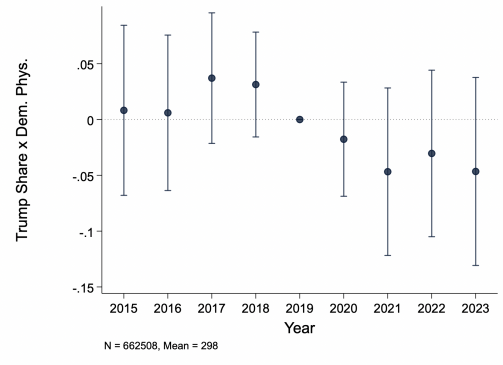
(b) Specialist Donors



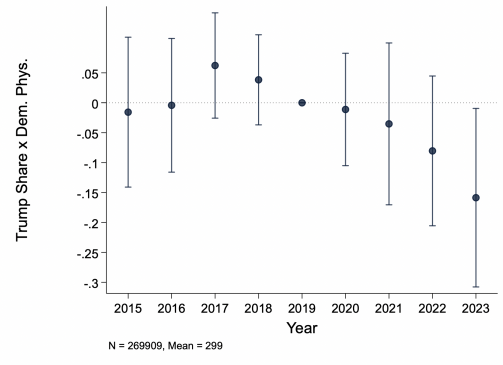
Notes: Figures report coefficients from physician-level regressions restricted to specialists of log Medicare patient volumes on the 2020 Trump vote share interacted with whether the physician is a Democrat and year dummies. Standard errors clustered at the county level and regressions include county-year 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

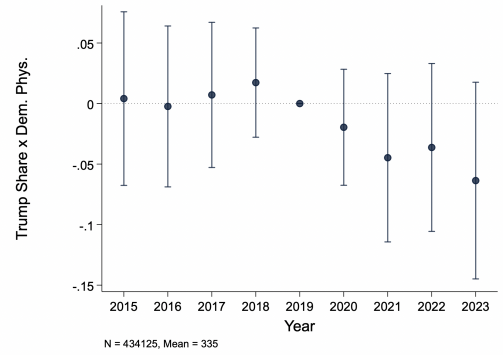
(a) By Party — Unbalanced Panel



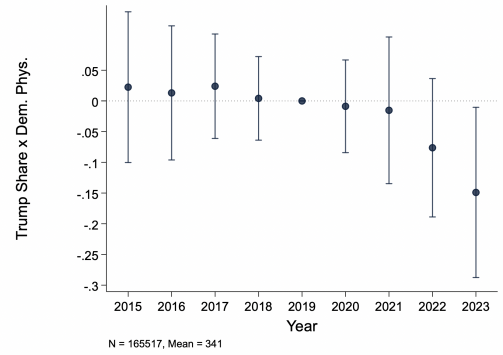
(b) By Donations — Unbalanced Panel



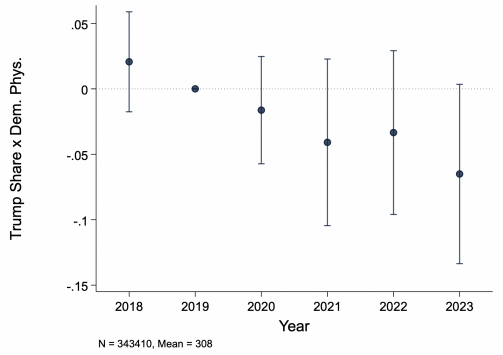
(c) By Party — with Moves



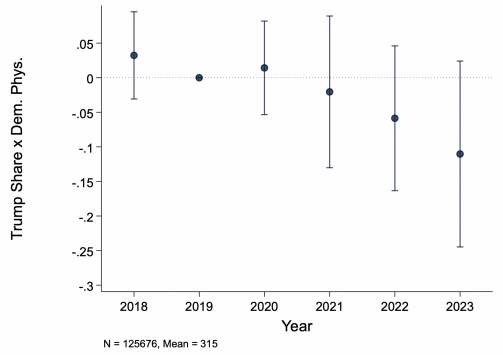
(d) By Donations — with Moves



(e) By Party — Reassign Location



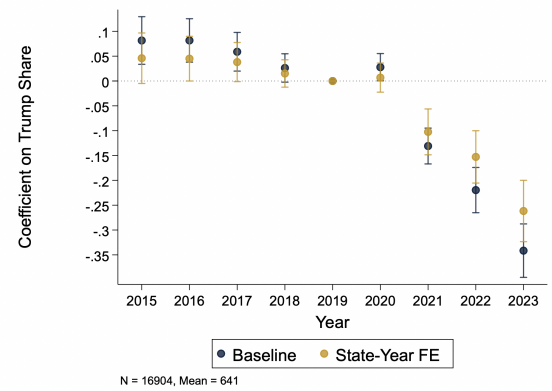
(f) By Donations — Reassign Location



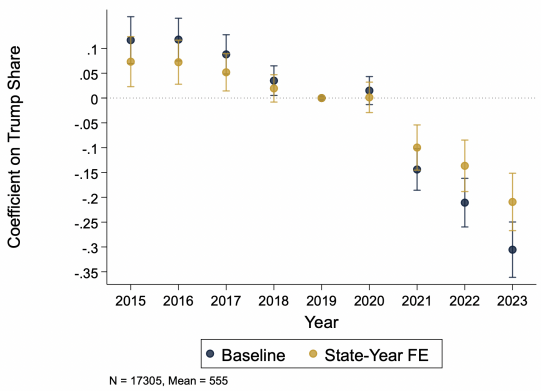
Notes: Figures report coefficients from physician-level regressions of log Medicare patient volumes on the 2020 Trump vote share interacted with whether the physician is a Democrat and year dummies. Standard errors clustered at the county level and regressions include county-year fixed effects to restrict 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) include 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: Specialist Patient Volumes

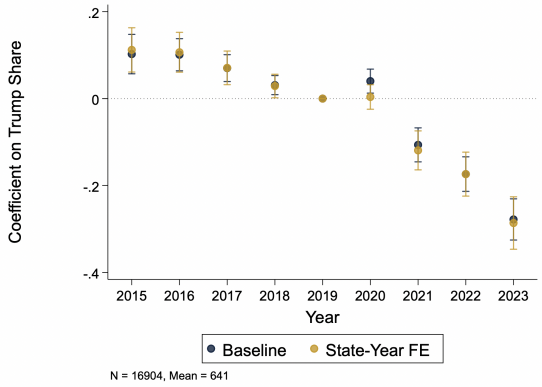
(a) Main Specification



(b) Unbalanced



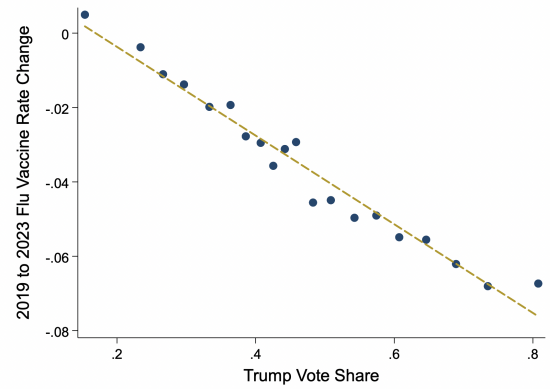
(c) Directly Adjusted



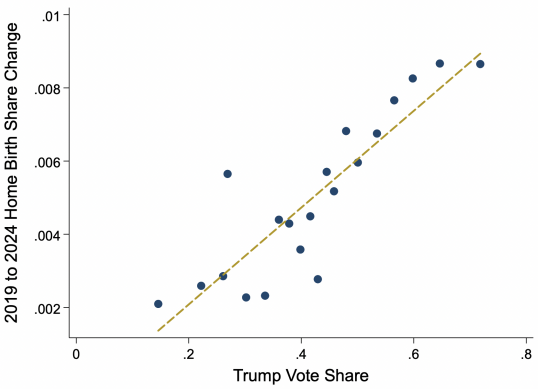
Notes: Figures report coefficients on the 2020 Trump vote share interacted with year dummies for either the baseline specification (blue) or the specification with state-year fixed effects included (gold). Part (a) restricts to a balanced panel of specialists while part (b) includes all specialists when calculating average patient volume; both control for the log of the ratio of patient volumes to specialists. Part (c) 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.12: Trust-Related Care Changes by Trump Vote

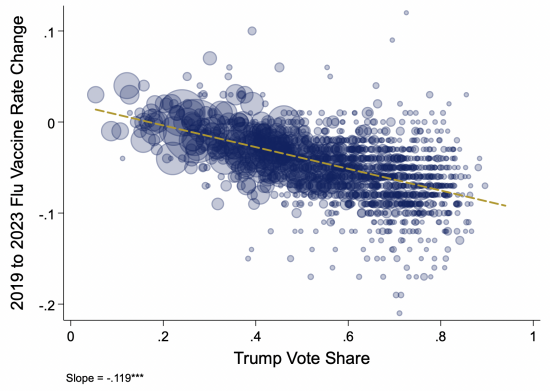
(a) Binned Flu Vaccinations



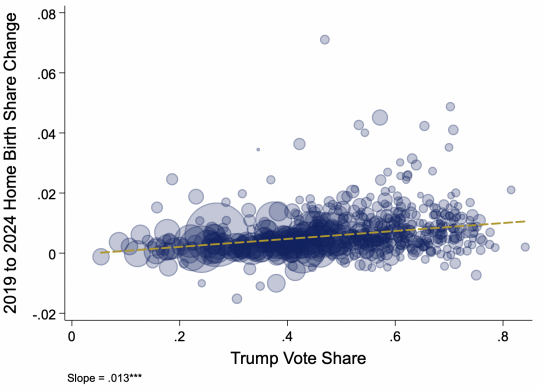
(b) Binned Home Births



(c) Flu Vaccinations



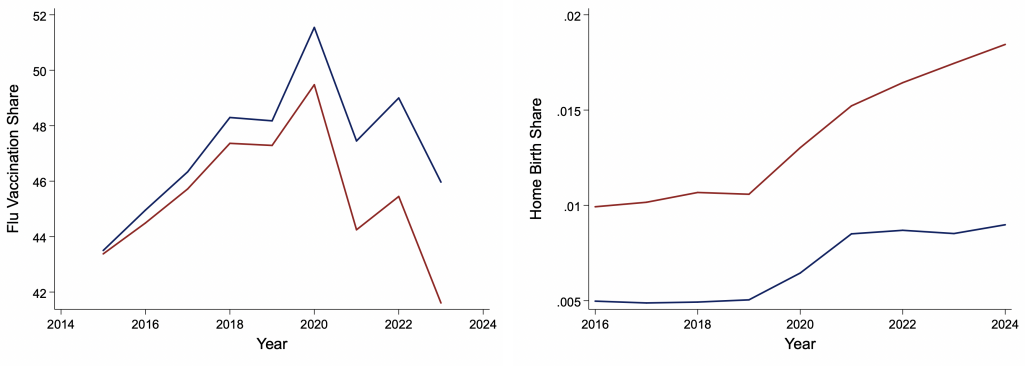
(d) Home Births



Notes: Figures report binned and raw scatter plots of the log change from 2019 to 2023 or 2024 in flu vaccination rates and home birth rates against the 2020 Trump county vote share.

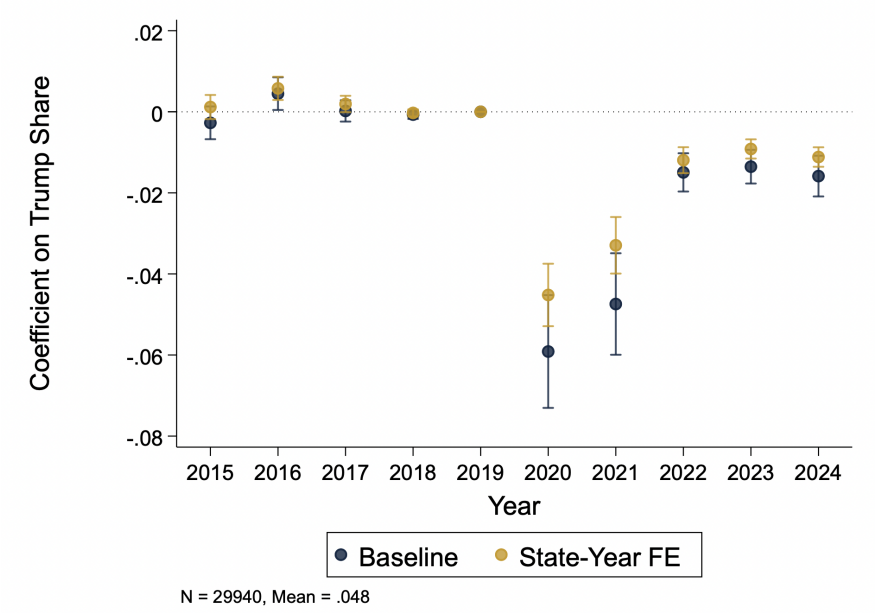
Figure A.13: Trust-Related Care — Raw Trends

(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. The raw scatter plots restrict to counties with greater than 25,000 residents to reduce noise. Flu vaccinations are reported as round percentages by CMS, distorting some patterns for smaller counties.

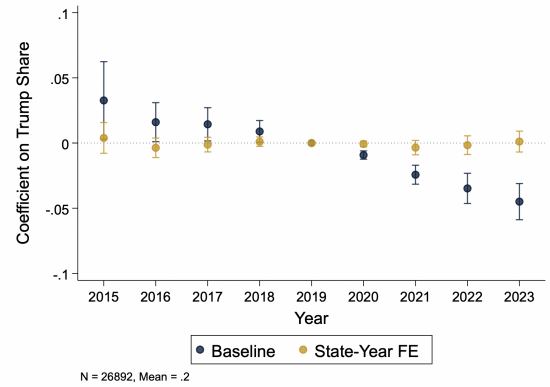
Figure A.14: Event Study Results — Unemployment Rate



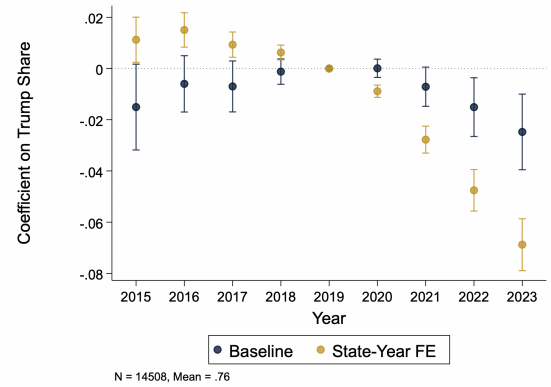
Notes: Figure reports coefficients on the 2020 Trump vote share interacted with year dummies for either the baseline specification (blue) or the specification with state-year fixed effects included (gold).

Figure A.15: Beneficiary Composition

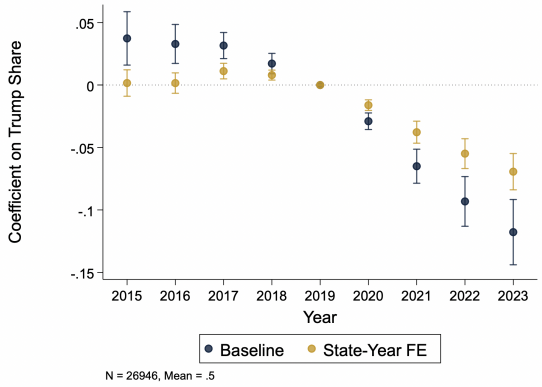
(a) Share Dual-Eligible



(b) Share White



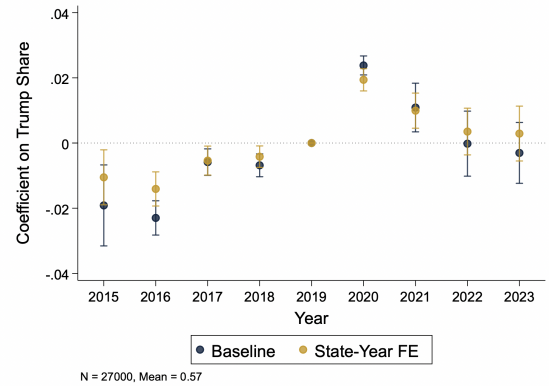
(c) Share Fee-For-Service



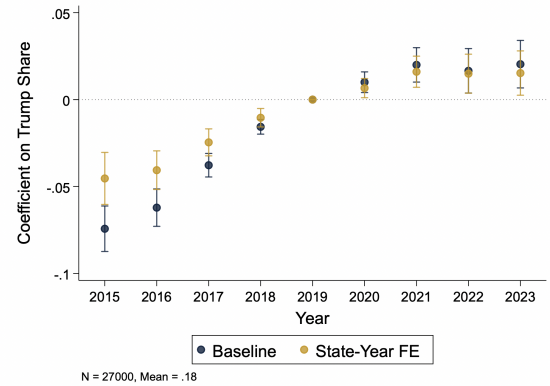
Notes: Figures report coefficients on the 2020 Trump vote share interacted with year dummies for either the baseline specification (blue) or the specification with state-year fixed effects included (gold). All regressions are run at the county level weighting by the 2020 population and with standard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

Figure A.16: Beneficiary Health and Age

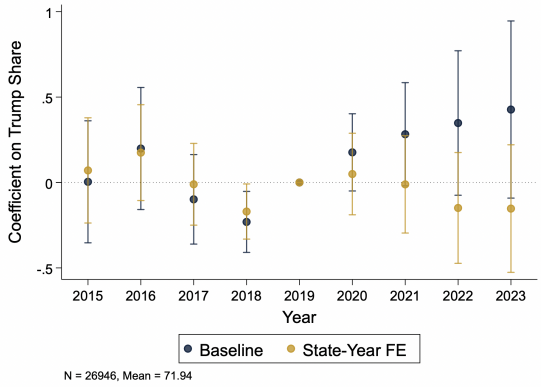
(a) Share with 3+ Chronic Conditions



(b) Obesity Rate



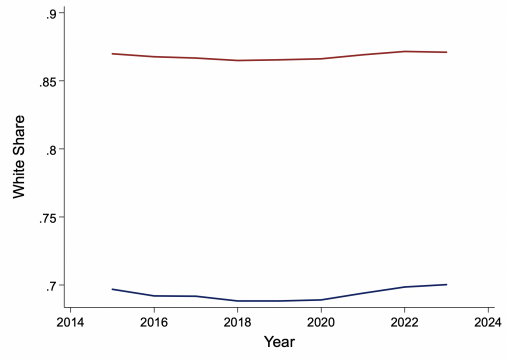
(c) Average Age



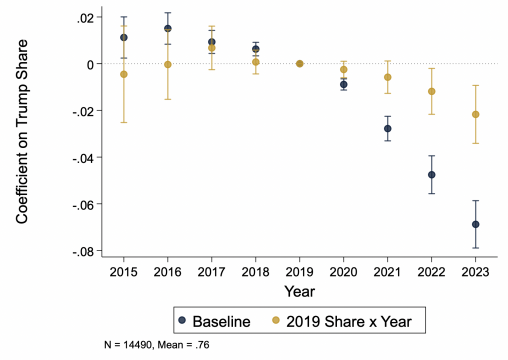
Notes: Figures report coefficients on the 2020 Trump vote share interacted with year dummies for either the baseline specification (blue) or the specification with state-year fixed effects included (gold). All regressions are run at the county level weighting by the 2020 population and with standard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

Figure A.17: Beneficiary White Share — Robustness

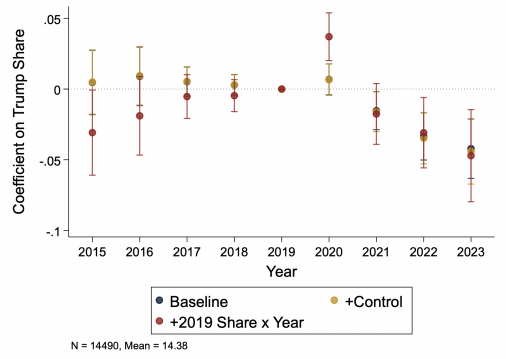
(a) Raw Trends



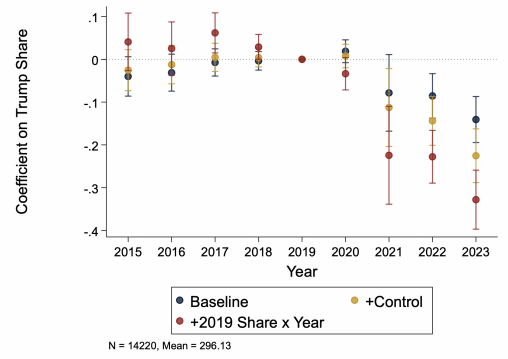
(b) Share White — Controls



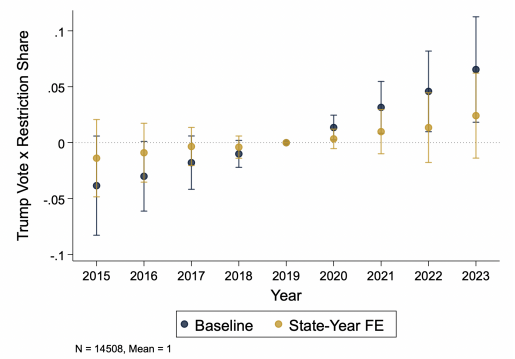
(c) Log E&M — Controls



(d) PCP Patient Vol. — Controls



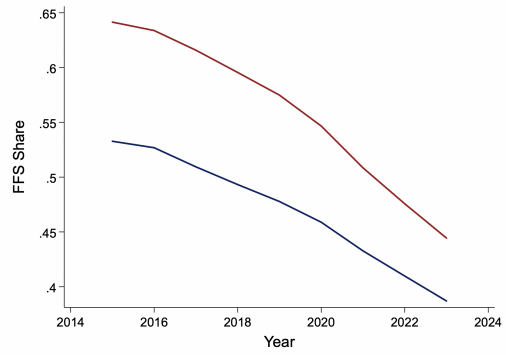
(e) White Share — Restriction Interaction



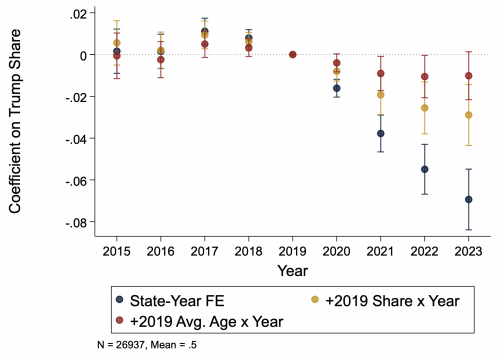
Notes: Part (a) reports raw trends for the white share of beneficiaries, splitting by counties where Trump got over (red) and under (blue) 50% of the 2020 vote. Parts (b) to (d) report coefficients on the 2020 Trump vote share interacted with year dummies for either the state-year fixed effect specification (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 dummies.

Figure A.18: Beneficiary FFS Share — Robustness

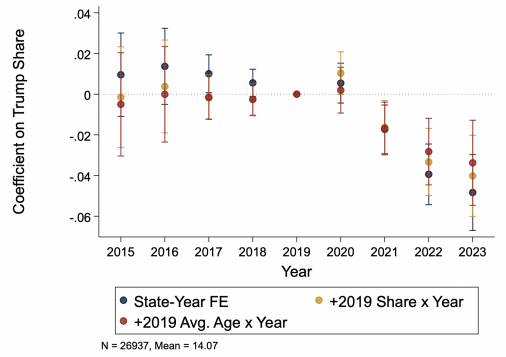
(a) Raw Trends



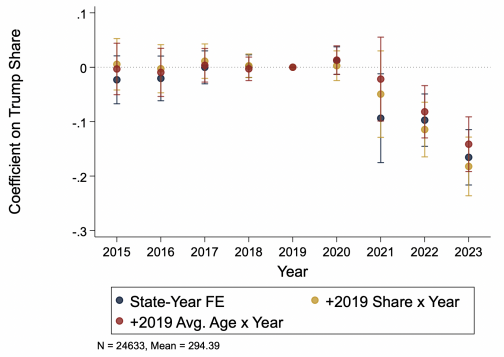
(b) Share FFS — Controls



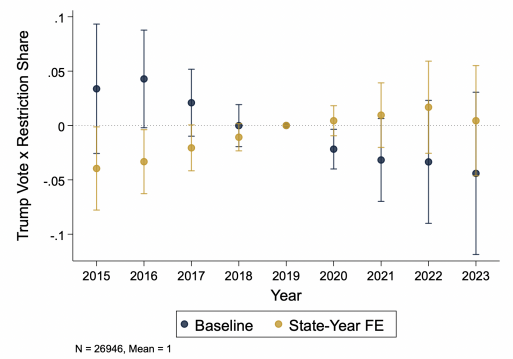
(c) Log E&M — Controls



(d) PCP Patient Vol. — Controls



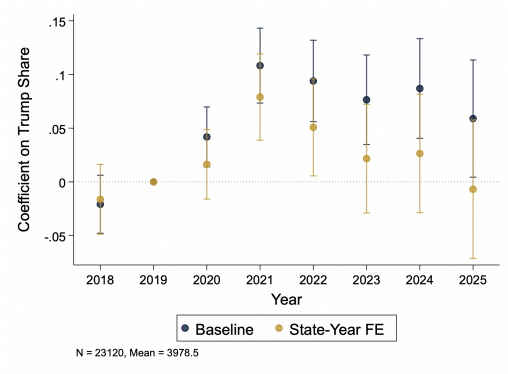
(e) FFS Share — Restriction Interaction



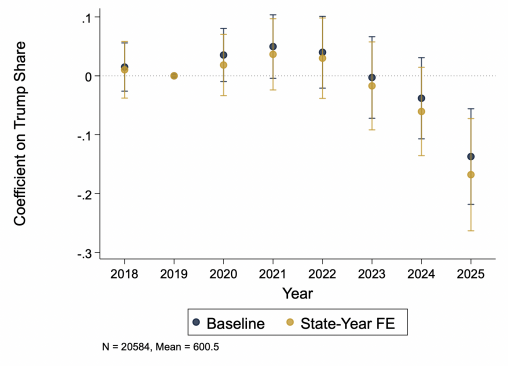
Notes: Part (a) reports raw trends for the FFS share of beneficiaries, splitting by counties where Trump got over (red) and under (blue) 50% of the 2020 vote. Parts (b) to (d) report coefficients on the 2020 Trump vote share interacted with year dummies for either the state-year fixed effect specification (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.19: Supply Side

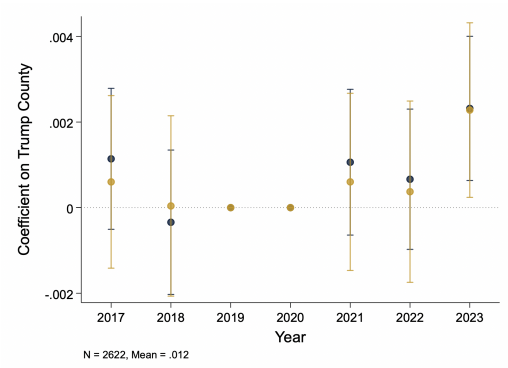
(a) Event Study Results — Log Providers



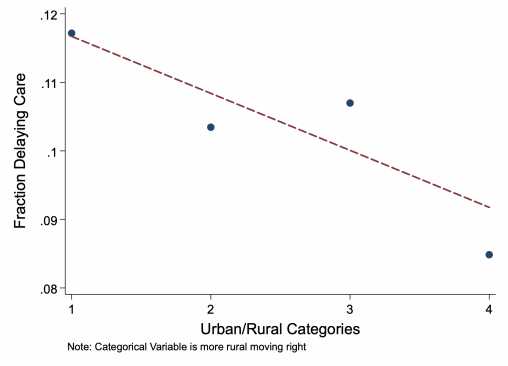
(b) Event Study Results — Log PCPs



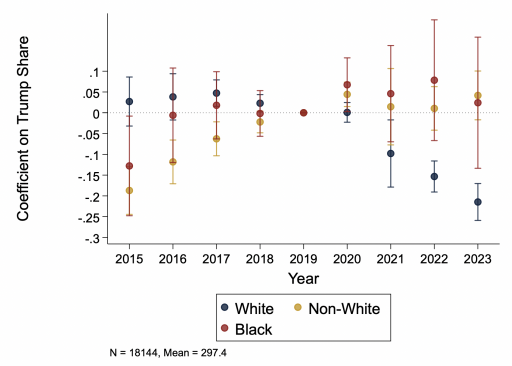
(c) Event Study Results — Nurses per Capita



(d) Delay Care — by Rurality



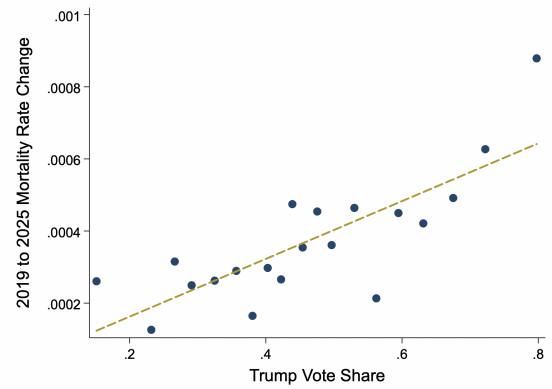
(e) PCP Patient Volume - by Benef. Race



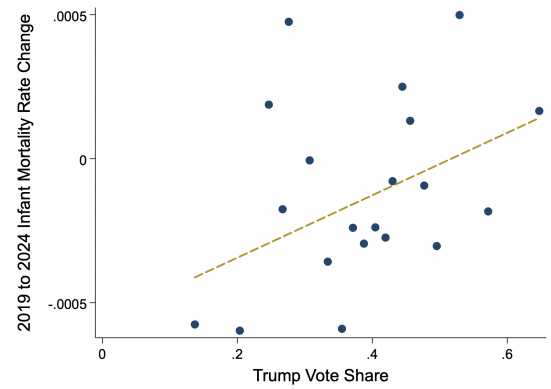
Notes: Parts (a)-(c) report coefficients on the 2020 Trump vote share interacted with year dummies for either the baseline specification (blue) or the specification with state-year fixed effects included (gold), while (e) reports coefficients by race of beneficiaries with state-year fixed effects included. 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.20: Mortality Changes by Trump Vote

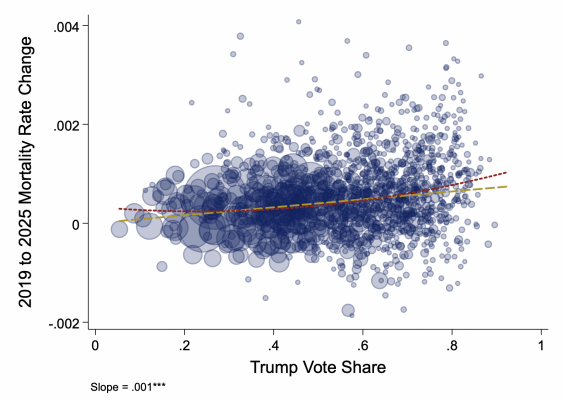
(a) Binned Mortality Rates



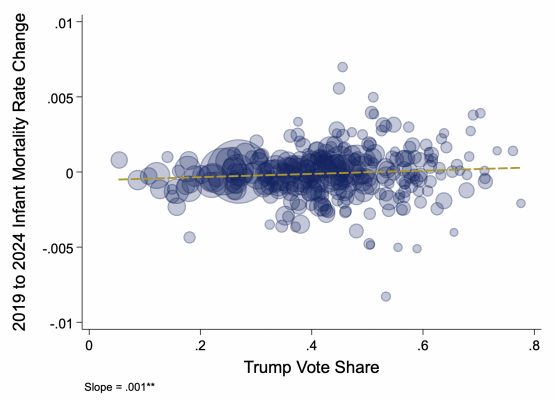
(b) Binned Infant Mortality Rates



(c) Mortality Rates



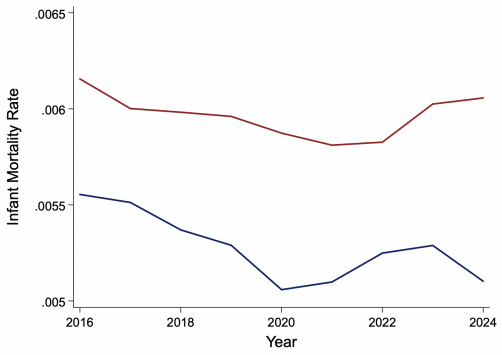
(d) Infant Mortality Rates



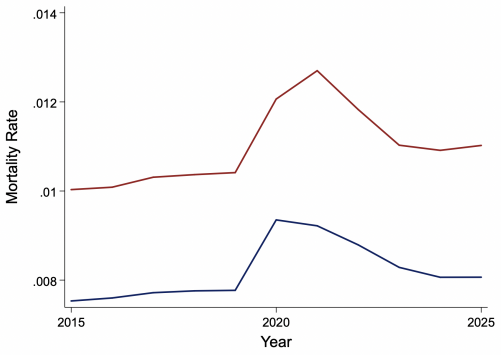
Notes: Figures report binned and raw scatter plots of the log change from 2019 to 2024 or 2025 in mortality rates against the 2020 Trump county vote share. The raw scatter plots restrict to counties with greater than 25,000 residents to reduce noise. For overall mortality, the red fitted line is quadratic while gold is linear.

Figure A.21: Mortality — Raw Trends

(a) Infant Mortality

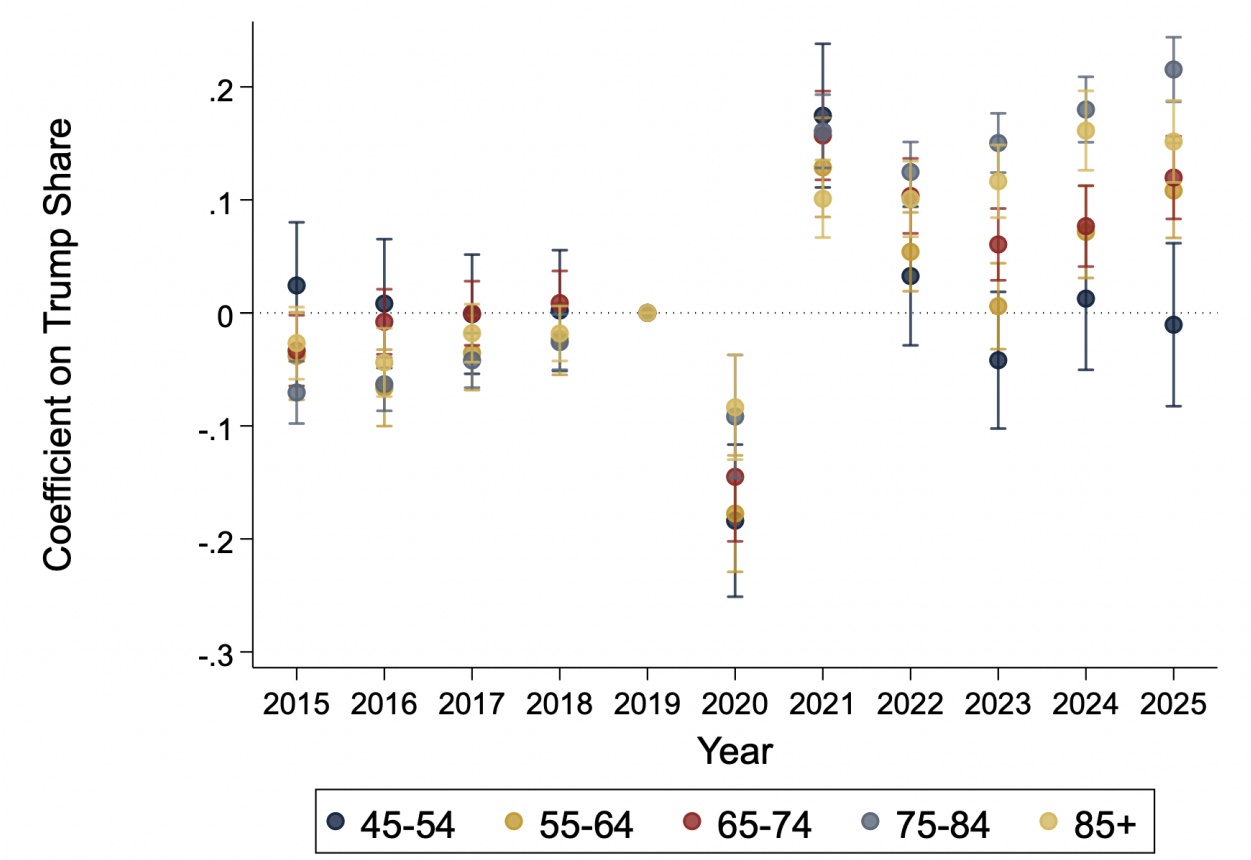


(b) Overall Mortality



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.22: 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 Visits

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 Figure 2a.

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 Figure 2b.

Table A3: 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 Figure 3a.

Table A4: 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 Figure 3b.

Table A5: 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 Figure 3c.

Table A6: 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 Figure 4.

Table A7: Trust-Related Care

VARIABLES	(1) Flu Vax	(2) Home Births
2015	0.0359***	
	(0.00495)	
2016	0.0227***	-0.00285***
	(0.00439)	(0.000738)
2017	0.0131***	-0.00138**
	(0.00348)	(0.000589)
2018	0.000964	0.000218
	(0.00284)	(0.000575)
2020	-0.0336***	0.00243***
	(0.00383)	(0.000790)
2021	-0.0742***	0.00648***
	(0.00426)	(0.00129)
2022	-0.0895***	0.0101***
	(0.00541)	(0.00143)
2023	-0.119***	0.0131***
	(0.00550)	(0.00158)
2024		0.0155***
		(0.00174)
Observations	26,982	5,553

Notes: Table reports coefficients corresponding to Figure 5.

Table A8: Health Outcomes

VARIABLES	(1) Inf. Mort	(2) Mort Rate
2015		-0.000343***
		(8.15e-05)
2016	0.000471	-0.000429***
	(0.000731)	(7.53e-05)
2017	0.000316	-4.94e-05
	(0.000711)	(6.78e-05)
2018	0.000347	-4.47e-05
	(0.000684)	(6.05e-05)
2020	0.00120*	-0.000181
	(0.000666)	(0.000220)
2021	3.28e-05	0.00241***
	(0.000643)	(0.000181)
2022	3.95e-05	0.00114***
	(0.000624)	(0.000117)
2023	0.000917	0.000289***
	(0.000611)	(9.38e-05)
2024	0.00126**	0.000726***
	(0.000618)	(0.000107)
2025		0.000969***
		(0.000111)
Observations	2,529	24,365

Notes: Table reports coefficients corresponding to Figure 6.