Agreeing to Disagree: Political Partisanship and Team Performance in Healthcare*

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[PRELIMINARY. PLEASE DO NOT CITE OR DISTRIBUTE.]

Abstract

This paper studies how political partisanship affects team performance. We link doctors' political affiliations from voter registration records to their patients' inpatient claims. In the context of heart attack treatment, we find that patient 30-day mortality rate is 7.7% lower when the doctor performing the procedure ("proceduralist") and the doctor providing inpatient care ("physician") are from different political parties. We exploit within-proceduralist variation in team political composition for identification and find no evidence that patient-provider selection or alternative team characteristics confound our estimates. We further show that politically mixed teams achieve better performance while using fewer medical resources, indicating improved productivity. Finally, we find that politically mixed teams choose more appropriate treatments for patients, suggesting reduced confirmation bias as a possible mechanism. Our results shed light on the potential costs of increased political segregation in the workplace.

Keywords: political partisanship, provider behavior, team performance

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I Introduction

Political partisanship influences a wide range of individual and household choices, including media consumption, residential location, and social relationships (Gentzkow and Shapiro, 2011; Levy, 2021; Brown et al., 2022; Kaplan et al., 2022; Huber and Malhotra, 2017; Iyengar et al., 2018). A growing literature also documents that partisan differences in beliefs shape professional decision-making across occupations, including among financial practitioners, entrepreneurs, and healthcare providers (Kempf and Tsoutsoura, 2021; Meeuwis et al., 2022; Dagostino et al., 2023; Engelberg et al., 2024; Kim, 2024). However, little is known about how partisan heterogeneity affects decision-making and performance in *teams*. Answering this question is important as teamwork is a central feature of production in many high-stakes environments—including business, law, and medicine—where individuals with different political ideologies routinely interact with each other.

This paper fills this gap by studying whether and how a team's political composition affects its performance. From a theoretical perspective, the effects of partisan composition are ambiguous. On the one hand, coordination costs may be lower among like-minded team members, facilitating more efficient collaboration among politically aligned coworkers (Becker and Murphy, 1992). On the other hand, teams composed of members with shared beliefs may be more susceptible to groupthink and confirmation bias, creating echo chambers that suppress valuable dissent (Levy and Razin, 2019). Empirically, answering this question is challenging because team formation is often endogenous: partisan workers with unobserved characteristics may sort into different teams. Moreover, team productivity is difficult to observe or measure in many settings.

To provide causal evidence, we study a healthcare setting in which team formation is plausibly quasi-random and team performance—measured by patient outcomes—is welfare-relevant. Our empirical setting is the treatment of heart attack patients admitted to hospitals through emergency departments. For each patient admitted for a procedure, a "proceduralist" is assigned to perform the operation, and at least one "physician" is assigned to oversee inpatient care before and after the procedure. Following the literature, we refer to both as "doctors" (Chen, 2021). Clinically, the roles of these doctors are interrelated, and effective coordination between them is critical for delivering high-quality care (Chen, 2021; Stecher and Ketcham, 2023).

This setting offers several advantages for identifying the causal effects of a team's political composition on its performance. First, heart attack patients admitted through the emergency department require immediate medical attention. As a result, patients typically have little scope to shop for preferred providers, and medical teams have limited ability to cherry-pick patients (Currie et al., 2016). Second, doctors' work schedules in hospitals are usually determined in advance to accommodate administrative, teaching, and research responsibilities, making it unlikely that proceduralists and physicians strategically coordinate their shifts to treat particular cases on specific days (Chen, 2021). Finally, team performance and resource use—such as 30-day patient mortality and Medicare payments—are well-defined and extensively validated by the literature (Chandra et al., 2016).

Central to our analysis is a novel data set that links the political affiliations of medical doctors to their patients' Medicare claims. Specifically, we obtain the 100% sample of Medicare fee-for-service claims for all heart attack patients admitted to U.S. hospitals from 2008 to 2019. For each proceduralist ("operating physician") and physician ("attending physician") in the inpatient data, we identify their political parties in the presidential election using a comprehensive database of voter registrations. This linkage is done through doctors' full names (first, middle, and last), birthdates, and locations, resulting in highly accurate matches. We then group these doctors into three camps: Republican, Democratic, and non-partisan, and define a medical team as politically mixed if the proceduralist and the physician belong to different camps.

The identification requires patients to be assigned to politically mixed or aligned teams in a quasi-random way. As our baseline specification, we include proceduralist fixed effects in the regression of patient mortality on team partisanship. This design is the same as in Chen (2021) and Branco et al. (2025), which effectively compares the outcomes of patients treated by the same proceduralist paired with different physicians. In other words, whether a proceduralist teams up with a politically different or similar physician should be independent of the potential outcomes for a particular patient. Given the emergent and unanticipated nature of heart attacks and the pre-scheduled work shifts of doctors, we think the assumption is plausible in our setting. As our primary sample, we also zoom into a subset of patients who are admitted to hospitals through Emergency Departments (EDs). The fact that these patients face even more time constraints helps minimize the possibility that our results are driven by patients sorting into different teams due to

unobserved factors. Lastly, we confirm through a balance test that patient characteristics are not correlated with team partisanship after controlling for the fixed effects.

Our main finding is that politically mixed teams perform significantly better than align teams—patient 30-day mortality rate is about 0.83 percentage points lower when the proceduralist and the physician have different political affiliations. This effect is economically meaningful, corresponding to about a 7.7% reduction from the average mortality rate in our sample (10.84 percentage points), and not far from the effect of shared experience among team members increasing by one standard deviation Chen (2021).

To further strengthen causality, we also consider a few extended specifications on top of the within-proceduralist approach. First, one may worry that proceduralists may improve their qualities over time in ways that correlate with their teammates' political affiliations. We therefore include proceduralist-by-time fixed effects to account for time-varying characteristics of proceduralists such as changing practice styles. Second, proceduralists may be more productive and in the meanwhile more likely to encounter dissident colleagues at certain hospitals. We therefore include proceduralist-by-hospital fixed effects to address this concern. Third, our estimate could be biased if proceduralists tend to partner with higher-quality physicians, even though they are from different political camps. We rule out this possibility by including physician fixed effects along with proceduralist fixed effects (i.e., two-way fixed effects). Across all these extended specifications, we find consistent evidence that politically mixed teams achieve better patient outcomes.

Finally, one may also suspect that the effect of team partisanship may be just picking up the effect of other team characteristics correlated with political composition. We consider three such alternative channels. First, our finding may be partially explained by specialty complementarity, if doctors of different political affiliations may have different training backgrounds and clinical expertise (Becker and Murphy, 1992). Second, physicians who have worked together before may accumulate team-specific human capital through shared experience, which contributes to higher team productivity (Chen, 2021). Third, medical teams with certain combinations of member demographics outperform in certain tasks. For example, all-female teams have been shown to decrease maternal morbidity in childbirth (La Forgia and Singh, 2025). We measure and include all these alternative team characteristics in our regression and find that our estimate remains stable.

How do politically mixed teams achieve better performance? We explore two potential mech-

anisms: (1) increased treatment intensity, and (2) improved productivity. First, we find that politically mixed teams actually use *fewer* medical resources, across all measures we consider such as total Medicare payments, DRG weights, length of stay, and number of procedures performed. Although not directly, this offers evidence for higher productivity as the mechanism underlying lower mortality rates.

We then try to open the black box of productivity improvements by looking into politically mixed teams' treatment choices. Specifically, we focus on a subset of patients who received one of the two most common procedures for heart attack: Coronary Artery Bypass Grafting (CABG, more aggressive) and Percutaneous Coronary Intervention (PCI, less aggressive). We hypothesize that politically different team members are more likely to hold heterogeneous beliefs about the effectiveness of CABG/PCI and express reservations about each other's approaches, leading to more appropriate treatment choices for patients eventually. To test this hypothesis, we first predict each patient's appropriateness to receive CABG versus PCI based on their observed characteristics. We then find that politically mixed teams are more likely to assign CABG-needed (PCI-needed) patients to CABG (PCI).

Our study relates to the literature on political partisanship. Existing work primarily documents partisan differences in decision-making at the individual level across a wide range of professions (Kempf and Tsoutsoura, 2021; Meeuwis et al., 2022; Dagostino et al., 2023; Engelberg et al., 2024; Kim, 2024). We extend this literature by shifting the focus from individuals to teams, examining how partisan heterogeneity within a team affects performance in a high-stakes healthcare setting. Given the prevalence of teamwork in modern organizations and rising political polarization, understanding how within-team partisanship shapes productivity and consumer welfare has become increasingly important.

Relatedly, our paper also contributes to the literature on political segregation by quantifying its social consequences. Prior work documents political sorting across industries, occupations, and social environments (Brown and Enos, 2021; Frake et al., 2025), and shows how individual choices can reinforce segregation along partisan lines (Breslow, 2016; Chinoy and Koenen, 2024; McCartney et al., 2024). We go beyond this work by studying a setting in which doctor team formation is plausibly quasi-random, allowing us to identify the causal effect of team political composition on performance. Our finding that politically mixed teams experience lower patient

mortality provides direct evidence of the welfare costs of political segregation, demonstrating that the increasing presence of politically aligned teams—an outcome of political segregation—can lead to worse real outcomes and reduced consumer welfare.

Finally, our paper speaks to the literature on team performance in both non-healthcare and healthcare contexts. In non-healthcare settings, prior studies show that team diversity can enhance productivity in some environments—for example, through differences in worker skill (Hamilton et al., 2003)—while other dimensions of diversity, such as ethnicity or nationality, can reduce productivity (Hjort, 2014; Lyons, 2017; Marx et al., 2021). In healthcare, existing work emphasizes the role of specific team characteristics, including shared experience (Chen, 2021; Stecher and Ketcham, 2023), overlap in medical expertise (Branco et al., 2025), and gender mix (La Forgia and Singh, 2025). We add to this literature by linking medical claims data with comprehensive voter registration records and providing novel evidence that political partisanship—a largely unexplored dimension of team composition—meaningfully affects team productivity.

II Setting

We focus on a healthcare setting where medical teams treat patients with heart attacks (or Acute Myocardial Infarction, AMI). Heart attacks are medical emergencies caused by the sudden blockage of blood flow to the heart muscle, leading to symptoms such as chest pain and shortness of breath. They are among the top reasons for hospital admissions in the U.S., with an estimated over 650,000 inpatient admissions each year (McDermott and Roemer, 2021). Timely treatment is crucial to reduce heart tissue damage and the risk of death (Antman et al., 2004; Anderson et al., 2007). Treatment for heart attacks includes medication (e.g., aspirin, beta-blockers, thrombolytics) and, in many cases, procedures that aim to restore blood flow to the coronary arteries. Common procedures include Percutaneous Coronary Intervention (PCI) and Coronary Artery Bypass Grafting (CABG). PCI involves inserting a catheter into the blocked artery and is often accompanied by the placement of a stent to keep the artery open. CABG, by contrast, is more invasive and involves creating a bypass around the blocked artery using grafted vessels from other parts of the body. The choice between PCI and CABG depends on the severity of the blockage and the patient's comorbidities, and is typically determined on a case-by-case basis by the medical team.

In this paper, we focused on heart attack patients who received at least one procedure during their inpatient stay.[1] Surgical patients are typically treated by a team of medical doctors, including a proceduralist who is in charge of performing the procedure and one or more physicians who oversee inpatient care before and after the procedure. The proceduralist is usually a cardiac surgeon (e.g., in the case of CABG) or an interventional cardiologist (e.g., in the case of PCI), and the physician is typically a generalist or a hospitalist with specializations related to cardiology or internal medicine. Roles and responsibilities of proceduralists and physicians are intertwined as they need each other's input to achieve high-quality care (Chen, 2021). For example, communication with physicians about patients' medical conditions before and after the procedure is important for proceduralists to execute the procedure and manage potential complications. Similarly, consultation with proceduralists after the procedure is crucial for physicians to monitor recovery and adjust treatment plans.

Like many other professions as well as other specialties within medicine, the labor force of cardiac doctors is highly politically polarized. For example, Hersh and Goldenberg (2016) link data of primary care physicians in 29 U.S. states to voter registration files, and find that about 49% of PCPs specializing in cardiology are Republicans. Combining Medicare data with political donation records, Kim (2024) finds a similar share of Republican affiliation among cardiologists.[2] Doctors of different political ideologies may have different practice styles. For instance, Republican doctors view abortion as a more serious issue than Democratic doctors (Hersh and Goldenberg, 2016); Republican physicians tend to treat more aggressively and adhere less to clinical guidelines (Kim, 2024). Given these heterogeneous beliefs and approaches, previous studies have highlighted the importance of lower communication costs, either through shared experiences or overlapped expertise, in coordinating patient care (Chen, 2021; Branco et al., 2025). However, disagreement in treatment choices among heart team members is not uncommon (Tsang et al., 2020; Scott-Herridge et al., 2022). In some cases, such disagreement can offer a more balanced decision-making process, by sharing knowledge and generating ideas, presenting a wider range of diagnosis and treatment options, and finally mitigating uncertainty and overcoming cognitive biases (Mazza et al., 2023).

[1] The margin of medication versus surgery is less relevant since all heart attack patients require some form of medication. Our primary sample includes all surgical patients, even if they receive surgeries other than CABG or PCI. Later, we also focus on a subset of surgical patients who receive either CABG or PCI when we study medical teams' treatment choices. Our main result holds in both samples.

[2] We find similar shares in our primary sample, with details discussed in Section III.

III Data

To conduct empirical analysis, we combine multiple data sources of both healthcare and political participation. In this section, we first describe each data source, then discuss how we construct our analytic sample and our key variable of team partisanship, and finally present descriptive statistics.

Medicare Inpatient Claims File. The main healthcare data for this study come from the Medicare Fee-For-Service Inpatient Claims File submitted by U.S. hospitals for reimbursement of facility costs.[3] We first extract a 100% sample of Medicare beneficiaries who have ever been diagnosed with a heart attack between 2007 and 2019. We then obtain the universe of inpatient claims (including but not limited to hospital stays related to heart attack) associated with these beneficiaries. The inpatient data contain detailed ICD diagnosis and procedure codes—which we use to measure patient conditions and treatment choices—as well as admission and discharge dates, DRG codes, and Medicare payments—which we use to measure treatment intensity.

A critical feature of the Medicare inpatient data is that they include the National Provider Identifier (NPI) number for the medical doctors involved in each inpatient stay. These doctors include the "operating physician" who performs the procedure (i.e., the proceduralist), and the attending physician who is primarily responsible for overseeing the hospital care before and after the procedure (i.e., the main physician). For about 9% of the stays, a third doctor is also included as the "other physician," whom we consider as an additional physician in the medical team. Using these doctors' NPIs, we supplement the inpatient data with the Medicare Data on Provider Practice and Specialty (MD-PPAS) and the National Plan and Provider Enumeration System (NPPES) from the CMS, which provide physician characteristics including full name, primary specialty, birthdate, gender, and other demographics.

We also merge the inpatient data with the Master Beneficiary Summary File (MBSF) using unique beneficiary identifiers. The MBSF provides rich information on patient demographics and chronic conditions, which allows us to adjust for patient comorbidities in the analysis. More importantly, the MBSF records the death dates of Medicare beneficiaries, enabling us to construct

[3] We obtain the inpatient data from the Centers for Medicare & Medicaid Services (CMS): https://resdac.org/cms-data/files/ip-ffs.

30-day and even longer-term mortality indicators for each admission. Finally, the inpatient claims can be linked to revenue center files to observe charges by emergency rooms, using which we identify patients admitted through emergency departments.

Voter Registration Data. To identify political affiliations of medical doctors, we rely on voter registration records provided by a non-partisan data vendor, L2 Inc.[4] L2 documents the political party affiliations of registered voters across all U.S. states, drawing on self-reported party affiliation from state voter registration files in all but fifteen states. In states that do not collect partisan affiliation at registration, L2 models the party affiliation using a proprietary machine-learning algorithm based on a rich set of public and private data sources, including primary election participation, demographic information from state voter files, presidential exit polls, commercial lifestyle indicators, census data, and self-reported party preferences from private polling sources.[5] Importantly, L2 has near-complete coverage of registered voters starting from 2014, and the accuracy of its partisan affiliation measures has been validated in previous studies (Brown and Enos, 2021; Bernstein et al., 2022; Dahl et al., 2023; Spenkuch et al., 2023; Engelberg et al., 2024).

In L2, registered voters can be broadly categorized into three groups based on their political affiliations: Republican, Democratic, and non-partisan (which includes independents in most cases and sometimes third-party affiliates). In addition to this partisanship information, L2 also provides rich voter demographics as well as donation counts and amounts recorded by the Federal Election Commission (FEC), which we use to identify politically active doctors.

Matching Doctors to L2 Voter Data. To link L2 voters to doctors in the Medicare data, we match on a combination of doctors' full name (first, middle, and last), gender, birth date, and state. We use two waves of L2 voter registration data to identify voting doctors and their political affiliations. Our primary matching wave draws on voter registration records from the 2016 presidential election, the first presidential election after L2's coverage became complete in 2014 and therefore the earliest wave likely to capture a comprehensive set of registered voters. To account for doctors who registered after 2016, we supplement this wave with voter registration records from the 2020

[4] https://www.l2-data.com/datamapping/

[5] L2 imputes party affiliation in the following states: HI, IL, WA, MT, ND, MN, WI, MI, VT, SC, MO, AL, TX, VA, and GA. Excluding doctors from these fifteen states yields similar results.

presidential election.

Using the 2016 wave alone, we successfully match 134,982 of the 248,689 doctors in our sample, corresponding to a matching rate of 54%. Incorporating the 2020 wave adds 24,007 additional doctors who appear uniquely in the later wave, yielding a total of 158,989 matched doctors and a final matching rate of 64%. When a doctor's party affiliation is identified in either wave, we treat it as time-invariant and retain it throughout the analysis.[6] In execution, we also carefully consider the complexity from doctors practicing in different locations over time. More details on the matching procedure are provided in Appendix A.

Sample Construction. We begin constructing our analytic sample by applying several basic filters. First, a patient can be admitted to multiple facilities or to the same facility multiple times on the same date. To avoid double counting, we keep only the admission with the highest total charges for each patient-date combination. Second, we keep only the first admission for each patient in an episode of care by requiring no prior admission in the past 365 days. Third, we drop patients who are within the first year of Medicare enrollment because we don't observe their medical history outside Medicare. We also keep only patients aged between 66 and 100 to ensure at least one year of prior claims data to measure pre-existing comorbidities. Fourth, we restrict the sample to inpatient stays no more than 100 days to avoid outliers. Lastly, we only keep ED patients by requiring a positive charge by the emergency department.

We also refine the sample with respect to the composition of medical teams. The first thing to note is that every inpatient is associated with an attending physician. We then keep only inpatients stays with non-missing operating physician (i.e., proceduralist). This steps essentially excludes patients who receive medication instead of surgical treatment. We further require the proceduralist and the main physician to be different doctors, as otherwise there is no team interaction. For the baseline results, we focus on cases with one proceduralist and only one physician documented in the inpatient data, which account for over 90% of cases. In one of the robustness checks, we show that our results remain also in multi-physician cases. Lastly, about 68% of proceduralists and 60% of physicians in our initial sample can be credibly linked to voter registration

[6] We assume that a doctor's political affiliation prior to 2016 is the same as the affiliation observed in 2016, as party switching is relatively rare: only 2.3% of proceduralists and 3.2% of physicians changed their registrations between 2016 and 2021.

records. We therefore keep only patients whose proceduralists and physicians can both be identified in the voter data. All together, these filters leave us with a final analytic sample of 385,893 heart attack admissions between 2008 and 2019, treated by 50,448 proceduralists and 63,749 physicians (or 226,050 unique medical teams).

Measure of Team Partisanship. In our primary analytic sample, about 44.8% of proceduralists and 39.2% of physicians treating heart attack patients are Republicans; 23.8% of proceduralists and 28.3% of physicians treating heart attack patients in EDs are Democrats; and the remaining are non-partisan or independents. Figures 1 and 2 visualize these compositions. Over time, the share of democrats remains stable over the years while Republican doctors increasingly switch to being non-partisan. We then define a binary indicator, for *politically mixed* teams, which equals one if the proceduralist and the physician have different political parties, and zero otherwise. According to this definition, about 58% of medical teams are politically mixed, who treat 56% of cases in our analytic sample. Figure 3 shows that the share of mixed teams increased from 2008 to 2012, both in terms of the number of teams and the number of cases. However, this share began to decline after 2012, particularly after 2016, a period marked by increasing political segregation in the U.S.

In the robustness checks, we consider a broader sample with multi-physician cases, where we find highly similar results. We also consider dropping non-partisan doctors (either proceduralist or physician) from our sample. Doing so forces the mixed teams to consist of members with opposite major parties (i.e., Republican vs. Democratic) and has little impact on our main findings.

Summary Statistics. Table 1 provides summary statistics by team political composition for our analytic sample. There are 217,165 (56%) and 168,728 (44%) cases treated by politically mixed teams and politically aligned teams, respectively. These two types of teams treat fairly similar patients, regardless of patient demographics or comorbidites. The similarity in patient characteristics provides preliminary evidence for limited patient-provider selection. We provide more fomal balance tests with respect to these patient characteristics in Section IV.B.

Table 1 also reports summary statistics along the dimensions of treatment intensity and patient mortality. Unconditionally, politically mixed teams achieve a lower 30-day patient mortality rate

(10.5%) than politically aligned teams (11.3%), while using fewer medical resources. At the same time, doctors in politically mixed teams seem to have less shared experience, more complementary specialties, and different demographics. In Section V.B, we provide more details on these team-level characteristics and show that they cannot explain our main results.

IV Empirical Design

IV.A Econometric Specification

A typical observation in our data is a patient i admitted to hospital h at time t treated by proceduralist j and main physician k. We estimate the following baseline specification.

$$y_{i,j,k,h,t} = \beta M_{j,k} + \mathbf{X}_i\gamma + \delta_{h,t} + \mu_j + \varepsilon_{i,j,k,h,t} \tag{1}$$

On the left-hand side of Equation (1), $y_{i,j,k,h,t}$ is the main outcome of interest—patient mortality, which equals one if patient i passed away within 30 days of hospital admission and zero otherwise.[7] On the right-hand side, $M_{j,k}$ is a binary indicator which equals one if the medical team members has mixed political affiliations as defined in Section III. For the main analysis, we estimate Equation (1) using a linear probability model to allow inclusion of high-dimensional fixed effects and more straightforward interpretation of the coefficients. Standard errors are clustered at the proceduralist level unless otherwise specified.

To ensure the analysis compare outcomes among clinically similar patients, we control for a vector of patient characteristics, $\mathbf{X}_i$. These characteristics include patient demographics such as dummies for five-year age bin, gender, Black race, Hispanic, Medicaid coverage, disability status, as well as indicators for comorbidities observed at hospital admission.[8] We also include hospital×time fixed effects, $\delta_{h,t}$, to account for confounds at the facility level such as time-varying hospital quality, capacity constraints, mergers and acquisitions. Note that $\delta_{h,t}$ also absorbs common time trends in patient outcomes with the time dimension here being calendar year-quarter (e.g., 2008-Q1). To capture more high-frequency effects in time, we also include dummies for

[7] Results are similar when defining 30-day mortality starting from the discharge date instead.

[8] We consider the same set of comorbidities as in Chen (2021), which include chronic kidney disease, chronic obstructive pulmonary disease, heart failure, Alzheimer's disease/dementia, diabetes, stroke, end-stage renal disease (ESRD), and cancer (lung/breast/colorectal/endometrial/prostate cancer).

month of year and day of week (based on the date of patient admission into the hospital), both interacted with hospital indicators.

Central to our identification is the inclusion of proceduralist fixed effects, μ_j. This design is similar to that of Chen (2021), and uses within-proceduralist variation in team political composition to identify the effect of political partisanship on team performance. In other words, we effectively compare cases treated by the same proceduralist but different physicians. Note that proceduralist fixed effects control for time-persistent characteristics such as clinical skills, practice style, as well as inherent political ideology. Although individual proceduralists of different political affiliations can affect patient outcomes in their own ways (Kim, 2024), our coefficient of interest, β, identifies the *team* effects of political partisanship. In Section V.B, we also consider an extended set of fixed effects to rule out confounds at more granular levels.

IV.B Identification

The identification of Equation (1) relies on the Conditional Independence Assumption (CIA) and the Exclusion Restriction. We discuss the plausibility of these assumptions below.

Conditional Independence Assumption. The CIA requires that, conditional on the proceduralist and hospital×time fixed effects, potential patient outcomes are mean independent of team political composition. Although it is impossible to directly test this assumption, we think it is plausible given the institutional feature of heart attack treatment and doctors' work shifts in hospitals, as discussed in Section II. We also provide several sets of supporting evidence to ensure that the assignment of patients to politically mixed or aligned teams is quasi-random.

We first show that patient characteristics, including demographics and comorbidities, are balanced across politically mixed and aligned teams. Specifically, we regress each of the patient characteristics on the mixed team indicator, along with the fixed effects included in the baseline specification. Figure 4 reports the coefficient from these individual regressions, none of which are statistically insignificant. We also use the mixed team indicator to predict patients' 30-day mortality rates, which are estimated using the full set of patient characteristics and a logit model. Coefficient from this regression is also insignificant (β=–0.01, p-val=0.73). Lastly, we also regress the mixed team indicator on all patient characteristics and the fixed effects, and find that the F-

statistic for all patient characteristics jointly being zero is 1.04 (p-val=0.41). In other words, we cannot reject the null hypothesis that patient characteristics are all uncorrelated with team political composition. Taken together, these tests support the argument that politically mixed teams do not treat patients with better or worse risk profiles.

Exclusion Restriction. The Exclusion Restriction requires that, conditional on the proceduralist and hospital×time fixed effects, other team-level characteristics that may affect patient outcomes are mean independent of team political composition. Violation of this assumption means that politically mixed or aligned teams can have other characteristics that are related to political composition but can also substantially affect their performance. For example, physicians of different political affiliations may also have different clinical specialties, in which case the effect of mixed political affiliations could merely reflect the effect of supplementary expertise. Similar arguments apply to other team-level characteristics such as shared experiences between the proceduralist and the main physician (Chen, 2021), gender mix (La Forgia and Singh, 2025), and etc. To rule out such alternative channels, we show in Section V.B that our main results remain stable when including these alternative team-level characteristics as additional controls. Also, to the extent that omitted team-level characteristics may still confound our estimates, we adopt the Oster (2019) approach and find that unobservables are unlikely to drive our results.

V Effect of Team Political Partisanship

We study how mixed political affiliations among medical teams affect their performance in treating heart attack patients. We first present the main results using the baseline model as specified in Equation (1) in Section V.A. We then strengthen the causal interpretation of our findings through a battery of additional tests in Section V.B. We also conduct a set of robustness checks in Section V.C. Finally, we explore the heterogeneity in the effects of political partisanship in Section V.D.

V.A Main Results

Table 2 reports the main results from estimating Equation (1). The dependent variable is a binary 30-day mortality indicator (scaled by 100 for easier interpretation). The key regressor of interest

is the dummy variable for politically mixed teams. We begin by estimating an unconditional version of Equation (1) in Column (1). The significantly negative coefficient before $M_{j,k}$ indicates that patients treated by politically mixed teams have a lower mortality rate.

We then progressively add controls on top of this unconditional regression from Column (2) to Column (4). Column (2) adds proceduralist fixed effects and again estimates a lower mortality rate for politically mixed teams. Importantly, proceduralist fixed effects ensure that this result is not driven by higher-quality proceduralists sorting into politically mixed teams, as the identifying variation comes from a given proceduralist pairing with physicians of different political affiliations. Column (3) further adds hospital$\times$time fixed effects to account for time-varying hospital characteristics, and finally, as our preferred baseline specification, Column (4) includes a full set of patient covariates as controls. The estimate remains stable at $\hat{\beta} = 0.833$, which is significant at the 99% significance level. Comparing Column (4) and Column (3), the coefficient changes little with the inclusion of patient covariates, which echoes the balance test results in Section IV.B and suggests that the difference in patient risk profiles cannot explain the performance gap between politically mixed and aligned teams.

The estimate in Column (4) implies that patients treated by politically mixed teams have a 0.83-percentage-point lower mortality rate compared to those treated otherwise. To put it into perspective, note that the average mortality rate among all patients in our sample is 10.84 percentage points. In other words, politically mixed teams outperform politically aligned teams by about 7.7% ($= 0.83/10.84$). This magnitude is economically non-trivial and comparable to some of the estimates in the literature (e.g., Doyle Jr et al., 2015; Chen, 2021; Branco et al., 2025).

V.B Additional Tests

We provide several additional tests below to rule out potential confounding channels. First, politically mixed teams can arise more frequently with certain providers such that the estimated effect of team partisanship could be biased by the intrinsic characteristics of these providers. We account for such "selection" channels by extending the baseline specification with more stringent fixed effects. Second, politically mixed teams can simultaneously exhibit other (team-level) characteristics that may also affect patient outcomes. We therefore include additional controls for these

other characteristics to ensure our estimate captures the pure effect of political partisanship.

Other Selection Channels. Our baseline specification has already included proceduralist fixed effects and accounted for time-invariant beliefs and practice styles of proceduralists. Therefore, higher-quality proceduralists in politically mixed teams cannot explain the main results. However, one may still worry that certain proceduralists may improve their qualities over time in ways that correlate with their teammates of different political affiliations. To address this issue, we include proceduralist×time fixed effects in the regression. Specifically, we interact proceduralist fixed effects with calendar year-quarter indicators to capture time-varying proceduralist characteristics. Column (1) of Table 3 reports this estimate, which closely aligns with the baseline level.

Politically mixed teams may also be more prevalent among certain hospitals, even conditioned on a given proceduralist. For example, some hospitals may have a more diverse pool of physicians, making it more likely for proceduralists to partner with colleagues of different political affiliations. If proceduralists' performance is also affected by the hospitals they practice in (Mourot, 2025), our estimate could be biased. To alleviate this concern, we compare patient outcomes among different teams with the same proceduralist and within the same hospital by including proceduralist×hospital fixed effects. The estimate, reported in Column (2) of Table 3, remains highly similar.

Finally, it is also possible that politically mixed teams are more likely to form among certain physicians. If proceduralists tend to team up with higher-quality physicians, even though they are from different political camps, our estimate could be biased. To rule out this possibility, we adopt the two-way fixed effects design proposed by Chen (2021) and include main physician fixed effects alongside proceduralist fixed effects. This approach helps to separate the effect of team political partisanship from that of time-invariant characteristics for both major doctors in a medical team. The estimate, reported in Column (3) of Table 3, is again close to the baseline level, suggesting that selection among physicians is unlikely to drive our results.

Other Team Characteristics. Our study focuses on the effect of political composition on team performance. However, political composition is only one of many team-level characteristics. To what extent is it correlated with other team characteristics that may also affect patient outcomes?

Or, in other words, does the effect of team partisanship merely reflect the effect of other team characteristics?

The first characteristic we consider is specialty complementarity among team members. Proceduralists and physicians of different political affiliations may also have different medical training backgrounds and clinical expertise. Specialty complementarity can potentially reduce medical errors through division of labor and specialization, but at the same time, it can increase coordination costs (Becker and Murphy, 1992; Branco et al., 2025). To begin with, we measure specialty complementarity using the doctors' primary specialties documented in MD-PPAS data.[9] We define a binary variable *Complementary Specialty*$_{j,k}$ which equals one only if the proceduralist j and the main physician k have different specialties (e.g., cardiac surgery and internal medicine). In our sample, about 75% of doctor teams have complementary specialties.

We note that a majority (81%) of politically mixed teams have complementary specialties, compared with 66% among politically aligned teams. This perhaps suggests that physicians' political affiliations are correlated with differences in training backgrounds and professional specialization. When we include *Complementary Specialty*$_{j,k}$ as an additional control in the regression, the coefficient before $M_{j,k}$, changes from -0.833 to -0.737, or shrinks by about 11.5% in magnitude (Column (1) of Table 4). This implies that the estimated effect of team partisanship is not fully driven by specialty complementarity among team members. Interestingly, the coefficient before *Complementary Specialty*$_{j,k}$ is significantly positive, suggesting that specialty complementarity helps team performance in a separate way.

The second team-level characteristic we consider is shared experience between team members. As shown in Chen (2021), physicians who have worked together before may accumulate team-specific human capital which contributes to higher team productivity. We conjecture that doctors of different affiliations are less likely to work with each other, given the increasing trend of political segregation. It is therefore important to evaluate whether the benefits of team partisanship was underestimated. Following Chen (2021), we measure shared experience between proceduralist j and physician k using the number of cases they treated together in the past two years. Including *Shared Experience*$_{j,k}$ as an additional control in the regression, we find little change in the coef-

[9]There are six major categories of doctor specialties for heart attack patients: cardiac surgery, thoracic surgery, interventional cardiology, general cardiology, internal medicine, and others (which summarizes all other minor specialties).

ficient before $M_{j,k}$ (Column (2) of Table 4). Notably, The estimate before *Shared Experience*$_{j,k}$ is significantly negative, a finding consistent with Chen (2021).[10]

Finally, we consider different combinations of doctor demographics, which the literature on team diversity often focuses on. For instance, La Forgia and Singh (2025) finds that female-only obstetrics teams achieve lower maternal complication rates than male-only or mixed-gender teams. Although not in a medical setting, diversity of race and ethnicity is also shown to be an important factor for organizational performance (Hjort, 2014; Lyons, 2017; Marx et al., 2021).

We begin by measuring the following demographic characteristics for each proceduralist and each physician. First, as we observe the birthdate of each doctor, we can calculate their age at the time of treatment. We then define a doctor as senior if their age is greater than the sample median. Second, we separate Black doctors with non-Black doctors using a predicted race/ethnicity. Specifically, we use a machine learning algorithm and infer a doctor's race/ethnicity based on their first and last names.[11] Third, we separate female and male doctors. Lastly, we include high-dimensional fixed effects of the aforementioned demographics for both team members (i.e., proceduralist's age-race-gender interacted with physician's age-race-gender) in the regression. Again, the main result remains stable (Column (3) of Table 4), suggesting that the effect of team partisanship arises beyond what demographics predict on average.

V.C Robustness Checks

To further validate our main results, we provide a series of robustness checks regarding alternative measures of patient mortality, alternative sample specifications. Results from these checks are summarized in Table 5 to Table 6.

Alternative Measures of Patient Mortality. In the main analysis, we use 30-day mortality as the primary measure of patient outcome. To ensure our results are not sensitive to this particular choice, we consider several alternative measures. First, instead of measuring mortality within 30 days of *admission*, we measure mortality within 30 days of *discharge*. This alternative approach

[10] We also notice that, in terms of magnitude, the effect of *Shared Experience*$_{j,k}$ is smaller than that estimated in Chen (2021). This is understandable as we are able to identify more patients and therefore more shared experiences among doctors using the 100% inpatient data, as opposed to the 20% MedPAR-Carrier linked sample used by Chen (2021).

[11] This algorithm is built on a recurrent neural network architecture and trained using Florida's voter registration data (Xie, 2022).

effectively precludes in-hospital deaths. The estimate, reported in Column (1) of Table 5, remains highly similar. Related to this, we also consider *in-hospital* mortality as the outcome variable. Column (2) of Table 5 shows that the estimate is again similar to the baseline level. Combining both in-hospital and post-discharge mortality, these results imply that the effect of medical team's political partisanship not only spans the inpatient stay but also possibly extends to post-discharge care, such as follow-up visits and medication adherence. Finally, we also consider *longer-term* mortality measures. For example, Columns (3)–(4) of Table 5 report the results using 90-day and 360-day mortality rates, respectively. The estimates are all negative and statistically significant, although the magnitude gradually diminishes as we prolong the time window.

Alternative Sample Specifications. In our primary sample, we include only patients who are admitted to hospitals through emergency departments. Although this restriction is useful in minimizing potential patient-provider selection, one may wonder if the estimated effect of team partisanship extends to a broader patient population. We therefore include non-ED patients (i.e., elective cases) in the sample and re-run the analysis. Column (1) of Table 6 reports the result, which is close to the baseline estimate.

In the main analysis, we focus on cases in which only one physician is present alongside the proceduralist, as interactions between the proceduralist and physicians are less clearly defined when multiple physicians are involved. Although this restriction excludes fewer than 10% of cases, the main results remain virtually unchanged when multi-physician cases are reintroduced into the sample (Column (2) of Table 6). We also consider a more restrictive definition of team partisanship, in which a team is classified as politically mixed only if both physicians have political affiliations that differ from that of the proceduralist. The results are again similar.

Also, recall that we group doctors into three political camps: Democrats, Republicans, and non-partisan. However, one may be concerned that the political distance from non-partisan individuals to Democrats/Republicans is closer than that between the two extremes, and therefore the true extent of political partisanship within a medical team could be overstated. To alleviate this concern, we drop non-partisan doctors from the sample and only consider teams formed by Democrats and Republicans. This restriction effectively requires physicians in politically mixed teams to belong to opposing camps (i.e., one Democrat and one Republican). Under this alter-

native sample, 38% of teams are classified as politically mixed. Even with this more restrictive definition, the results remain similar, as shown in Column (3) of Table 6.

Relatedly, some doctors may not actively participate in politics or hold strong political views, even though they are registered for elections. To address this concern, we focus on a subsample of "politically active" doctors. Specifically, we classify a doctor as politically active if they have ever made a donation to their affiliated party. Because L2 only records donation activity reported to the FEC, only 13.8% of proceduralists and 9.5% of other physicians in our sample are classified as donors. We then restrict the sample to teams in which both members are donors. Under this restriction, the estimated effect of team partisanship is similar in magnitude, although less precisely estimated due to the substantially smaller sample size (Column (4) of Table 6).

V.D Heterogeneity

We next examine heterogeneity in the effects of team partisanship. Conceptually, politically mixed teams are more likely to arrive at appropriate treatment decisions through deliberation and the exchange of diverse perspectives. However, these advantages may be attenuated for higher-risk patients, whose clinical profiles constrain feasible treatment options. We therefore hypothesize that the effects will be larger for medium- and low-risk patients, for whom clinical decision-making is less constrained and more likely to benefit from careful discussion and debate.

We measure case complexity using predicted patient mortality. Specifically, for each patient in the sample, we use patient-level characteristics—including demographics and comorbidities—to predict 30-day mortality using a Logit model.[12] We then divide patients into three equal-sized groups—low-, medium-, and high-risk—and estimate the baseline model separately for each group. Table 7 reports the results. The benefits of politically mixed teams are largest among medium-risk patients (Column (2), $\beta = -1.15$) and low-risk patients (Column (1), $\beta = -0.85$). In contrast, the estimate for high-risk patients is smaller in magnitude and statistically insignificant (Column (3), $\beta = -0.49$).

[12] We estimate this model separately by year to account for changes in medical norms.

VI Mechanisms

Previous sections have established the main empirical result that medical teams with members from different political parties have better performance in terms of heart attack patient outcomes. We next investigate the underlying mechanisms that explain this finding. Two possible channels are: (1) increased treatment intensity, and (2) improved productivity. In this section, we first provide supporting evidence for improved productivity. We then explore potential pathways through which higher productivity is realized, such as more appropriate treatment choices.

VI.A Treatment Intensity

We begin by examining whether politically mixed teams achieve lower mortality rates by increasing treatment intensity. Previous studies such as Doyle Jr et al. (2015) have revealed the returns of more medical input to better patient survival. Increased treatment intensity is especially possible if proceduralists and physicians from diverse political backgrounds "defensively" exert more effort to avoid being held accountable by one another. In addition, different beliefs about optimal treatment may also lead to inefficient coordination or even a waste of resources used by politically different team members. To the extent that higher treatment intensity requires higher medical costs, the welfare implication in this case is less clear.

To measure treatment intensity, we consider four commonly used metrics: (1) (logged) total Medical payments, (2) (logged) DRG weights of the hospitalization, (3) length of stay (in days), and (4) number of procedures performed during the inpatient stay. Table 8 reports the regression results using these four measures as outcomes. Across all columns, we find that treatment intensity unanimously decreases when the medical team is politically diverse. For example, Column (1) shows that politically mixed teams use about 2.9% less resource as measured by total medical payments. Column (3) shows that team political diversity reduces patient length of stay by about 1.3%.

Overall, these results suggest that the political mixed teams are able to secure lower patient mortality rates without using more medical resources, which is consistent with the channel of improved productivity. We provide further evidence on this channel in the next subsection.

VI.B Treatment Choice

Productivity improvements may arise from fewer medical errors or more accurate treatment decisions, even with the same or lower treatment intensity. For instance, consider a case where a Republican proceduralist who holds a strong belief in the effectiveness of more invasive surgeries (e.g., Coronary Artery Bypass Grafting, or CABG) treats a heart attack patient who is indeed less suitable for such procedures. If no other team member questions the proceduralist's belief, the patient may end up receiving an overly aggressive treatment that could potentially lead to worse outcomes. However, if the proceduralist works with a Democratic physician who endorses more conservative approaches (e.g., Percutaneous Coronary Intervention, or PCI), the two may discuss and arrive at a treatment decision that better fits the patient's condition.

We hypothesize that politically different team members are more likely to hold heterogenous beliefs and express reservations about each other's approaches, leading to more appropriate treatment choices for patients eventually. To test this hypothesis, we focus on a subset of patients (about 80% of all heart attack cases) who received either PCI or CABG—the two most common procedures performed for heart attack patients. These patients are more homogeneous in the sense that they all require interventions to restore blood flow in the coronary arteries. However, medical teams have discretion in choosing between CABG (more aggressive) and PCI (less aggressive), depending on their beliefs and practice styles (Currie et al., 2016).

We focus on the intensive margin of treatment choice between CABG and PCI.[13] We begin by estimating the appropriateness of each patient to receive CABG as opposed to PCI. Specifically, we fit a logit model including all patient-level characteristics controlled in our baseline specification. We estimate the model parameters for each year separately to account for potential changes in clinical guidelines over time. Following the literature (e.g., Currie and MacLeod, 2017), we then predict the probability of patient i to receive CABG if the treatment choice were to be purely based on patient conditions, $P(\widehat{CABG})_i$.[14] Finally, we define treatment inappropriateness as the deviation of actual treatment from the predicted probability, $\left|1\{CABG\}_i - P(\widehat{CABG})_i\right|$. A higher value of this measure indicates that the actual treatment choice is further away from the treatment

[13] All patients in our primary sample received some sort of procedure (either CABG/PCI or others). We therefore do not consider the extensive margin of surgery versus medication.

[14] A higher value of $P(\widehat{CABG})_i$ (closer to one) indicates that the patient is more suitable for CABG relative to PCI. This approach effectively assumes that the average patient receives the appropriate treatment choice.

the patient should have received—either over-treatment (CABG, when PCI is more appropriate) or under-treatment (PCI, when CABG is more appropriate).

Table 9 reports the regression results for the subset of CABG/PCI patients. In Column (1), we first replicate our main result—namely lower mortality rate—within this group of patients. Then, in Column (2), we use patients' predicted probabilities for CABG, $P(\widehat{CABG})_i$, as outcome and confirm that politically mixed teams do *not* systematically see more or fewer patients who need a specific type of treatment. Finally, in Column (3) where the outcome dependent variable is $\left|1\{CABG\}_i - P(\widehat{CABG})_i\right|$, we find that politically mixed teams significantly reduce treatment inappropriateness by assigning CABG-needed (PCI-needed) patients to CABG (PCI).

VII Conclusion

TBD

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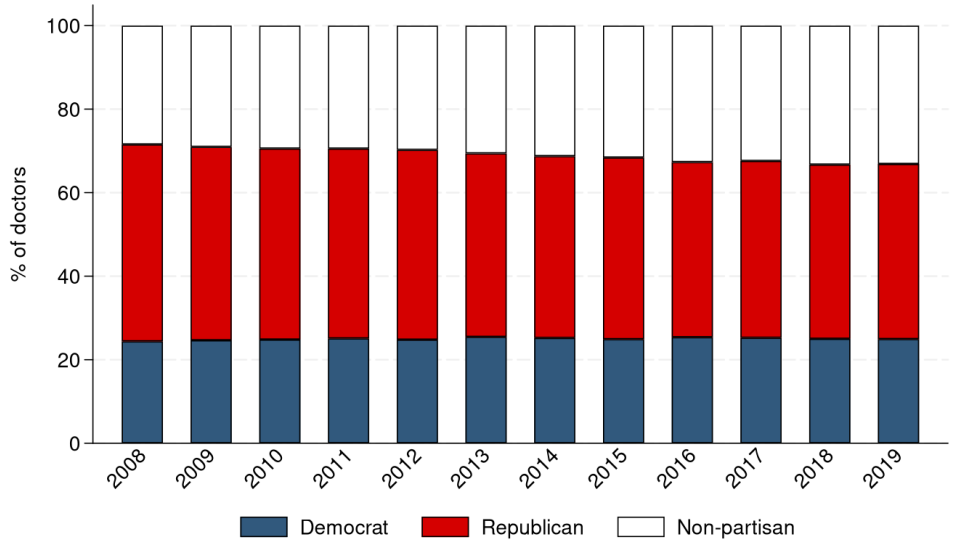
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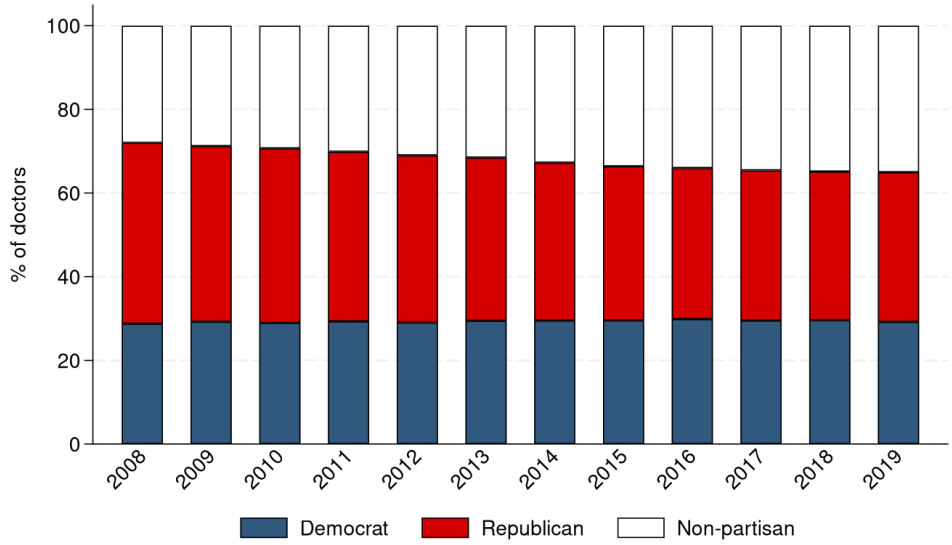
Figures and Tables

Figure 1. Political Affiliation of Proceduralists



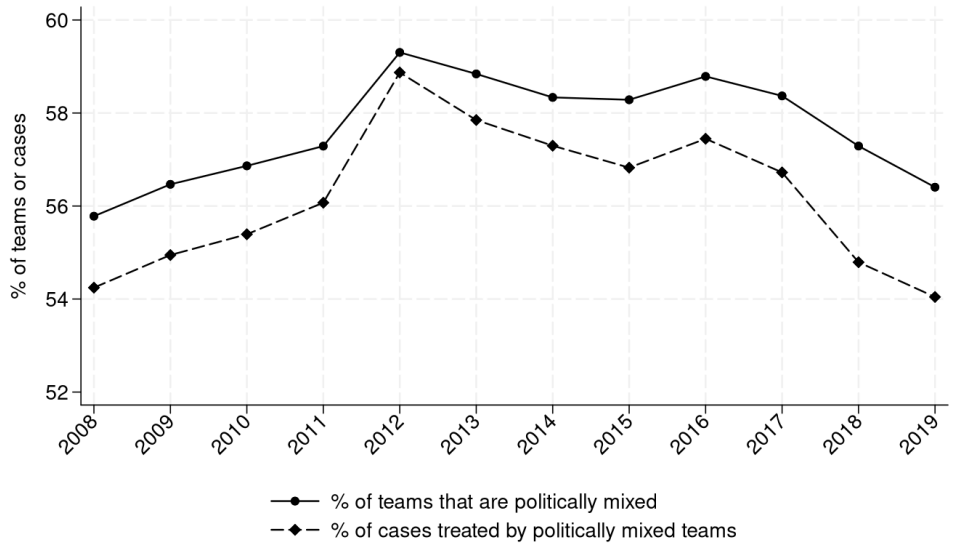
Notes: This figure reports the annual shares of proceduralists who are registered as Republican, Democrat, or non-partisan, in the analytic sample. Details on sample construction are provided in Section III and Appendix A.

Figure 2. Political Affiliation of Physicians



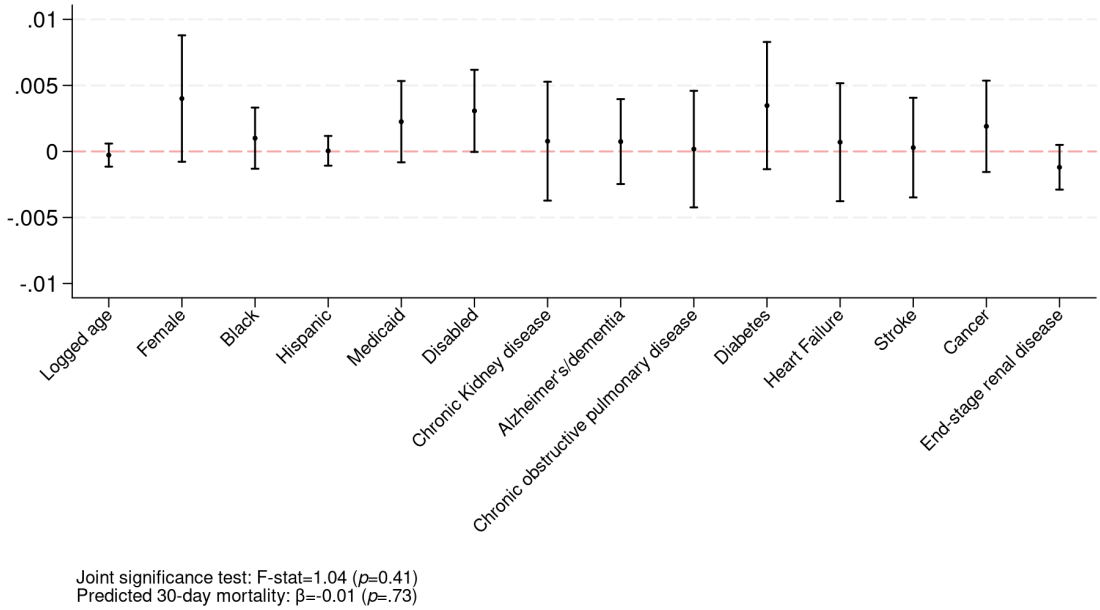
Notes: This figure reports the annual shares of physicians who are registered as Republican, Democrat, or non-partisan, in the analytic sample. Details on sample construction are provided in Section III and Appendix A.

Figure 3. Shares of Politically Mixed Teams Over Years



Notes: This figure reports the annual share of politically mixed teams among all heart attack teams in the analytic sample. The solid line is calculated using the number of unique teams; the dashed line is calculated by the number of cases treated by these teams. Details on the definition of team political composition are provided in Section III.

Figure 4. Balance Test on Patient Characteristics



Notes: This figure presents the results of the balance tests described in Section IV.B. Coefficient estimates and 95% confidence intervals from separate regressions of patient characteristics on team political composition are reported. Patient characteristics include demographic variables and individual risk indicators. All regressions include the hospital $\times$ time fixed effects and proceduralist fixed effects from the baseline specification. F-statistic from a joint significance test ($F = 1.04$, $p = 0.41$), as well as the coefficient from a regression using the predicted 30-day mortality rate as the outcome ($\beta = -0.01$, $p = 0.73$), are also reported.

Table 1. Summary Statistics

	Politicall aligned teams		Politicall mixed teams	
Patient characteristics				
Log(age)	4.342	[0.098]	4.344	[0.098]
Female	0.439	[0.496]	0.452	[0.498]
Non-Hispanic Black	0.076	[0.266]	0.080	[0.272]
Hispanic	0.016	[0.126]	0.018	[0.133]
Medicaid	0.150	[0.357]	0.157	[0.364]
Disabled	0.128	[0.334]	0.131	[0.338]
Chronic Kidney disease	0.391	[0.488]	0.400	[0.490]
Alzheimer's/dementia	0.153	[0.360]	0.158	[0.365]
Chronic obstructive pulmonary disease	0.343	[0.475]	0.351	[0.477]
Diabetes	0.482	[0.500]	0.492	[0.500]
Heart Failure	0.415	[0.493]	0.430	[0.495]
Stroke	0.211	[0.408]	0.217	[0.412]
Cancer	0.163	[0.370]	0.166	[0.372]
End-stage renal disease	0.047	[0.212]	0.048	[0.215]
Predicted 30-day mortality rate	0.108	[0.062]	0.109	[0.063]
Medical treatment				
Log(Medicare payment)	9.118	[1.907]	9.038	[1.878]
Log(DRG weight)	1.193	[0.431]	1.129	[0.380]
Length of stay	5.589	[5.482]	5.121	[5.029]
Number of procedures	5.215	[3.118]	4.898	[2.842]
30-day mortality rate	0.113	[0.317]	0.105	[0.306]
Doctor characteristics				
Proceduralist is Democrat	0.206	[0.404]	0.263	[0.440]
Proceduralist is Republican	0.493	[0.500]	0.413	[0.492]
Main Physician is Democrat			0.343	[0.475]
Main Physician is Republican			0.314	[0.464]
Team characteristics				
Shared experience	1.580	[3.544]	0.911	[2.029]
Complementary specialty	0.665	[0.472]	0.811	[0.392]
Female plus male	0.169	[0.375]	0.223	[0.416]
Black plus non-Black	0.174	[0.379]	0.202	[0.401]
Senior plus junior	0.400	[0.490]	0.495	[0.500]
Observations	168728		217165	

Notes: This table presents descriptive statistics for politically mixed and politically aligned teams. The analytic sample includes heart attack admissions from 2008 to 2019. Details on the data sources and sample construction are provided in Section III. For each variable, the sample mean (left column) and standard deviation (right column, in brackets) are reported. Statistics are shown for four groups of variables: patient characteristics, medical treatment, physician characteristics, and team characteristics.

Table 2. Effects on Patient Mortality: Baseline Estimates

	30-day mortality rate			
	(1)	(2)	(3)	(4)
Politically mixed team	-0.807***	-0.679***	-0.844***	-0.833***
	(0.112)	(0.129)	(0.130)	(0.129)
Hospital × time FE		✓	✓	✓
Proceduralist FE			✓	✓
Patient covariates				✓
Mean (Dep. Var.)	10.84	10.84	10.84	10.84
Observations	385,893	385,893	385,893	385,893

Notes: This table reports baseline estimates from patient-level regressions of 30-day mortality on the medical team's political composition, estimated using a linear probability model as specified in Equation (1). The sample period spans 2008–2019. The outcome variable is a binary indicator for 30-day mortality, scaled by 100. The main independent variable is a binary indicator for politically mixed teams, with the corresponding coefficient reported. Column (1) presents the unconditional estimate. Column (2) additionally includes hospital × time fixed effects, where the time dimension comprises calendar quarter, month of year, and day of week. Column (3) further includes proceduralist fixed effects. Column (4) additionally controls for patient characteristics, including demographics and comorbidities. Standard errors are clustered at the proceduralist level and reported in parentheses.

Table 3. Ruling Out Other Selection Channels

	30-day mortality rate		
	(1)	(2)	(3)
Politically mixed team	-0.665***	-0.822***	-0.522***
	(0.196)	(0.133)	(0.166)
Patient covariates	✓	✓	✓
Hospital × time FE	✓	✓	✓
Proceduralist × time FE	✓		
Proceduralist × hospital FE		✓	
Proceduralist FE + physician FE			✓
Mean (Dep. Var.)	10.84	10.84	10.84
Observations	385,893	385,893	385,893

Notes: This table reports estimates from patient-level regressions of 30-day mortality on the medical team's political composition, estimated using extended fixed effects relative to Equation (1). The sample period spans 2008–2019. The outcome variable is a binary indicator for 30-day mortality, scaled by 100. The main independent variable is a binary indicator for politically mixed teams, with the corresponding coefficient reported. All specifications include patient covariates, hospital × time fixed effects, and proceduralist fixed effects, as in the baseline specification. Column (1) additionally includes proceduralist × time fixed effects, where time is defined at the calendar-quarter level. Column (2) additionally includes proceduralist × hospital fixed effects. Column (3) includes both proceduralist fixed effects and physician fixed effects. Standard errors are clustered at the proceduralist level and reported in parentheses.

Table 4. Controlling For Other Team Characteristics

	30-day mortality rate		
	(1)	(2)	(3)
Politically mixed team	-0.737***	-0.846***	-0.752***
	(0.128)	(0.129)	(0.129)
Complementary specialties	-1.494***		
	(0.205)		
Shared experience		-0.0772**	
		(0.0313)	
Demographic combination			✓
Patient covariates	✓	✓	✓
Hospital × time FE	✓	✓	✓
Proceduralist FE	✓	✓	✓
Mean (Dep. Var.)	10.84	10.84	10.84
Observations	385,893	385,893	385,893

Notes: This table reports estimates from patient-level regressions of 30-day mortality on the medical team's political composition, controlling for other team characteristics. The sample period spans 2008–2019. The outcome variable is a binary indicator for 30-day mortality, scaled by 100. The main independent variable is a binary indicator for politically mixed teams, with the corresponding coefficient reported. All specifications include patient covariates, hospital × time fixed effects, and proceduralist fixed effects, as in the baseline specification. Column (1) additionally includes a binary indicator for whether the proceduralist and the physician have complementary specialties. Column (2) additionally includes a measure of shared experience between the proceduralist and the physician. Column (3) further controls for high-dimensional fixed effects based on both doctors' demographics, defined as interactions between the proceduralist's and physician's age, race, and gender. Standard errors are clustered at the proceduralist level and reported in parentheses.

Table 5. Alternative Measures of Patient Mortality

	Alternative measures of patient mortality			
	(1) 30-day mortality since discharge	(2) In-hosp. mortality	(3) 90-day mortality	(4) 360-day mortality
Politically mixed team	-0.828***	-0.759***	-0.839***	-0.900***
	(0.133)	(0.106)	(0.148)	(0.175)
Patient covariates	✓	✓	✓	✓
Hospital × time FE	✓	✓	✓	✓
Proceduralist FE	✓	✓	✓	✓
Mean (Dep. Var.)	9.85	5.66	12.74	20.36
Observations	385,893	385,893	385,893	385,893

Notes: This table reports estimates from patient-level regressions of alternative measures of patient mortality on the medical team's political composition, estimated using a linear probability model as specified in Equation (1). The sample period spans 2008–2019. The outcome variable is a binary indicator for 30-day mortality, scaled by 100. The main independent variable is a binary indicator for politically mixed teams, with the corresponding coefficient reported. All specifications include patient covariates, hospital × time fixed effects, and proceduralist fixed effects, as in the baseline specification. Column (1) uses the 30-day mortality rate measured from the date of discharge. Column (2) uses in-hospital mortality. Columns (3) and (4) use 90-day and 360-day mortality, respectively, measured from the date of admission. All mortality measures are scaled by 100. Standard errors are clustered at the proceduralist level and reported in parentheses.

Table 6. Alternative Sample Specifications

	30-day mortality rate			
	(1) Include non-ED patients	(2) Include teams w/o multiple physicians	(3) Exclude non-partisan doctors	(4) Keep donating doctors only
Politically mixed team	-0.875***	-0.837***	-0.626***	-0.745
	(0.106)	(0.123)	(0.228)	(2.803)
Patient covariates	✓	✓	✓	✓
Hospital × time FE	✓	✓	✓	✓
Proceduralist FE	✓	✓	✓	✓
Mean (Dep. Var.)	8.86	9.38	8.79	8.52
Observations	508,256	421,253	190,197	11,974

Notes: This table reports estimates from patient-level regressions of 30-day mortality on the medical team's political composition, estimated using alternative samples and a linear probability model as specified in Equation (1). All alternative samples period spans 2008–2019. The main independent variable is a binary indicator for politically mixed teams, with the corresponding coefficient reported. All specifications include patient covariates, hospital × time fixed effects, and proceduralist fixed effects, as in the baseline specification. Column (1) additionally includes patients who are admitted to hospitals but not through emergency departments. Column (2) includes cases treated by teams with more than one physician. Column (3) excludes patients treated by non-partisan proceduralist or physician. Column (4) only keep patients treated by teams in which both the proceduralist and the physician ever have donations. Standard errors are clustered at the proceduralist level and reported in parentheses.

Table 7. Heterogeneous Effects by Patient Risk

	30-day mortality rate		
	(1) Low-risk	(2) Med-risk	(3) High-risk
Politically mixed team	-0.850***	-1.146***	-0.490
	(0.232)	(0.324)	(0.458)
Patient covariates	✓	✓	✓
Hospital × time FE	✓	✓	✓
Proceduralist FE	✓	✓	✓
Mean (Dep. Var.)	3.99	7.39	14.19
Observations	128,641	128,628	128,624

Notes: This table reports estimates from patient-level regressions of 30-day mortality on the medical team's political composition, estimated using alternative samples and a linear probability model as specified in Equation (1). All alternative samples period spans 2008–2019. The main independent variable is a binary indicator for politically mixed teams, with the corresponding coefficient reported. All specifications include patient covariates, hospital × time fixed effects, and proceduralist fixed effects, as in the baseline specification. Column (1) additionally includes patients who are admitted to hospitals but not through emergency departments. Column (2) includes cases treated by teams with more than one physician. Column (3) excludes patients treated by non-partisan proceduralist or physician. Column (4) only keep patients treated by teams in which both the proceduralist and the physician ever have donations. Standard errors are clustered at the proceduralist level and reported in parentheses.

Table 8. Effects on Treatment Intensity

	Measures of treatment intensity			
	(1) Log(Medicare payments)	(2) Log(DRG weights)	(3) Length of stay	(4) # procedures
Politically mixed team	-0.0292***	-0.0120***	-0.0128***	-0.0245***
	(0.00859)	(0.00159)	(0.00355)	(0.00193)
Patient covariates	✓	✓	✓	✓
Hospital × time FE	✓	✓	✓	✓
Proceduralist FE	✓	✓	✓	✓
Mean (Dep. Var.)	9.08	1.17	5.23	5.29
Observations	385,893	385,893	385,893	385,893

Notes: This table reports estimates from patient-level regressions of treatment intensity on the medical team's political composition. The sample period spans 2008–2019. The main independent variable is a binary indicator for politically mixed teams, with the corresponding coefficient reported. All specifications include patient covariates, hospital × time fixed effects, and proceduralist fixed effects, as in the baseline specification. Columns (1)–(4) use log Medicare payments, log DRG weights, length of stay (in days), and the number of procedures performed as measures of treatment intensity, respectively. Columns (1)–(2) are estimated using a linear model, while columns (3)–(4) are estimated using a Poisson model. Standard errors are clustered at the proceduralist level and reported in parentheses.

Table 9. Effects on Treatment Choice

	Treatment choice: CABG vs. PCI		
	(1) 30-day mortality rate	(2) Predicted CABG rate	(3) Procedure inappropriateness
Politically mixed team	-0.885***	0.00863	-0.186**
	(0.164)	(0.0135)	(0.0801)
Patient covariates	✓	✓	✓
Hospital × time FE	✓	✓	✓
Proceduralist FE	✓	✓	✓
Mean (Dep. Var.)	6.26	14.62	24.55
Observations	214,487	214,487	214,487

Notes: This table reports estimates from patient-level regressions using a sample of patients who receive either CABG or PCI following a heart attack. The sample period spans 2008–2019. The main independent variable is a binary indicator for politically mixed teams, with the corresponding coefficient reported. All specifications include patient covariates, hospital × time fixed effects, and proceduralist fixed effects, as in the baseline specification. Column (1) uses the 30-day mortality rate (scaled by 100) as the outcome variable. Column (2) uses the predicted probability of receiving CABG (scaled by 100), where the probability is estimated using patient covariates in a logit model. Column (3) uses a measure of procedural inappropriateness, defined as the absolute deviation between the actual procedure and the predicted probability, $\left|\mathbf{1}\{CABG\}_i - P(\widehat{CABG})_i\right|$. Standard errors are clustered at the proceduralist level and reported in parentheses.

Online Appendix

A Matching Doctors to L2 Voter Registration Data

We use two waves of L2 voter registration data. Our primary wave uses voter records from the 2016 presidential election, and we supplement these with a second wave from the 2020 presidential election. Below we describe the matching procedure for the 2016 wave. The procedure for the 2020 wave is identical.

The matching is performed state by state, as L2 voter registration data are organized by state. Accordingly, we first partition the doctor sample by state using practice location information from the National Plan and Provider Enumeration System (NPPES). Because doctors may practice in multiple states, we keep such doctors in each of their practice states to maximize the probability of a correct match. In our data, 68,978 out of 248,689 doctors (28%) are associated with more than one state.

Within each state, we begin by identifying all exact matches on first and last names between doctors and L2 voters. We do not allow for spelling errors or name variations (e.g., "Chris" versus "Christopher" versus "Kris"). This initial step can yield many-to-many matches. We then progressively refine the matches using additional identifiers. First, we match on middle names: when both records contain full middle names, we require an exact match; when at least one record reports only a middle initial, we match on the initial. Second, we match on exact birth year-month-date. The vast majority of L2 voter records contain an exact date of birth. A small fraction reports birth date with the day coded as the first day of the month, effectively indicating year-month information. For these observations, we match on birth year-month. Observations with different birth dates (or year-months) are dropped. [1] Third, we require an exact match on gender.

If a doctor remains matched to multiple voter records after these steps, we keep the match only if all corresponding voter records report the same party affiliation; otherwise, the match is dropped. Conversely, if multiple doctors (NPIs) are matched to the same voter record, we conservatively drop all such doctors.

Finally, we append the matched doctors from all states. In the rare cases where a doctor is

[1] The vast majority of L2 voter records contain an exact date of birth. A small fraction report birth date with the day coded as the first day of the month, effectively indicating year-month information. For these observations, we match on birth year-month. Overall, 93% of matched doctors are identified using an exact birth date match.

matched in more than one state (1,405 out of 248,689, or 0.6%), we keep the doctor only if the party affiliation information is consistent across states; otherwise, the doctor is dropped. After completing these steps, we obtain the final matched sample based on the 2016 wave. We then repeat the same procedure using the 2020 voter registration data, identifying an additional 24,007 doctors who do not appear in the 2016 wave. Our final sample consists of all doctors matched in the 2016 wave together with these additional 24,007 doctors from the 2020 wave.

This matching rate exceeds those in the literature using campaign donation records, which have matching rates of around 28% (Kim, 2024), probably because most individuals do not make political donations. Our matching rate should nonetheless be interpreted as a conservative lower bound of the true share of doctor registrants. This is because we require exact matches on full names, which precludes matches with misspellings or name variations (e.g., Chris vs. Christopher vs. Kris), and because we conservatively drop all doctors in cases where multiple doctors match to the same voter record. For context, in 2016 the voter registration rate among U.S. citizens of voting age was approximately 64%, and about 78% among citizens holding an advanced degree beyond a bachelor's degree.[2]

[2] https://www.census.gov/data/tables/time-series/demo/voting-and-registration/p20-580.html