

# Ideological Sorting of Physicians in Both Geography and the Workplace

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## Abstract

**Context:** The distribution of physicians across geography and employers has important implications for the delivery of medical services. This study examines how the political beliefs of physicians influence their decisions about where to live and work.

**Methods:** Physician relocation and employment patterns are analyzed with a panel constructed from the National Provider Identifier directory. Data on political donations are used to measure the political preferences of physicians.

**Findings:** The “ideological fit” between a physician and his or her community is a key predictor of both relocation and employment decisions. A Democratic physician in a predominantly Republican area is twice as likely to relocate as a Republican counterpart living there; the reverse is also true for Republicans living in Democratic areas. Physicians who do not share the political orientation of their colleagues are more likely to change workplaces within the same geographic area.

**Conclusions:** Physicians are actively sorting along political lines. Younger physicians have trended sharply to the left and are increasingly drawn to urban areas with physician surpluses and away from rural areas suffering from physician shortages. The findings also help explain why physician shortages are more prevalent among left-leaning specialties such as psychiatry.

**Keywords** physician politics, partisan sorting, geography, labor market, health care access

Political ideology is a predictor of the geographic mobility of physicians. Physicians tend to move when their political ideology differs from that of the geographic area where they practice. When they do move, it tends to be to an area congruent with their political ideology. Similarly, physicians that change employers within a geographic area tend to make their

political ideology congruent with that of other physicians in their new place of employment. We do not claim that our results show that political preferences alone cause mobility. Rather, politics may be a marker of other preferences—for example, liberals preferring urban settings to rural ones.

Bonica, Rosenthal, and Rothman (2014) showed that physician ideology is highly stable in time. It is thus appropriate to use ideology as an exogenous variable in studying mobility. Moreover, we show here that personal ideology is largely unaffected by changes in geographic location or employment.

Physicians' ideological fit with their current community influences the decision to relocate and to where. The effect is sizable. A Democratic physician in a predominantly Republican area is twice as likely to relocate as a Republican counterpart living there; the reverse is also true for Republicans living in Democratic areas. When Democratic physicians relocate, they resettle in more liberal areas than do Republicans.

Physicians are an excellent group to study partisan sorting patterns. First, mobility observations for physicians are available. The NPI (National Provider Identifier) directory reports mandatory annual reporting of geographic location. Combining the NPI data across years yields a panel that tracks which physicians relocate and to where. We can also observe changes with respect to career, employer, and specialty using NPI data. Second, physicians are professionals whose skills are in high demand and thus are relatively unconstrained in deciding where to live and work. Third, physicians have broadly similar career trajectories. After graduating from medical schools, physicians enter residency programs before moving on to practice. The transition from residency to practice is a major driver of sorting.

The National Resident Matching Program (NRMP) generates an initial geographical distribution of physicians at the onset of their careers. Fourth-year medical students and residency programs rank each other; applicants and programs are then “matched” using an algorithm developed by NRMP. Centralized matching requires that applicants respond to the geographic distribution of available positions. Due to the matching process, applicants ultimately do not have complete control of their residency locations. Upon completion of residency, physicians are free to relocate. The result is a period of heightened migration during which physicians are most likely to sort. Although migration continues at a lower rate for the years after finishing residency, sorting continues to be congruent with political ideology.

Geographic sorting by physicians has implications beyond the standard concerns about political polarization and its impact on representation. Where physicians choose to practice is a matter of public interest. The

maldistribution of physicians, especially primary care providers, can limit access to health care services in underserved areas and negatively affect health care outcomes (Goodfellow et al. 2016). At the same time, other regions boast surpluses of physicians. Indeed, the increased geographic concentration of physicians defies market incentives.<sup>1</sup> The areas with the largest surpluses of physicians are among the most expensive in terms of cost of living and are the most poorly compensated. Salaries for primary care providers in areas with some of the highest costs of living, such as New York City and Washington DC, are among the lowest in the nation (Doximity 2016).

On average, physicians migrate from more liberal (or blue) to more conservative (or red) areas. This is a consequence of residencies being concentrated in liberal areas but the demand for physicians covering a national market. The transition from residency to practice reduces the geographic concentration present in residency.

In addition to the study of geographic sorting, we are also able to explore sorting with respect to workplace and employer. We provide evidence that physicians are actively sorting by workplace and employer. Physicians who do not share the political orientation of their colleagues are significantly more likely to change their workplace while staying within a geographic area. Physicians seek out nearby workplaces in which colleagues tend to share their political views.

An important omission from our analysis is compensation. It would be desirable to control for physician earnings pre- and postmovement. We can partially mitigate this problem (and others) with fixed effects for medical school attended, residency program, and specialty.

The remainder of this article proceeds as follows. First, we review the literature on political sorting and occupational mobility of physicians. Then we describe the data in detail. After that, we demonstrate that the political preferences of physicians are temporally stable. Next we present a preliminary description of the mobility of physicians. In the remaining three sections, respectively, we describe our data analysis model, present our central results, and discuss the results before we conclude.

## Political and Geographic Sorting

Geographic polarization in the electorate is well documented (Bishop 2009; Gelman 2009; Rodden 2010). Studies have consistently shown that

1. Maldistribution has motivated previous research on the geographic distribution of physicians. See, for example, Goodman 2004; Hancock et al. 2009; and Matsumoto et al. 2010. See also Goodfellow et al. 2016 for a review of the literature.

residential preferences correlate with partisanship. Democrats express a preference for urban areas, while Republicans generally prefer rural areas (Williamson 2008; Lewis and Baldassare 2010). A recent study demonstrates that how a community voted in the previous election has an independent effect on how partisans rate the desirability of a neighborhood (Mummolo and Nall 2017).

Nevertheless, evidence that voters are actively sorting is not entirely forthcoming. In a study of migration patterns using state voter files, Tam Cho, Gimpel, and Hui (2013) offer only qualified evidence that voters are sorting with respect to geography. They find that decisions about where to relocate are conditioned on partisanship but that members of both parties tend to move to destinations that are more conservative than their origin. As a result, Democrats who move are more likely to mix than sort. Mummolo and Nall (2017) provide further evidence that partisans express preferences suggestive of sorting, but they argue that voters often lack the means or opportunity to act on them. In practice, schools, jobs, and housing take priority in deciding where to live. Given these constraints, most people lack the resources or job opportunities to move to places they may find more desirable. Sorens (2016) offers a partial explanation for why such constraints might be asymmetric with respect to party. He shows that housing prices are highest in the most Democratic states and that cost of living correlates positively with Democratic vote shares. Thus, cost of living is likely to push people to migrate from liberal areas to conservative areas.

### Mobility of Physicians

Several studies have compared the geographic distribution of physicians at two or more points of time. One line of research emphasizes the geographic maldistribution of physicians (see, e.g., Goodman 2004; Hancock et al. 2009; and Matsumoto et al. 2010). Another focuses on the effect of state malpractice legislation on physician geographic distribution (Chou and Lo Sasso 2009; Encinosa and Hellinger 2005; Kessler, Sage, and Becker 2005). States that limit malpractice awards have, *ceteris paribus*, a higher density of physicians than do states that are more generous to plaintiffs. Hancock et al. (2009) and Kazanjian and Pagliccia (1996) use surveys to study the motivations of geographic location. They emphasize the tradeoff between economic incentives and lifestyle considerations. Our article conceptualizes political preferences as a proxy for lifestyle.

We know of only two studies (Ricketts 2010, 2013) that analyze the mobility of individual physicians. Ricketts investigates physicians who

changed counties between 2006 and 2011. His independent variables are restricted to covariates that we use. For the covariates, his results are similar to ours. He does not investigate political preferences.

## Data

Our data on employment location comes from the federal NPI database for the years 2007–16.<sup>2</sup> Physicians enter the NPI when they begin residency following medical school. We have matched the NPI data to that in the PECOS (Provider Enrollment, Chain, and Ownership System) database, which gives us the medical school attended by the physicians and the year of graduation from medical school.<sup>3</sup>

Our measure of ideology is the CFscore (Bonica 2014) of physicians making campaign contributions. (Another measure of ideological distance is the percentage of donations to Republicans by the physician. Results for this measure are in the online appendix.) Our measures of the preferences of geographic areas rely on CFscores of all contributors.

Campaign contribution data is from the DIME archive site at Stanford University (Bonica 2016). The “raw” data is in reports filed with the Federal Election Commission and the Internal Revenue Service. DIME contains records linked using matching algorithms to provide a record of contributions for each individual donor across the 16 election cycles from 1979 to 2016. (For details, see Bonica, Rosenthal, and Rothman (2014).) The contribution records are also scaled to provide a measure of liberal-conservative ideology, the CFscore, for each donor. The CF scaling is not limited to the contributions of physicians but also uses data from all contributors. The CFscores of physicians used in our main analysis are static, invariant with time.

The data on physician specialty, employment type, and geographic location come from the NPI database. The NPI data provide an annual snapshot of each physician’s specialty, employment type, and geographic location. Gender is inferred from a first-name algorithm that has very high reliability.

Using the NPI data improves on the basic matching algorithm used to construct DIME. Records of contributions made by doctors that move from one place to another might not be linked by DIME’s record linkage algorithm. For example, a John Smith in Ohio might not be linked to a John Smith in Oregon because John Smith is too common a name to match

2. The NPI registry was created in 2007. We rely on historical snapshots of the NPI data to construct our panel, which we obtained from [data.nber.org](http://data.nber.org).

3. Obtained from [pecos.cms.hhs.gov](http://pecos.cms.hhs.gov).

records on name and occupation if the location does not also match. This problem is alleviated by the addition of the NPI directory since the NPI ID is unchanged when a physician changes address.

The data on medical school attended is from PECOS. PECOS contains a subset of more than half of the NPI physicians.<sup>4</sup> For the period covered by our study, 2007–2014, we identified 1,027,708 unique physicians from the NPI. Of these, 248,321 matched against donor records in DIME with CFscores.<sup>5</sup> The subset covered by PECOS represents 685,973 physicians of whom 176,520 had CFscores.

Concern is warranted as to how representative our matched physicians are of the larger population of physicians. It should be noted, however, that our matched contributors are not a narrow slice but nearly one quarter of all physicians. A physician enters our sample even if the physician donated only once in the period 1997–2016. Most of our sample contributed only after residency. Moreover, the political engagement of our contributors is limited. Only 48% of our contributors gave more than \$500 in any election cycle. Overall, donors are about 33% less likely to move during a given cycle. But this is largely because donors in our sample tend to be much older. After controlling for age and other variables included in our main regression, the estimated coefficient on mobility for a donor is  $-0.009$ . A significant effect remains but is very small, corresponding to less than a percentage point difference in the likelihood of moving. Future research, using, for example, public records of partisan voter registration, would be likely to confirm our findings.

### Stability of Political Preferences

We demonstrate the stability of political preferences in table 1. The static CFscores would be a concern if donations changed in response to geographic location. This might result if physicians are likely to adopt the politics of others living in their community or if there is a tendency to donate to local candidates. We construct a time-varying measure based on contribution patterns. For each cycle in which a physician donates, we estimate a period-specific CFscore based on donations made during the 2-year period. This enables us to track changes in individual-level giving behavior from one

4. The main trigger for registering is accepting Medicare payments. There are several other triggers, but Medicare is by far the most common. This skews our sample with respect to specialty. In particular, PECOS excludes a much higher percentage of pediatricians, who are less likely to treat patients on Medicare.

5. Another 62,540 physicians were matched against donation records in DIME but who had only given to medical association PACs or otherwise did not meet the donation requirements for estimating a CFscore.

**Table 1** Period-Specific CFscores Are Insensitive to Changes in Geography and Employer

| Ordinary least squares estimates<br>Independent variable | Geography model |                 | Employment model |                |
|--|-----------------|-----------------|------------------|----------------|
|  | (1)             | (2)             | (3)              | (4)            |
| Zip3 CFscore   | -0.01<br>(0.02) | -0.02<br>(0.02) |                  |                |
| Employer/practice CFscore                                |                 |                 | 0.02<br>(0.02)   | 0.02<br>(0.02) |
| Individual fixed effects                                 | Y               | Y               | Y                | Y              |
| Cycle fixed effects                                      | Y               | Y               | Y                | Y              |
| R2   | 0.934           | 0.930           | 0.943            | 0.951          |
| Number of observations                                   | 213,598         | 17,100          | 77,263           | 17,410         |

Dependent variable: period-specific physician CFscores.

*Note:* Models 1 and 3 cover all physicians who donated in two or more cycles. Models 2 and 4 further restrict the observations to physicians who moved geographically at least once (model 2) or changed employer at least once (model 4). Observations are weighted by the square root of the number of contributions used in calculating a physician-cycle score. The standard deviation of zip3 CFscores is 0.41. The standard deviation of period-specific physician CFscores is 1.05. Standard errors in parentheses.

period to the next. We use these scores to test whether donation patterns are sensitive to changes in location.

We cannot say with certainty that an individual's first donation is not affected by where they live or work. Nonetheless, the results presented in this section demonstrate quite conclusively that when established donors move to a new area or start work at a new practice/employer, their ideological giving patterns do not change in response to their new surroundings. (As an additional robustness check, we have replicated our main results with a set of CFscores recovered from donations made prior to the start of our panel in 2007. Results are reported in the online appendix.)

We first filter on physician-cycle observations for those who donate in two or more cycles. This results in an unbalanced panel with 213,598 observations. We then regress period-specific CFscores on the zip3 code and individual fixed effects.<sup>6</sup> To account for potential variability in estimated period-specific CFscores due to small samples, we weight observations by the square root of the number of contributions used in calculating a physician-cycle score.

6. The zip3 code is the first three digits of the standard US Postal Service code. For example, 152 is a portion of western Pennsylvania that includes Pittsburgh.

The individual fixed effects capture 92 percent of the temporal variation in CFscores with nothing being added by changes in the political orientation (model 1, table 1). Most physicians in the sample do not relocate during the period under study. To ensure that physicians who do not vary their geographic location are not attenuating the effect, we further subset on physicians who moved at least once during the panel in model 2. Thus, there are no individuals in model 2 for whom zip3 does not vary.

Models 3 and 4 perform the same analysis with respect to changes in employer/practice. We measure employer ideology as the average CFscore of physicians listing the practice/employer. We exclude practices with fewer than five affiliated physicians with CFscores. This excludes most small private practices and sole proprietors. The resulting unbalanced panel has 77,263 observations. Model 4 is further limited to physicians who change employer/practice at least once. There are more observations for model 4 than for model 2 because physicians change employers within a zip3 code.

### Age and Cohort Effects

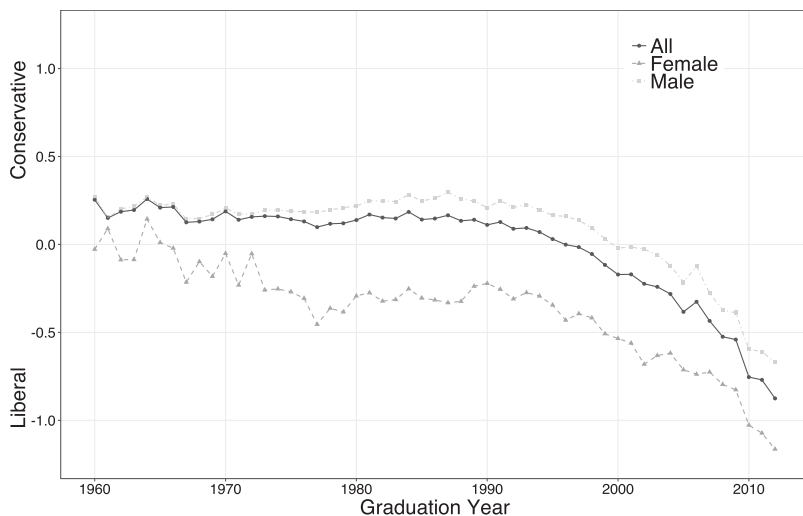
The stability of preferences may relate to contributions starting relatively late in the career of a physician. In the online appendix, we compare physicians to lawyers. The proportions of members from both professions on record as donors steadily increase with years since graduation. Physicians are much slower to become donors early in their careers. A year out from graduating, 10% of lawyers have donated compared with 2% of physicians. This likely reflects residency requirements that retard the immediate earning capacity of physicians. Contributing typically starts mid-career. Roughly 20% of physicians 15 years into their careers have donated. The proportion doubles to 40% of physicians 30 years into their career. (About 45 years after graduation, the proportion contributing peaks.)

Although individual preferences are stable, there are strong cohort effects. Figure 1 plots the average CFscores by year of graduation.<sup>7</sup> The trend line for graduating classes up through the early 1990s is essentially flat, with the average physician leaning slightly right of center. Starting in the mid-1990s, the trend line shows a dramatic shift to the left. The shift in preferences is primarily generational—that is, determined by year of graduation, which proxies for year of birth—rather than a function of age.

Consistent with Ghitzza and Gelman's (2014) recent work on cohort effects, political outlook is established during one's formative years and is

7. These are not the period-specific CFscores used in table 1 but a CFscore estimated assuming a constant ideology over time. Results are similar using period-specific scores.





**Figure 1** Average physician CFscore by year of graduation and gender.

Sources: NPI and DIME; authors' calculations.

heavily influenced by the political events of that period. The leftward shift of cohorts reflects demographic trends, especially with respect to growing numbers of women entering the profession. Younger physicians in our sample (i.e., those most likely to relocate) are more liberal than older physicians. The overall trend line remains closer to the male trend line as males are contributors more frequently than females.<sup>8</sup>

Because physicians who are campaign contributors tend to have stable partisanship and tend to contribute only in mid-career and beyond, it is clear that political preferences can encapsulate preferences that drive career decisions. Changes in locations or careers do not appear to be a major determinant of already established contribution preferences.

## Mobility of Physicians

Physician mobility raises two questions. First, why do physicians move? Second, where do they move to? We look at professional address changes using a cutoff of 100 kilometers (62 miles). The motivation for the cutoff is

8. The same patterns also appear in party registration data. We matched 80% of NPI physicians practicing in Florida to the voter registration file for that state. This provides individual-level data on race and party registration for 45,736 physicians. The voter registration data simultaneously allows for comparisons between Florida physicians and Florida voters. See the online appendix for results.

to exclude local occupational changes, such as a dermatologist who moves from Columbia-Presbyterian to Mount Sinai or to private practice in New York City. (Sensitivity explored in the online appendix.) We find substantial mobility, especially in physicians' early careers.

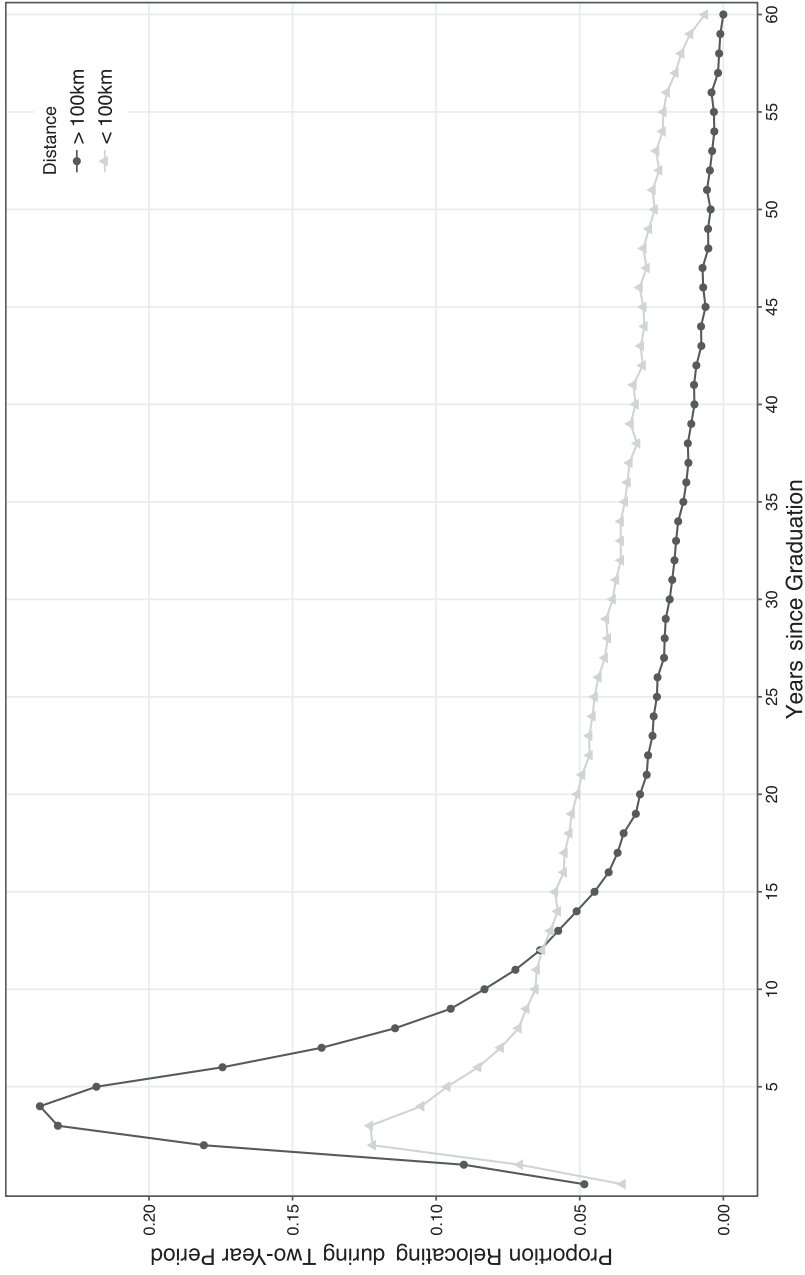
Figure 2 shows the proportion of physicians in PECOS relocating during a 2-year period by years since graduating from medical school. The 2-year periods run from the start of one election cycle to the start of the next. Mobility spikes during the first decade of one's career. Nearly one-fourth of physicians 4 years out of medical school will relocate more than 100 kilometers within the following 2 years. (Another 11% will have moved less than 100 kilometers). Half of all relocations occur within 10 years after graduation. Since residency requirements vary by specialty (from 3 to 7 years), we use the average length of residency programs for 19 common specialties to group physicians. Spikes in movement rates correspond to post-residency windows. (Results reported in the online appendix.) Mobility more than 100 kilometers (62 miles) is very limited for physicians after 25 years beyond medical school graduation. Those who do move later in their careers are about twice as likely to relocate within a 100-kilometers radius.

### Migration Patterns

Physicians are migrating, on average, from places with more physicians to places with fewer. Figure 3 shows the average number of physicians per 100,000 population in zip3 codes from which physicians are emigrating (in black) and to which they are migrating (in grey). The difference is most pronounced early on in physicians' careers. This is not unexpected; hospitals with residency programs are clustered in regions with the greatest concentrations of physicians per capita. But the pattern persists past residency.

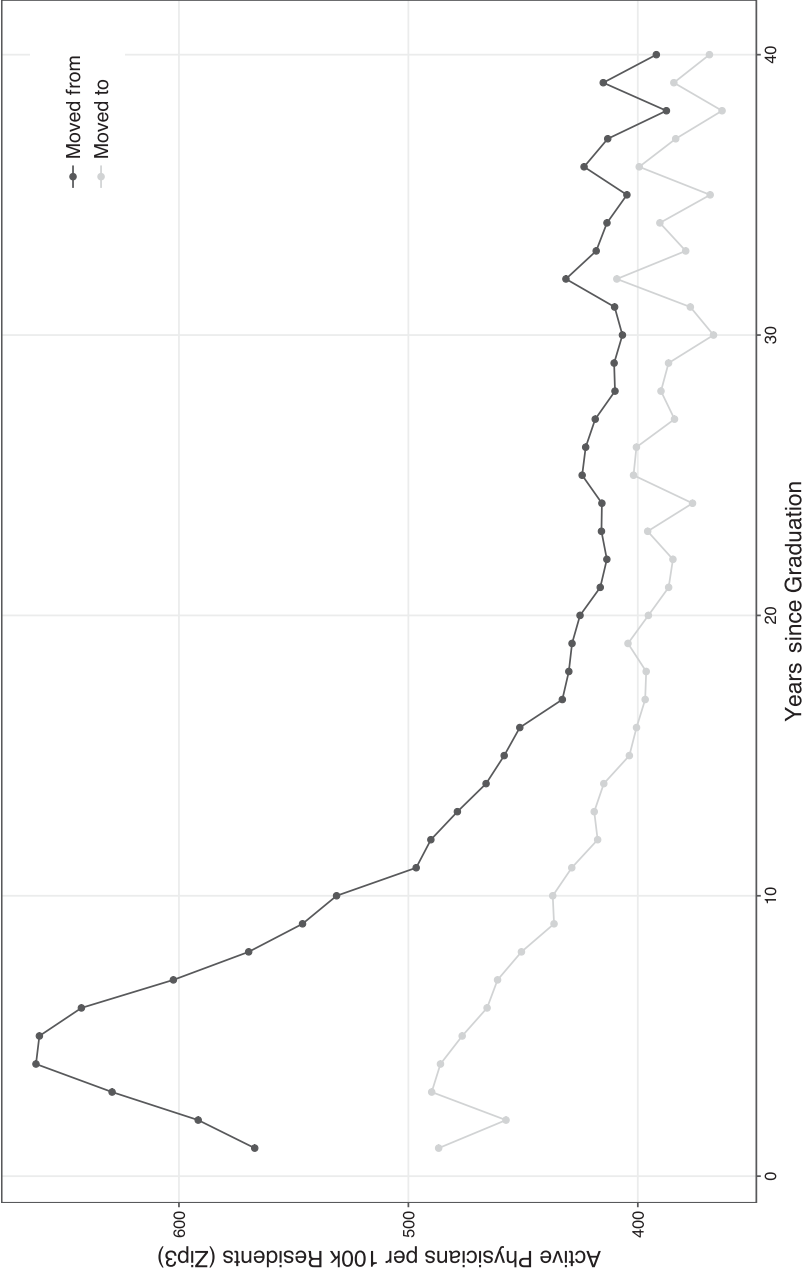
Medicare has funded residency programs since its inception in 1965. However, the Balanced Budget Act of 1997 capped this funding, effectively freezing the 1996 distribution of residencies. This advantaged residency programs in metropolitan areas, particularly in the Northeast (Institute of Medicine 2014). While attempts have been made to correct this distribution, the density of residents continues to vary greatly. In Washington, DC, there are 241.6 residents per 100,000 population, while in Montana there are only 5.6 residents per 100,000 population (AAMC 2017).

This legislation advantaged predominantly liberal areas. Health care institutions in liberal areas can offer more Medicare funded residencies



**Figure 2** Proportion relocating by years since medical school graduation.

Source: NPES downloadable file; authors' calculations.



**Figure 3** Migration patterns conditional on physician supply and years since graduation.

Source: NPPES downloadable file; authors' calculations.

than those in conservative areas. After residency (and, for some, fellowship), physicians enter a national market where the geographic distribution of positions is far less constrained.

## Model Specification

To investigate geographic mobility more fully, we estimate a two-equation Heckman model. The selection equation estimates, using probit, the probability of relocation of more than 100 kilometers by physicians in the NPI/PECOS matched to a CFscore in DIME. The basic observation is a physician-donor in an election cycle. There are 668,031 such observations.

There is an existing literature on modeling residential mobility and location choice (see Schirmer, van Eggermond, and Axhausen 2014 for a comprehensive review of the literature). Early contributions of Lerman (1976) and McFadden (1978) were the first to model location choice in a discrete choice framework. Individuals are assumed to have preferences about housing characteristics, cost of living, neighborhood, schools, urban density, proximity to “points of interest,” and access to transportation and commuting times. Given a set of alternatives, a decision maker selects the location that maximizes utility based on their preferences and constraints. Because each location represents a bundle of attributes, individuals face trade-offs in deciding between alternatives.

The standard formulation models the choice to relocate and the choice of destination as distinct but related stages in the decision process. McFadden (1978) used a nested-logit framework. In the first stage, individuals decide whether to remain in their current locations or to relocate. Conditional on moving, an individual must then decide where to relocate.

Here, we are less concerned with uncovering location preferences of physicians per se. Our primary interest is how migration decisions relate to political preferences—in particular, the ideological distance between physicians and their zip codes. Factors identified in the past studies as important enter the model as controls.

The utility of physician  $i$  for geographic location  $j$  in election cycle  $k$  is expressed as

$$U_{ijk} \sim \alpha + d(\theta_i, \delta_j) + s(t_i) + \beta X_{ij} + \gamma Z_{ip} + \text{state}_i + \text{cycle}_k + \epsilon_{ijk},$$

where  $\alpha$  is a baseline propensity to relocate;  $d(\cdot)$  operationalizes ideological fit between physician  $i$ 's CFscore ( $\theta_i$ ) and the average CFscore for all donors in zip code  $j$  ( $\delta_j$ );  $s(\cdot)$  captures career stage as a function of the

number of years since graduating from medical school ( $t_i$ );  $X_{ij}$  is a set of location characteristics; and  $Z_{ip}$  is a set of occupational and employer characteristics for practice  $p$ . There are fixed effects for election cycle. Fixed effects, not shown in (1) for simplicity, are also included for specialty and medical school attended. Note that the ideology of the physician and the geographic location are treated as temporally invariant during the period of our study, 2007–16.

Geographic control variables in  $X_{ij}$  include population density, physicians per 100,000 capita, local and state tax rates, per capita income, and state fixed effects. Population density is measured for zip3 codes.<sup>9</sup> Average tax rates are calculated from IRS SOI zip code level data and measure the combined state and local taxes for individuals with incomes of more than \$50,000.<sup>10</sup> State fixed effects pertain to the 50 states and the District of Columbia.

The occupational and employer characteristics in  $Z_{ip}$  control for practice size, employer type—(1) non-profit, (2) government, or (3) for-profit, with for-profit as the default category—and specialty. There are dummy variables for 93 specialties reported by at least 1,000 physicians.<sup>11</sup>

We additionally control for individual-level characteristics. First, we control for gender. Second, we control for years since graduation from medical school as a measure of experience, which in turn proxies for age. We capture nonlinearity with an eighth-degree polynomial. (Figure A1 in the online appendix shows the effect for years since graduation to be highly nonlinear.) Third, we control for medical school attended through dummy variables for 152 schools with at least 1,000 graduates in our sample.<sup>12</sup> Medical school location is an important predictor of practice location. Nearly a third of physicians practice in the state where they attended medical school. If a degree from an elite medical school improves employment

9. Zip code boundaries come from ZIP Code Tabulation Area (ZCTA) shapefiles at census.gov. Estimates of population density also are from census.gov.

10. The IRS reports annual statistics aggregated to the zip code level. For consistency, we aggregate results to the first three digits of zip codes. The income and tax rate estimates for the original 5-digit zip codes are weighted by population when aggregating to three-digit zip codes. The estimates are updated in each two-year period included in the panel corresponding to the 2008, 2010, 2012, and 2014 IRS annual releases.

11. An additional catch-all category is used for physicians in rare specialties who could not be placed in a more general specialty. Such physicians account for about half of a percent of the physicians included in our sample.

12. Data on medical school attended and year of graduation are from the PECOS national provider file. Physicians who graduated from schools with fewer than 1,000 total alumni in our sample are placed into a catch-all category. In contrast to specialty, a large percentage of physicians fall into this category, because medical school is only reported for graduates of American universities, with “other” being listed for graduates of foreign universities.

opportunities, it might affect mobility and allow for additional control over choice of location.

Note that the controls allow us to capture many of the effects stressed in the earlier literature. For example, the state dummy variables control for variation in regulatory environments, scope of practice, medical malpractice liability and insurance premiums, and other state-level policies.

Physicians with preferences that better match their location should be less likely to relocate. By location preferences we mean the average CFscore of all donors in the zip3 code. Of central interest in the selection model is the ideological distance between the physician and their zip3 operationalized as  $d(\theta_i, \delta_j)$ . We model ideological fit in two ways. First, we interact physician CFscores with the average donor CFscore for zip codes. The interaction term represents a direct test of our main hypothesis regarding the decision to relocate—that physicians who do not match the ideology of their locality are more likely to relocate. The coefficient on the main interaction term (*Physician CFscore* × *Zip3 CFscore*) for the selection equation is expected to be negative. Positive values indicate a physician shares the ideological leaning of their zip code. A negative value indicates a liberal physician living in a conservative zip code, or *vice versa*. Second, we calculate the *signed* distance between physician CFscores and the average donors in their zip code such that,  $d(\theta_i, \delta_j) = (\theta_i - \delta_j)$ . We model nonlinearity in ideological distance first as a second-degree polynomial and then using a generalized additive model (GAM). A parallel treatment is used for ideological match between physician and workplace.

## Modeling Location Choice

Our selection equation models the binary decision to relocate or stay put; we also model the ideological location of the new address. The destination choice is conditioned on the initial decision to relocate. The specification is in the second stage of the Heckman model.<sup>13</sup>

Stage 1:

$$Y_{ijk} \sim \alpha + d(\theta_i, \delta_j) + s(t_{ik}) + \beta X_{ij} + \gamma Z_{ip} + \text{state}_{ik} + \text{cycle}_{k} + \epsilon_{ijk}$$

where  $Y_{ijk} = 1$  if the physician relocates from location  $j$  and  $Y_{ijk} = 0$  otherwise.

13. Conditional on moving in the first stage, the second-stage decision is often difficult to model due to the large number (1,232 zip3 codes) of potential outcome locations. Were the choice space in the second stage limited to a handful of outcome locations, multinomial-logit could be used, but this method quickly becomes unwieldy as the number of potential outcome locations grows.

Stage 2:

$$\delta_{ij'k} \sim \alpha + \theta_i + \delta_j + s(t_{ik}) + \beta X_{ij'} + \gamma Z_{ip} + \text{state}_{ik} + \text{cycle}_k + \epsilon_{ij'k}$$

where  $\delta_{ij'k}$  is the CFscore of geographic location  $j'$  where physician  $i$  relocates. The exclusion restriction is met by not including years in practice and ideological distance in the second equation. The idea is that these variables will trigger or inhibit relocation but not affect the choice of destination. This choice depends on the physician's own ideology.

We note that Heckman models are often used to correct for selection bias when the results from the second-stage regression are of primary interest. We reiterate that this is not the case here. The decision to relocate is of as much, if not greater, interest as the choice of destination/practice.

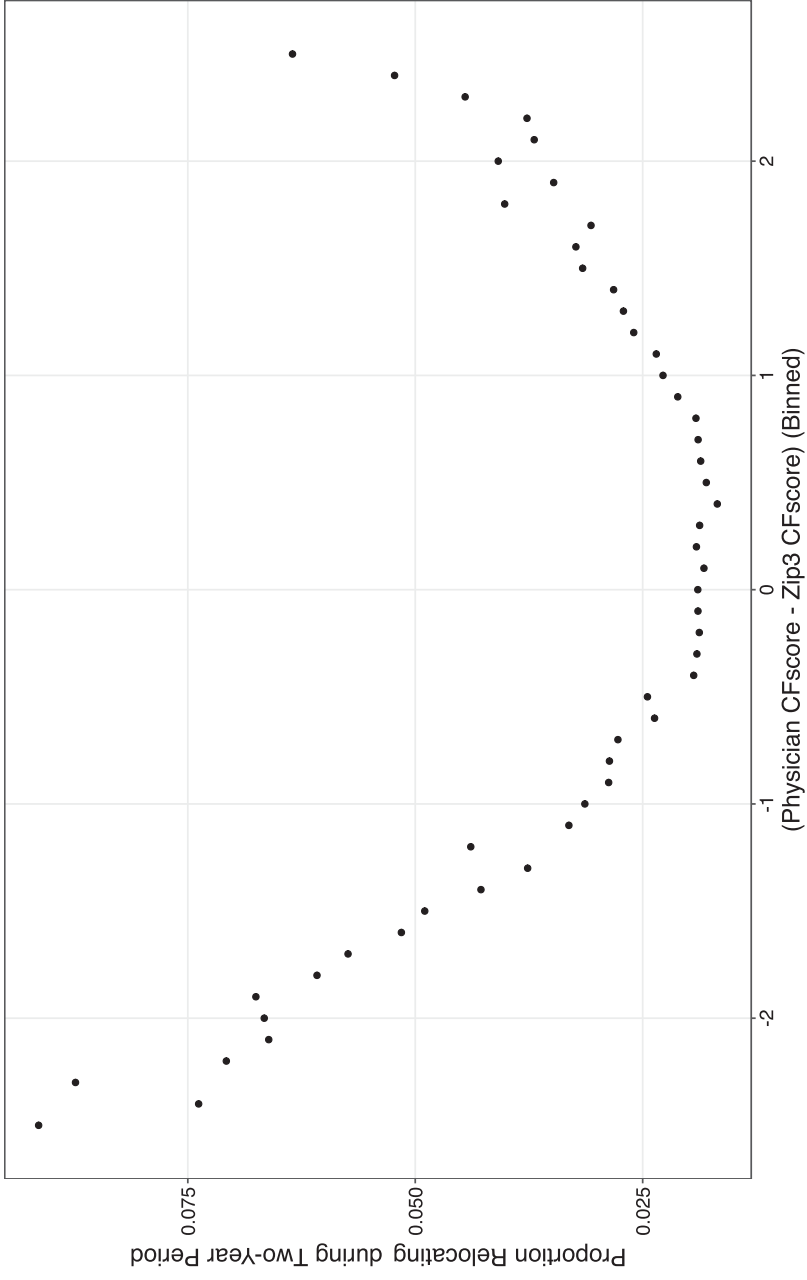
## Results

We begin by presenting the bivariate relationship between ideology and the decision to relocate. Figure 4 plots the percentage of physicians relocating in a 2-year period against the ideological distance between a physician and his or her location. The x-axis plots the signed distance between the physician's CFscore and the average donor in his or her zip3 code. Figure 5 does the same for the signed distance between a physician's CFscore and the average CFscore of other physicians at their workplace. The observations are binned into intervals of width 0.1. The points show the proportions relocating/changing practices for physicians that fall within each bin.

Even absent controls, propensity to relocate closely relates to ideological fit. Physicians who are either too liberal or too conservative relative to other donors in their area are significantly more likely to relocate. As compared to physicians with perfect matches to zip code, physicians who are 1.5 standard deviations to the left or right of their zip codes are twice as likely to relocate. The relation appears to be roughly quadratic in ideological distance. The smoothness of the binned averages is largely a function of sample size, with many thousands of observations fitting with each bin. The results are similar with respect to the decision to change workplaces.

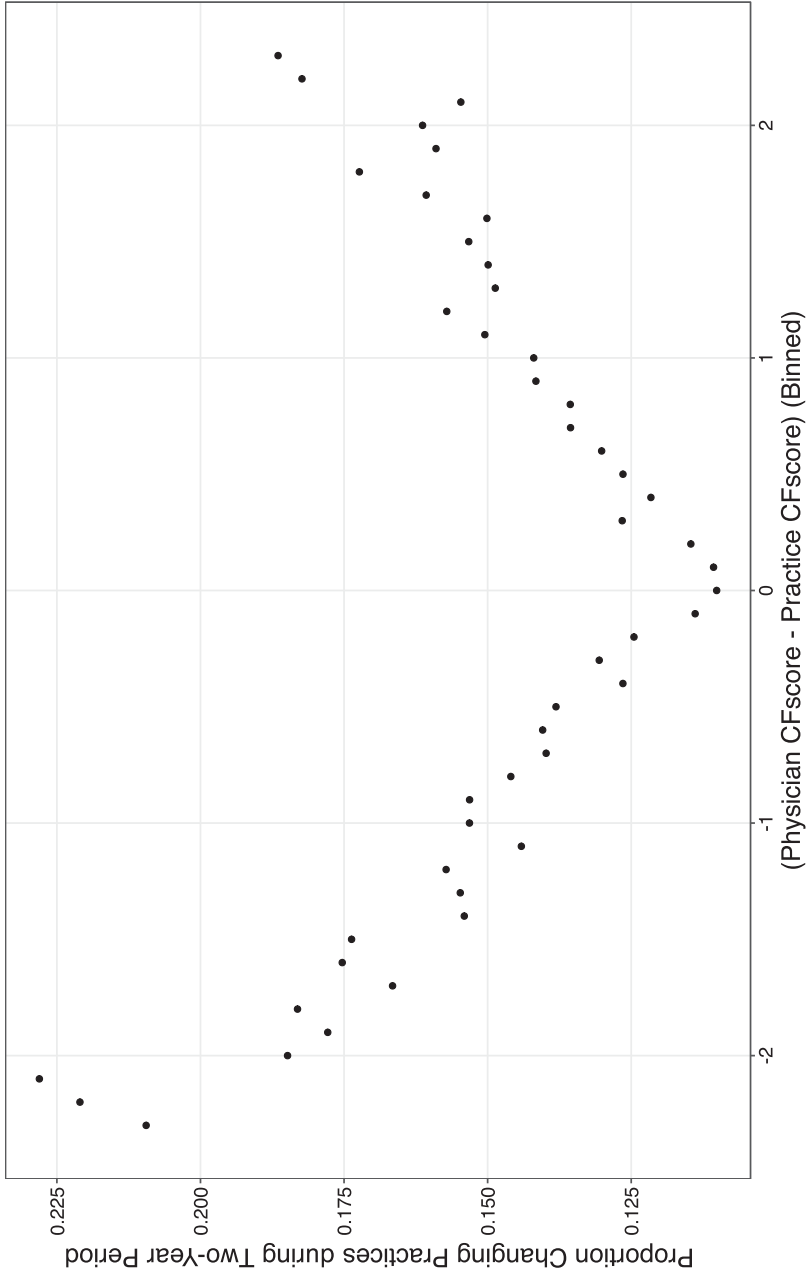
We model mobility as a function of ideological fit and other relevant variables in table 2. We observe slight but statistically significant effects related to employment type. Government and nonprofit employment are both associated with an increased probability of relocating. Physicians with such employers would not have the capital investments in, for example,





**Figure 4** Ideological distance from zip code and proportion relocating.

*Note:* The points represent the proportion of physicians within each 0.1 window that relocated during a 2-year period.  
*Source:* NPPES downloadable file and DIME; authors' calculations.



**Figure 5** Ideological distance from workplace and proportion changing practices.

*Note:* The points represent the proportion of physicians within each 0.1 window that relocated during a 2-year period.  
*Source:* NPPES downloadable file and DIME; authors' calculations.

**Table 2** Probability of Geographic Relocation: Probit, NPI/PECOS Sample

|   | (1)<br>Interacted | (2)<br>2-degree<br>polynomial | (3)<br>GAM        |
|---|-------------------|-------------------------------|-------------------|
| Intercept                                       | -1.516<br>(0.168) | -1.652<br>(0.167)             | -1.578<br>(0.167) |
| Physician CFscore                               | -0.020<br>(0.003) |                               |                   |
| Zip3 CFscore                                    | -0.022<br>(0.015) |                               |                   |
| Physician CFscore × zip3 CFscore                | -0.111<br>(0.007) |                               |                   |
| Physician CFscore – zip3 CFscore                |                   | -0.006<br>(0.003)             |                   |
| (Physician CFscore – zip3 CFscore) <sup>2</sup> |                   | 0.072<br>(0.003)              |                   |
| Female  | -0.004<br>(0.008) | -0.006<br>(0.008)             | -0.008<br>(0.008) |
| Nonprofit                                       | 0.156<br>(0.008)  | 0.154<br>(0.007)              | 0.153<br>(0.007)  |
| Government                                      | 0.069<br>(0.024)  | 0.067<br>(0.024)              | 0.067<br>(0.024)  |
| Log practice size                               | -0.034<br>(0.002) | -0.034<br>(0.002)             | -0.034<br>(0.002) |
| Log population density (zip3)                   | -0.034<br>(0.001) | -0.034<br>(0.001)             | -0.034<br>(0.001) |
| Physicians per 1,000 capita (zip3)              | 0.010<br>(0.001)  | 0.010<br>(0.001)              | 0.010<br>(0.001)  |
| Log average income (zip3)                       | -0.088<br>(0.019) | -0.075<br>(0.018)             | -0.082<br>(0.019) |
| Local and state tax rate (zip3)                 | -0.011<br>(0.007) | -0.012<br>(0.006)             | -0.011<br>(0.007) |
| Significance of smoothed term (GAM)             |                   |                               | EDf: 9.96         |
| Cycle fixed effects                             | Y                 | Y                             | Y                 |
| Years since graduation polynomial               | Y                 | Y                             | Y                 |
| State fixed effects                             | Y                 | Y                             | Y                 |
| Specialty fixed effects                         | Y                 | Y                             | Y                 |
| Medical school fixed effects                    | Y                 | Y                             | Y                 |
| AIC   | 168881            | 168465                        | 168355            |
| Log likelihood                                  | -84141            | -83934                        | -83871            |
| Deviance  | 168282            | 167869                        | 167743            |
| Number of observations                          | 680,692           | 680,692                       | 680,692           |

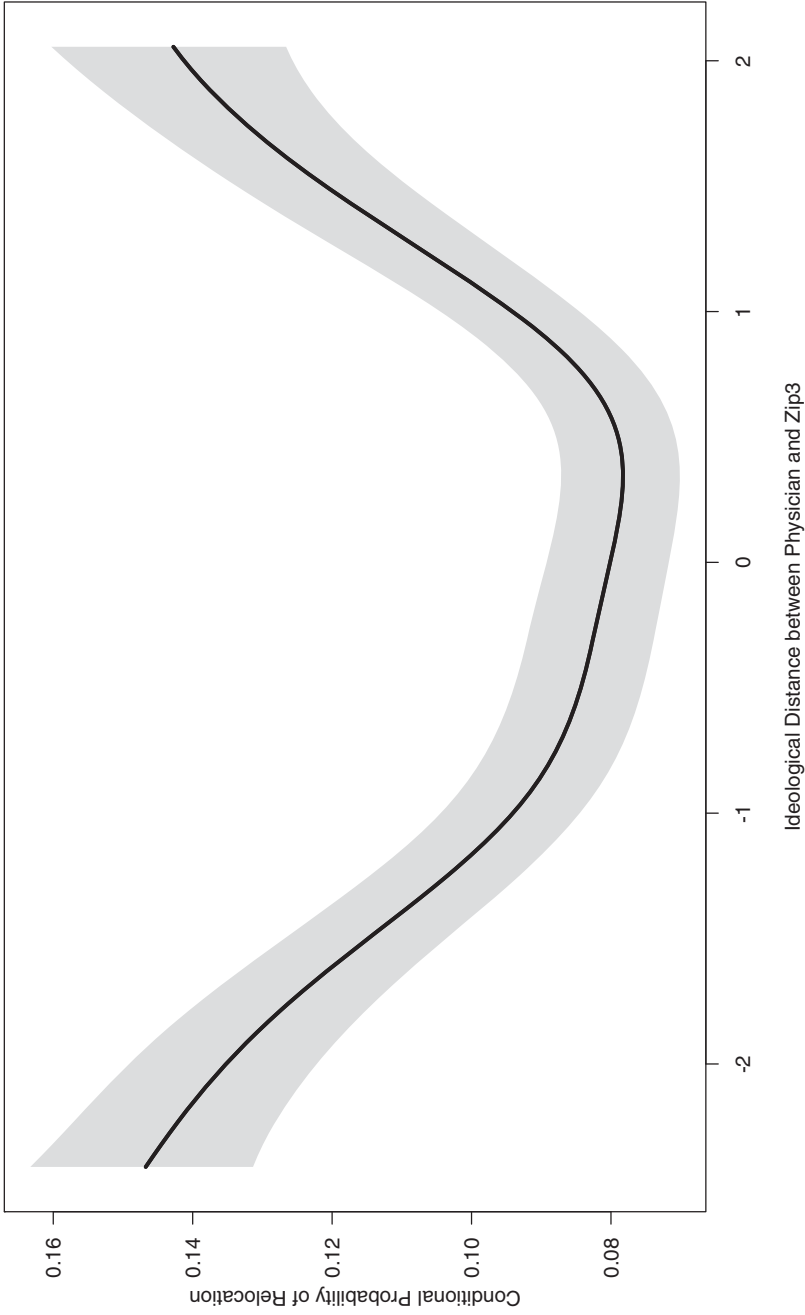
Dependent variable: physician relocated more than 100 kilometers (62 mi.). Standard errors in parentheses.

medical equipment or patient goodwill found in a private practice or partnership. Larger practices are associated with slightly lower relocation rates. The estimated effect of *Log Population Density* is small but negative, indicating that physicians in less populous areas are slightly more likely to relocate. Physicians per capita in the zip3 code has a strong and positive association with probability of relocation. This is consistent with the patterns observed in Figure 3. The tax rate effects suggest that relocation decisions are weakly related to variation in local and state taxes—although not necessarily in the expected direction. Physicians are less likely to leave areas with higher taxes, perhaps preferring high tax areas where state and local governments may provide higher-quality education and other services.

Controlling for years since graduation is associated with sizable improvement in model fit. Figure A1 in the online appendix displays the estimated polynomial trend of years since graduating. The combined improvement in model fit from all other control variables is relatively modest by comparison.

Mobility increases sharply with ideological distance. The main effect is captured by the interaction variable (*Physician CFscore* × *Zip3 CFscore*) in model 1. The coefficient on the interaction term is precisely estimated and in the expected direction. The negative sign indicates a reduced likelihood of relocating when the political orientation of physicians matches their locality. The effect is robust to the inclusion of fixed effects for state, specialty, and (in the PECOS sample) medical school. The relationship holds when we replace the interacted specification with direct measures of ideological distance in models 2 and 3. The coefficient on squared ideological distance indicates the effect is nonlinear. Physicians are more sensitive to increases in ideological distance the further they get from the average ideology of their zip code. This is consistent with the relationship observed in the raw data, as shown in figure 4.

We model this nonlinearity with greater flexibility using a GAM smoother in model 3. Figure 6 plots the predicted probability of relocating conditional on ideological distance from the smoothed term. The smoothed effect is roughly quadratic with a few noticeable deviations. Within a distance of about 0.5 in either direction the trend is mostly flat, suggesting that physicians are largely insensitive to small-to-moderate ideological differences with their location. The effect turns up sharply for distances exceeding this threshold. The estimated effect on mobility is substantial. Physicians at a distance of 1.0 from their locations are about 55% more



**Figure 6** Predicted probability of relocating conditional on ideological distance.

*Note:* Predicted probabilities are from model 3 in table 2. The reference observation is a male internist who graduated 10 years ago. Shaded area shows 95% confidence interval.

likely than those at a distance of 0.0 to relocate within a 2-year period. Physicians at a distance of 2.0 from their locations are about twice as likely to relocate.

### Decision of Where to Relocate

Ideology predicts whether a physician moves. We now model decisions about where to relocate. Table 3 reports the second stage regression results for models 1 and 2 from table 2. (We do not estimate a second-stage Heckman equation for the GAM model.) The third column reports the uncorrected OLS estimates. The dependent variable is the average CFscore of donors in the new zip3 following a move. Only the subset of observations in which a physician relocates to a new zip code are included.

Physician ideology is related to the ideology of the destination zip code. The coefficient on *Physician CFscore* is positive and precisely estimated. A one standard deviation shift in *Physician CFscore* is associated with just under a half a standard deviation shift in the *Zip3 CFscore* of the choice of destination. This finding holds while controlling for the ideology of the zip code from which they originated.<sup>14</sup> We report in the online appendix model estimates for the sample grouped by years since graduation. The findings hold for younger physicians who are fewer than 10 years out from graduation and for more experienced physicians who are 10 or more years out from graduation.

### Sorting by Workplace

This section examines sorting by the average ideology of physicians in the workplace rather than by location. As noted above, there are fewer observations here from the exclusion of practices with small numbers of donors. The results are in tables 4 and 5.

The likelihood of changing workplace is related to ideological fit. The more a physician differs from his or her colleagues in political views, the more likely he or she is to change workplaces. Again, the estimates are robust to the inclusion of state, specialty, and medical school fixed effects. Controlling for specialty is especially important. Physicians' political preferences are sorted by specialty to a similar extent as by geography.

14. The positive coefficient on the inverse Mills ratio indicates that propensity to relocate is, *ceteris paribus*, associated with moving to more conservative destinations.

**Table 3** Relocation Decisions: NPI/PECOS Sample

|  | (1)<br>Interacted | (2)<br>2-degree<br>polynomial<br>(second stage) | (3)<br>Uncorrected<br>OLS |
|--|-------------------|---|---------------------------|
| Intercept                                    | 0.251<br>(0.139)  | 0.125<br>(0.129)                                | 0.213<br>(0.129)          |
| Physician CFscore                            | 0.076<br>(0.003)  | 0.071<br>(0.002)                                | 0.073<br>(0.002)          |
| Zip3 CFscore (originating)                   | 0.047<br>(0.012)  | 0.046<br>(0.011)                                | 0.053<br>(0.011)          |
| Female                                       | -0.039<br>(0.006) | -0.037<br>(0.006)                               | -0.040<br>(0.006)         |
| Nonprofit                                    | -0.018<br>(0.006) | -0.018<br>(0.006)                               | -0.028<br>(0.005)         |
| Government                                   | 0.006<br>(0.019)  | 0.005<br>(0.018)                                | 0.002<br>(0.018)          |
| Log practice size (originating)              | -0.006<br>(0.001) | -0.005<br>(0.001)                               | -0.004<br>(0.001)         |
| Log population density (originating)         | -0.003<br>(0.001) | -0.002<br>(0.001)                               | -0.001<br>(0.001)         |
| Log average income (originating)             | 0.001<br>(0.001)  | 0.001<br>(0.001)                                | -0.000<br>(0.001)         |
| Local and state tax rate (originating)       | -0.105<br>(0.015) | -0.097<br>(0.014)                               | -0.095<br>(0.014)         |
| Physicians per 1,000 capita<br>(originating) | 0.015<br>(0.005)  | 0.014<br>(0.005)                                | 0.013<br>(0.005)          |
| Inverse mills ratio                          | 0.050<br>(0.007)  | 0.039<br>(0.006)                                |                           |
| Cycle fixed effects                          | Y                 | Y   | Y                         |
| State fixed effects                          | Y                 | Y   | Y                         |
| Specialty fixed effects                      | Y                 | Y   | Y                         |
| Medical school fixed effects                 | Y                 | Y   | Y                         |
| R <sup>2</sup>                               | 0.258             | 0.237   | 0.228                     |
| RMSE   | 0.390             | 0.362   | 0.362                     |
| Number of observations                       | 22,571            | 22,571  | 22,571                    |

Dependent variable: average CFscore of donors in new zip3 code. Standard errors in parentheses.

**Table 4** Probability of Changing Practice/Employer: Probit, NPI/PECOS Sample

|   | (1)<br>Interacted | (2)<br>2-degree<br>polynomial | (3)<br>GAM        |
|---|-------------------|-------------------------------|-------------------|
| Intercept   | -0.713<br>(0.186) | -0.712<br>(0.187)             | -0.751<br>(0.187) |
| Physician CFscore                                   | -0.005<br>(0.004) |                               |                   |
| Practice CFscore                                    | -0.172<br>(0.010) |                               |                   |
| Physician CFscore × practice CFscore                | -0.102<br>(0.006) |                               |                   |
| Physician CFscore – practice CFscore                |                   | 8.526<br>(1.645)              |                   |
| (Physician CFscore – practice CFscore) <sup>2</sup> |                   | 30.371<br>(1.588)             |                   |
| Female  | 0.005<br>(0.009)  | 0.016<br>(0.009)              | 0.014<br>(0.009)  |
| Nonprofit   | 0.023<br>(0.008)  | 0.058<br>(0.008)              | 0.053<br>(0.008)  |
| Government  | -0.014<br>(0.025) | -0.014<br>(0.025)             | -0.015<br>(0.025) |
| Log practice size                                   | -0.025<br>(0.002) | -0.025<br>(0.002)             | -0.025<br>(0.002) |
| Log population density (zip3)                       | -0.005<br>(0.001) | -0.007<br>(0.001)             | -0.006<br>(0.001) |
| Physicians per 100k (zip3)                          | 0.002<br>(0.001)  | 0.003<br>(0.001)              | 0.003<br>(0.001)  |
| Log average income (zip3)                           | -0.104<br>(0.020) | -0.079<br>(0.020)             | -0.083<br>(0.020) |
| Local and state tax rate (zip3)                     | 0.045<br>(0.007)  | 0.051<br>(0.007)              | 0.053<br>(0.007)  |
| Significance of smoothed term (GAM)                 |                   |                               | EDf: 9.164        |
| Cycle fixed effects                                 | Y                 | Y                             | Y                 |
| Years since graduation polynomial                   | Y                 | Y                             | Y                 |
| State fixed effects                                 | Y                 | Y                             | Y                 |
| Specialty fixed effects                             | Y                 | Y                             | Y                 |
| Medical school fixed effects                        | Y                 | Y                             | Y                 |
| AIC   | 166332.339        | 166628.180                    | 166535.771        |
| Log likelihood                                      | -82867.169        | -83016.090                    | -82964.729        |
| Deviance  | 165734.339        | 166032.180                    | 165929.459        |
| Number of observations                              | 238,542           | 238,542                       | 238,542           |

Dependent variable: changed employer/practice. Standard errors in parentheses.



**Table 5** Average Ideology of Destination Workplace (Conditional on Relocating), NPI/PECOS Sample

|  | (1)<br>Interacted<br>(second stage) | (2)<br>2-degree<br>polynomial<br>(second stage) | (3)<br>Uncorrected<br>OLS |
|--|-------------------------------------|---|---------------------------|
| Intercept                                    | -0.373<br>(0.145)                   | -0.372<br>(0.145)                               | -0.571<br>(0.144)         |
| Physician CFscore                            | 0.112<br>(0.004)                    | 0.111<br>(0.004)                                | 0.111<br>(0.004)          |
| Practice CFscore (originating)               | 0.351<br>(0.010)                    | 0.331<br>(0.010)                                | 0.316<br>(0.009)          |
| Female                                       | 0.029<br>(0.008)                    | -0.031<br>(0.008)                               | -0.021<br>(0.008)         |
| Nonprofit                                    | -0.028<br>(0.008)                   | -0.033<br>(0.008)                               | -0.020<br>(0.008)         |
| Government                                   | 0.036<br>(0.024)                    | 0.037<br>(0.024)                                | 0.035<br>(0.024)          |
| Log practice size (originating)              | -0.004<br>(0.002)                   | -0.004<br>(0.002)                               | -0.007<br>(0.001)         |
| Log population density (originating)         | 0.005<br>(0.001)                    | 0.005<br>(0.001)                                | 0.004<br>(0.001)          |
| Log average income (originating)             | -0.001<br>(0.001)                   | -0.001<br>(0.001)                               | 0.000<br>(0.001)          |
| Local and state tax rate (originating)       | -0.014<br>(0.020)                   | -0.017<br>(0.020)                               | -0.025<br>(0.020)         |
| Physicians per 1,000 capita<br>(originating) | -0.035<br>(0.007)                   | -0.036<br>(0.007)                               | -0.027<br>(0.007)         |
| Inverse mills ratio                          | -0.124<br>(0.014)                   | -0.126<br>(0.014)                               |                           |
| Cycle fixed effects                          | Y                                   | Y   | Y                         |
| State fixed effects                          | Y                                   | Y   | Y                         |
| Specialty fixed effects                      | Y                                   | Y   | Y                         |
| Medical school fixed effects                 | Y                                   | Y   | Y                         |
| R <sup>2</sup>                               | 0.586                               | 0.587   | 0.556                     |
| RMSE   | 0.419                               | 0.418   | 0.419                     |
| Number of observations                       | 16,343                              | 16,343  | 16,343                    |

Dependent variable: average CFscore of physicians at new workplace. Standard errors in parentheses.

### Sorting by Workplace within Geographic Region

Our second analysis looks only at physicians who change employers while remaining in the same area. Employer ideology is strongly associated with geography. By focusing on physicians who change jobs but not geographic locations, we can be more confident that political sorting by practice is occurring independently from geographic sorting. Tables 6 and 7 show that highly significant political sorting occurs even for physicians who do not relocate to another zip3 code. Many physicians may face constraints on geographic mobility because of family considerations. These physicians can still switch workplace to improve ideological fit.

### Ideology and the Geographic Distribution of Specialties

Physician supply is uneven across the United States. Provider shortages are especially acute for specialties, such as pediatrics, dominated by liberal physicians. This relationship can also be seen more generally. For each specialty, we observe the total number of physicians practicing in each zip code. We divide this by the total population in the zip code to calculate the number of physicians per 1,000 people. This yields a general metric of whether a physician is practicing in an over- or underserved area. We then calculate the average physicians per capita and average CFscore by specialty. In figure 7, we plot trend lines for primary care specialties and other specialties. Both lines show that physicians in liberal specialties tend to cluster in overserved areas. Meanwhile, the observed generational shift to the left among physicians shown in figure 1 suggests that the problem is likely to worsen. Note that figure 1 indicates that female physician-contributors, for every medical school cohort, are more liberal than male ones. Moreover, female cohorts have been increasingly liberal over time, starting in the 1960s, and male ones in the 1990s. These temporal shifts may reflect the shift by physicians away from entrepreneurial small practices to working as employees in large organizations.<sup>15</sup> At the same time, the increasing percentage of females in each cohort has also contributed to shifting the overall ideology of the profession in a liberal direction. The geographic preferences of the now liberal medical profession may make it more difficult to address the geographic maldistribution of physicians.

15. See Kane 2017; Physicians Advocacy Institute 2018; and Short and Ho 2019.

**Table 6** Probability of Changing Practice/Employer within Geographic Region: Probit, NPI/PECOS Sample

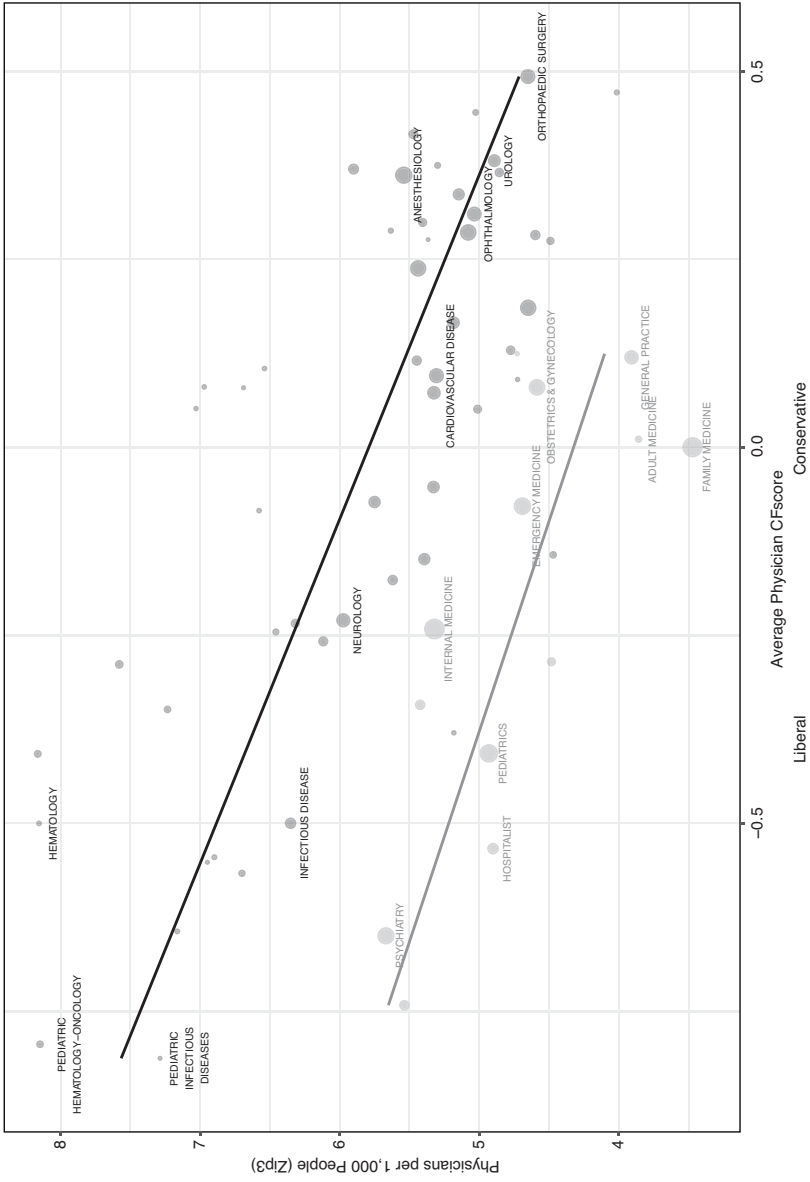
|   | (1)               | (2)                 | (3)               |
|---|-------------------|---------------------|-------------------|
|   | Interacted        | 2-degree polynomial | GAM               |
| Intercept   | -1.042<br>(0.203) | -1.060<br>(0.203)   | -1.062<br>(0.203) |
| Physician CFscore                                   | 0.001<br>(0.005)  |                     |                   |
| Practice CFscore                                    | -0.121<br>(0.011) |                     |                   |
| Physician CFscore × practice CFscore                | -0.054<br>(0.007) |                     |                   |
| Physician CFscore – practice CFscore                |                   | 6.402<br>(1.836)    |                   |
| (Physician CFscore – practice CFscore) <sup>2</sup> |                   | 15.772<br>(1.778)   |                   |
| Female  | 0.035<br>(0.010)  | 0.044<br>(0.010)    | 0.043<br>(0.010)  |
| Nonprofit   | -0.030<br>(0.009) | -0.006<br>(0.008)   | -0.008<br>(0.009) |
| Government  | -0.056<br>(0.028) | -0.057<br>(0.028)   | -0.058<br>(0.028) |
| Log practice size                                   | -0.022<br>(0.002) | -0.021<br>(0.002)   | -0.022<br>(0.002) |
| Log population density (zip3)                       | 0.007<br>(0.002)  | 0.006<br>(0.002)    | 0.006<br>(0.002)  |
| Physicians per 100k (zip3)                          | -0.002<br>(0.001) | -0.001<br>(0.001)   | -0.001<br>(0.001) |
| Log average income (zip3)                           | -0.072<br>(0.022) | -0.056<br>(0.022)   | -0.057<br>(0.022) |
| Local and state tax rate (zip3)                     | 0.064<br>(0.008)  | 0.069<br>(0.008)    | 0.070<br>(0.008)  |
| Significance of smoothed term (GAM)                 |                   |                     | EDf: 6.203        |
| Cycle fixed effects                                 | Y                 | Y                   | Y                 |
| Years since graduation polynomial                   | Y                 | Y                   | Y                 |
| State fixed effects                                 | Y                 | Y                   | Y                 |
| Specialty fixed effects                             | Y                 | Y                   | Y                 |
| Medical school fixed effects                        | Y                 | Y                   | Y                 |
| AIC   | 128347.335        | 128469.254          | 128449.572        |
| Log likelihood                                      | -63874.667        | -63936.627          | -63921.851        |
| Deviance  | 127749.335        | 127873.254          | 127843.701        |
| Number of observations                              | 227,905           | 227,905             | 227,905           |

Dependent variable: changed employers/practices (excludes physicians who change geographic location). Standard errors in parentheses.

**Table 7** Average Ideology of Destination Workplace (Conditional on Moving to a New Workplace in the Same Geographic Region), NPI/PECOS Sample

|  | (1)<br>Interacted<br>(second stage) | (2)<br>2-degree<br>polynomial<br>(second stage) | (3)<br>Uncorrected<br>OLS |
|--|-------------------------------------|---|---------------------------|
| Intercept                                    | -0.550<br>(0.145)                   | -0.561<br>(0.144)                               | -0.762<br>(0.135)         |
| Physician CFscore                            | 0.064<br>(0.004)                    | 0.063<br>(0.004)                                | 0.063<br>(0.004)          |
| Practice CFscore (originating)               | 0.473<br>(0.011)                    | 0.455<br>(0.009)                                | 0.451<br>(0.009)          |
| Female                                       | -0.008<br>(0.008)                   | -0.009<br>(0.008)                               | -0.001<br>(0.008)         |
| Nonprofit                                    | -0.011<br>(0.007)                   | -0.015<br>(0.007)                               | -0.014<br>(0.007)         |
| Government                                   | 0.120<br>(0.024)                    | 0.121<br>(0.024)                                | 0.115<br>(0.024)          |
| Log practice size (originating)              | -0.004<br>(0.002)                   | -0.004<br>(0.002)                               | -0.006<br>(0.001)         |
| Log population density (originating)         | 0.003<br>(0.001)                    | 0.003<br>(0.001)                                | 0.003<br>(0.001)          |
| Log average income (originating)             | -0.004<br>(0.001)                   | -0.004<br>(0.001)                               | -0.004<br>(0.001)         |
| Local and state tax rate (originating)       | 0.033<br>(0.019)                    | 0.030<br>(0.019)                                | 0.023<br>(0.019)          |
| Physicians per 1,000 capita<br>(originating) | -0.055<br>(0.008)                   | -0.055<br>(0.008)                               | -0.043<br>(0.007)         |
| Inverse mills ratio                          | -0.124<br>(0.032)                   | -0.119<br>(0.030)                               |                           |
| Cycle fixed effects                          | Y                                   | Y   | Y                         |
| State fixed effects                          | Y                                   | Y   | Y                         |
| Specialty fixed effects                      | Y                                   | Y   | Y                         |
| Medical school fixed effects                 | Y                                   | Y   | Y                         |
| R <sup>2</sup>                               | 0.754                               | 0.754   | 0.736                     |
| RMSE   | 0.329                               | 0.329   | 0.329                     |
| Number of observations                       | 11,099                              | 11,099  | 11,099                    |

Dependent variable: average CFscore of physicians at new workplace. Standard errors in parentheses.



**Figure 7** Physicians per capita against average ideology by specialty.

*Note:* Separate trend lines are fit for primary care specialties (gray) and all other specialties (black).

## Discussion

Our findings contribute to a growing literature on political sorting. Recent studies have noted a disconnect between citizens' stated preferences for "politically compatible" residential communities and their observed behavior. This disconnect likely reflects the ways in which household finances, living costs, and employment opportunities constrain residential choices (Mummolo and Nall 2017). Physicians' high incomes and flexible labor market make them an interesting test case. Not only do physicians exercise greater freedom in choosing where to live and work, they also are less likely to be forced to relocate due to loss of employment or because rising housing prices have made their current neighborhood less affordable. Physicians also enjoy high levels of job security and one of the lowest unemployment rates of any occupation.<sup>16</sup> Our results offer strong observational evidence that ideological fit is a powerful predictor of relocation decisions. A liberal physician residing in a predominantly conservative area is about twice as likely to relocate as a conservative physician living there is, and *vice versa*. And when they do relocate, they move on average to places that better match their politics.

Another reason why studying the geographic mobility of physicians is especially revealing is the unique system of residency requirements. At the onset of their careers, physicians disperse across the nation through a centralized process. Physicians rank residencies but may not obtain their first or even second choice. Upon completion of residency, physicians are free, and able, to move. The starting point for other observational studies on geographic sorting is based on an already sorted population. We generally do not get to observe the counterfactual of how partisans would respond to living in the types of places that they would actively avoid. The National Resident Matching Program ensures that this will be true for a sizable percentage of physicians. Figures 4 and 6 reveal that the effect of ideological distance on relocation decisions is roughly quadratic, suggesting that physicians are relatively insensitive to small deviations but become highly sensitive to large ones. This may help explain why the observed effect sizes are larger for physicians earlier in their career.<sup>17</sup> In 2015, 19.3% of

16. The Bureau of Labor Statistics estimates the unemployment rate for physicians to be 0.5%. See [www.bls.gov/emp/ep\\_table\\_102.htm](http://www.bls.gov/emp/ep_table_102.htm).

17. We reestimated the regression models separately for physicians earlier in their careers ( $\leq 10$  years since graduating) and those who are more established ( $> 10$  years since graduating). Results reported in the online appendix confirm that the effect of ideological distance on relocating is significantly larger for younger physicians; the coefficient on the interaction effect (*Physician CFscore*  $\times$  *Zip3 CFscore*) is  $-0.176$  (0.012) for physicians starting out versus  $-0.082$  (0.009) for those who are more established.

physicians within 10 years of graduation were living in places that did not match their preferences (defined physician CFscore with an absolute distance of greater than 1.5 from their zip3 CFscore). Of physicians who were at least 10 years since graduation, only 9.3% lived in places that did not match their politics.

What is perhaps most surprising about our results is that the geographic choices of physicians appear to override economic incentives. Younger physicians are increasingly opting to live in large cities where they face lower wages and higher living costs. This, in turn, has important implications for health care delivery. Physicians' choices about where to live and work affect the quality and availability of care. According to the Health Resources and Services Administration, some 75 million Americans reside in areas that suffer from physician shortages. Rural areas, in particular, have struggled to attract and retain enough physicians to meet demand. Our results suggest that the geographic maldistribution of physicians is likely not only to continue but also to worsen given the increasing presence of female physicians and a generational shift to a liberal orientation.

Among our more novel findings is ideological sorting by workplace. Ideological fit between a physician and workplace is a powerful predictor of decisions to change jobs. This result is important for several reasons. First, a well-known blind spot in the existing research on geographic mobility is a firm understanding of how career and employment opportunities influence decisions about where to live. Our data simultaneously track changes in employment and geography. One implication of our results is that the impetus to relocate to an area that better fits one's politics might be muted by the opportunity to work with colleagues with similar political views. At the same time, tables 6 and 7 demonstrate that physicians are sorting by workplace within geographic regions. Some of the observed hiring patterns may be driven by the ideological preferences of employers/colleagues making the hiring decisions as well as the ideological preference of the physician who changes employer.

We have fortuitously observed sorting at a time when the medical profession is in ideological transition. Were we to have looked at the profession in 1960, we would just have found conservatives everywhere. If the current trend to liberalism continues, more liberal physicians will by necessity appear, albeit with relative undersupply, in conservative areas of the country.

## Conclusion

Physicians are polarized politically. A once conservative profession has tended in a liberal direction as females have become more present in recent cohorts and as both males and females in the cohorts have become more liberal. At the same time, physicians are professionally mobile. Of the 1,027,708 physicians in the NPI database between 2007 and 2014, 51% changed either their geographic location or local place of employment at least once. Fully 19% moved more than 100 kilometers at least once.

The major source of mobility occurs in the move from residency programs to professional practice. This move engenders a major ideological sorting of physicians as the result of the need to move from the relatively small number of geographically concentrated institutions with residency programs. The programs tend to be in liberal areas. Liberal physicians tend to stay in these areas while conservative physicians tend to move to conservative ones. The alignment of the physician's ideology, as measured by the CFScore, with the average ideology of the locale and workplace continues throughout the physician's career. Although physicians 25 years out of medical school rarely move, when they do move ideological sorting takes place.

There are potentially important implications for the delivery of medical services from the trend to political liberalism of physicians coupled with ideological sorting. Conservative, rural areas are likely to be underserved. The problem of underserved areas most likely cannot be solved by raising physicians' pay in those areas, particularly in a period of resistance to increasing health care expenditures. It might be addressed by an Americorps-type solution through which free medical school tuition and board is exchanged for a several-year commitment to practice in underserved areas or by expanding the use of telemedicine.

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