Rural Physician Shortages and Policy Intervention*

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PRELIMINARY AND INCOMPLETE
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Abstract

Although 14.5 percent of the U.S. population lives in rural areas, only 10.4 percent of primary care physicians (PCPs) practice medicine in rural areas. Populations in areas with PCP shortages have measurably worse health outcomes, including higher rates of preventable hospitalizations and higher mortalities from preventable chronic diseases like diabetes and heart disease. This problem has persisted for decades despite the introduction of numerous government programs that attempt to combat physician shortages. In this paper, we estimate a model of physician location decisions and use it to simulate the effects of incentive programs intended to eliminate physician shortages. We find that physicians are relatively unresponsive to differences in salaries across locations and strongly prefer to practice medicine close to their home state. These results imply that current physician incentive payments are too small to have a meaningful impact on shortages. We suggest that policymakers who wish to address physician shortages focus on recruiting more physicians who were raised in shortage areas to stay and practice medicine there.

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1 Introduction

Achieving equal access to healthcare for all citizens of the United States has long been a goal of policymakers. Healthcare provision is labor-intensive, requiring a large and highly trained workforce of nurses and physicians. However, there are persistent shortages of primary care physicians (PCPs) in many rural areas of the United States.[1] Although 14.5 percent of the U.S. population lives in rural areas, only 10.4 percent of PCPs practice medicine there. Areas with fewer PCPs per capita have measurably worse health outcomes, including higher rates of preventable hospitalizations, higher mortalities from preventable chronic diseases like diabetes and heart disease, and higher incidence of mental illness. All of these health outcomes can be improved through preventative care typically provided by PCPs.

Rural areas lack many amenities that well-educated people like physicians tend to desire, making these areas unattractive places to live. While the theory of compensating differentials would predict that wages should adjust to compensate workers for poor conditions, government intervention in the healthcare marketplace prevents this from fully occurring for physicians. Medicare, the primary insurer for people 65 and over, dominates the landscape of healthcare spending and accounts for twenty percent of all healthcare expenditures in the United States.[2] Medicare adjusts its reimbursement rates for the costs of living and running a medical practice in a particular geographic location.[3] Since rural areas tend to be less expensive than urban areas, physicians in rural areas are paid less than their urban counterparts for the same procedure billed to Medicare. Furthermore, recent evidence suggests that Medicare has a powerful influence on reimbursement rates for private insurers; Clemens and Gottlieb (2017) find that a $1.00 increase in Medicare's fees increases the reimbursement rates of private insurers by $1.16. As a result, wages for physicians in attractive urban areas are actually adjusted upwards relative to the level that compensating differentials would predict.[4] This generates a friction in the labor market that causes shortages. Figure 1 shows a heat map of PCP shortages across the country, which appear to be especially severe in rural areas.[5]

[1] Primary care physicians perform the essential tasks of diagnosing medical conditions and prescribing drugs or other forms of treatment, sometimes referring patients to a more specialized physician.

[2] `https://www.cms.gov/research-statistics-data-and-systems/statistics-trends-and-reports/nationalhealthexpenddata/nhe-fact-sheet.html`

[3] The geographic adjustment (called the Geographic Practice Cost Index, or GPCI) consists of three components. These are the Work GPCI, which adjusts for the costs of labor in a given area, the Practice Expense GPCI, which reflects differences in the fixed costs of running a medical practice in a certain area, and the Malpractice GPCI, which reflects the cost of medical malpractice insurance.

[4] Table 3 suggests that some degree of compensation does occur, but it is clearly not enough to fully compensate for the lack of amenities in rural areas.

[5] These shortage calculations from the Health Resources and Services Administration (HRSA) are based on physician work capacity, demand for health care (demographics), health care access (time to nearest source

In order to combat PCP shortages, several states have introduced policies to incentivize physicians to practice in rural areas. For example, 20 states give tax credits or other direct monetary payments to physicians who agree to practice in rural areas. These tax credits usually amount to $5,000 per year for the first five years of their careers. Another 39 states have student loan repayment or forgiveness programs that offer an average of $92,088 in debt relief. Table 1 summarizes these programs. Despite these efforts, shortages have persisted for decades and have intensified in certain areas.

In this paper, we seek to determine if the incentive programs designed to attract physicians to rural areas are (or have the potential to be) effective at reducing shortages. To do so, we estimate a static discrete choice model of physician location decisions similar to those commonly used in the migration literature. Our model accounts for salaries, home prices, and other location-specific amenities (both observed and unobserved) that may be important factors for physicians. We also incorporate physicians' preferences for living close to their home state (here proxied by the location of their medical school), which the migration literature has shown to be extremely important for other workers. We address the endogeneity of salaries (which tend to be negatively correlated with unobserved amenities) by using an instrument that exploits exogenous variation in Medicare's compensation scheme across locations.

We find that physicians are relatively unresponsive to small differences in salaries across locations and strongly value living near their native location. The income elasticity for the average location is 0.68, meaning a one percent increase in annual salaries generates just a 0.68 percent increase in the fraction of PCPs who choose to practice medicine in that location.

We then use our parameter estimates to simulate policies intended to reduce physician shortages. In our first such counterfactual, we imitate policies already in place by giving $5,000 tax credits to new PCPs who decide to practice in shortage areas. We find that this policy has almost zero effect on shortages after ten years. We also increase the amount of the tax credit to $100,000 per year; this policy does somewhat better but still does not substantially reduce shortages. Finally, we simulate several revenue-neutral policies that tax new PCPs who decide to practice in non-shortage areas and subsidize those who practice in shortage areas. At best, these policies reduce shortages by only one third over ten years. Given these results, it is clear that incentive payment programs are unable to alter physicians' location decisions in a way that creates a meaningful reduction in shortages.

The rest of this paper proceeds as follows. The next section discusses the related litera-

of care) and a measure of the healthiness of the population in the area. Our definition of shortages is slightly different, as will be discussed below.

ture on physician shortages, physician location decisions, and static migration models more generally. Section 3 introduces our model of physician location decisions and discusses how elasticities are calculated. Section 4 explains how our data is constructed, how shortage areas are defined, and presents summary statistics. Section 5 discusses our two-step estimation procedure and Section 6 displays the results. Section 7 uses the model and parameter estimates to simulate policies intended to reduce physician shortages. Finally, Section 8 concludes.

2 Related Literature

The existence of physician shortages is well established among policymakers (IHS Inc., 2016; Petterson et al., 2012; Goodman et al., 1996; Schwartz, 2011). Petterson, Rayburn and Liaw (2016) estimate that by 2025, the US may require 51,880 additional PCPs. Nevertheless, physician shortages have received little attention in the economics literature due to a lack of publically available data and the difficulty of pinning down the frictions that cause shortages (Newhouse et al., 1982). We fill this gap in the literature.

Physician shortages are related to two decisions that physicians make: the choice of speciality and the choice of location. Since PCPs tend to earn less than more specialized physicians, medical school graduates increasingly decide against becoming generalists (Schwartz et al., 2005). The role of income in the location decision has not been studied extensively. There is some evidence suggesting that medical school and residency location are important determinants of practice location (Burfield, Hough and Marder, 1986). Additionally, certain types of medical school graduates (e.g., D.O.s, whose training focuses on a more holistic approach to health than the training for M.D.s) tend to locate in rural areas more than others (Chen et al., 2010). Some researchers have suggested licensing other medical personnel such as physician assistants or nurse practitioners to perform tasks typically carried out by PCPs (Bodenheimer and Smith, 2013; Traczynski and Udalova, 2014).

One might argue that physician shortages are only a problem if they lead to adverse health outcomes in shortage areas. The evidence on health outcomes by metropolitan status is mixed. Reschovsky and Staiti (2005) find no differences between rural and urban health care in terms of delayed care and long waiting periods for an appointment. Unsurprisingly, they find that along measures of convenience (travel time to PCP) rural areas do much worse (Chan, Hart and Goodman (2005) find very similar results). They also conclude that access to mental health care is considerably worse in rural areas.

The incidence of preventable hospitalizations[6] is often used as a measure of quality of

[6]These are also referred to as "ambulatory care sensitive conditions" in the medical literature. The diseases

health care access. If preventative care is effective, there should be no hospitalizations for these diseases. Laditka, Laditka and Probst (2009) find that rates of preventable hospitalizations in rural areas are 90 percent higher in rural areas than in urban areas for patients aged 18-64 and 45 percent higher for patients over 64 (Ansari, Laditka and Laditka (2006) provide further evidence). Liu et al. (2008) show that bypassing[7] local primary care is much more likely in rural than in urban areas.

This paper is most closely related to Hurley (1991) and Bolduc, Fortin and Fournier (1996). Hurley (1991) uses a nested logit framework to model physicians' choices of specialty, location, and type of practice. The author finds that shrinking differences in income across alternatives would cause more doctors to choose primary care but would not significantly affect location decisions. While we abstract away from specialty choices and instead focus on location decisions, our model allows physicians to choose among 200 distinct locations across the United States rather than the seven simplified "community sizes" that proxy for locations in Hurley (1991). Furthermore, our methodology allows us to address the endogeneity of salaries as well as break the independence of irrelevant alternatives (IIA) property present within the nests of the nested logit model, generating more realistic substitution patterns. Bolduc, Fortin and Fournier (1996) is somewhat closer to our paper; it focuses on the initial location decisions of general practitioners in Québec, Canada. Specifically, the authors partition Québec into 18 regions and estimate a multinomial probit model of location decisions. In contrast to our paper, they find that physicians responded relatively strongly to geographic changes in the compensation scheme, finding an income elasticity of 1.11 for the average location. Our estimate of this elasticity is 0.68. However, we note that Québec is much more homogeneous than the United States. As a result, locations in Québec are likely much closer substitutes for each other than are areas of the United States. With this in mind, the fact that we find physicians to be less sensitve to changes in income than Bolduc, Fortin and Fournier (1996) do should not be surprising.

Our work is also related to several papers that propose static models of individual migration decisions. For example, Diamond (2016) uses a spatial equilibrium model to explain increased inequality between low- and high-skilled workers over the past few decades, Piyapromdee (2017) uses a similar model to determine how native workers are affected by immigration, and Colas and Hutchinson (2017) applies the framework to study how federal income taxes affect the sorting of workers across locations. All three of these papers incorporate a static discrete choice model à la Berry, Levinsohn and Pakes (2004) to explain

used in the definition include pneumonia, urinary tract infections, and dehydration, among others.

[7]Bypassing means using medical facilities that are not the closest available due to unavailability of required services (Bronstein, Johnson and Jr. (1997)).

workers' location choices; we closely follow this modeling strategy.

3 Model

This section introduces our model of how physicians choose where to practice medicine. Our model closely resembles the static discrete choice model in Berry, Levinsohn and Pakes (2004), who use data on individual purchase decisions to estimate the demand for automobiles. In the migration literature, this approach has been adopted by Diamond (2016), Piyapromdee (2017), and Colas and Hutchinson (2017) to model worker migration decisions.

3.1 Setup

The indirect utility physician i receives from choosing to practice medicine in location $j \in \{1, 2, \ldots, J\}$ ten years after graduating from medical school is

$$\begin{aligned} u_{ij} = {} & \overbrace{\alpha_1 \ln(w_j) + \mathbf{x}_j' \boldsymbol{\alpha}_2 + \xi_j}^{\equiv \delta_j} \\ & + \beta_1 \text{State}_{ij} + \beta_2 \text{Region}_{ij} + \text{Female}_i \mathbf{v}_j' \boldsymbol{\beta}_3 + \epsilon_{ij} \end{aligned}$$

where w_j is the average annual salary (which we interchangeably call the wage) of physicians in location j, $\mathbf{x}_j$ is a vector of observed amenities, ξ_j represents amenities that are unobserved by the econometrician, State_{ij} indicates whether location j is in the same state as physician i's medical school, Region_{ij} indicates whether location j is in the same region (i.e., Census Division) as physician i's medical school, Female_i indicates whether physician i is female, $\mathbf{v}_j$ is a vector containing wages and a subset of the observed amenities in $\mathbf{x}_j$, and ϵ_{ij} is an i.i.d. Type 1 Extreme Value idiosyncratic preference shock. All physicians agree on the value of the common component of utility $\delta_j \equiv \alpha_1 \ln(w_j) + \mathbf{x}_j' \boldsymbol{\alpha}_2 + \xi_j$ but differ in their preferences as a result of the location of the medical school they attended, their gender, and the realization of their idiosyncratic preference shocks. The common component of utility for location one (in our case, rural Alabama) is normalized to zero. Physicians choose to practice medicine in the location which maximizes their indirect utility.

We include the State_{ij} and Region_{ij} variables to account for preferences for living close to home; the migration literature has generally found that movers tend to remain close to the place they were raised. Since we do not observe birth or native states in our data, we instead use medical school states. While this is not a perfect proxy for nativity, medical school location may itself be an important factor; Burfield, Hough and Marder (1986) report that a large fraction of physicians practice medicine in the state where they received their medical education.

We also include the interaction of Female_i with location characteristics $\mathbf{v}_j$ for two reasons. First, interacting consumer characteristics with attributes of the choices (as is commonly done in the empirical industrial organization literature) breaks the independence of irrelevant alternatives property (IIA) and allows for richer substitution patterns among choices. Second, while we were unable to find accurate data on PCP salaries in each location by gender, there appear to be large differences in pay between male and female physicians and surgeons in the ACS.[8] Incorporating an interaction between gender and log salaries allows the model to partially reflect the fact that women are paid less than men.[9]

3.2 Elasticities

Since our main policy counterfactuals are concerned with the changes in physician shortages that result from changes in salaries in different locations, our results rely crucially on the own- and cross-wage elasticities produced by our model. The calculation of these is described below.

Let $\boldsymbol{\delta} = (\delta_1, \delta_2, \ldots, \delta_J)'$ be the vector of the common components of utility, and let $\boldsymbol{\beta} = (\beta_1, \beta_2, \boldsymbol{\beta}_3')'$. Under the distributional assumption on ϵ_{ij}, the probability that physician i chooses to practice medicine in location j is given by

$$\hat{s}_{ij}\left(\boldsymbol{\delta}, \boldsymbol{\beta}; \text{State}_{ij}, \text{Region}_{ij}, \text{Female}_i, \mathbf{v}_j\right) = \frac{\exp\left(\delta_j + \beta_1 \text{State}_{ij} + \beta_2 \text{Region}_{ij} + \text{Female}_i \mathbf{v}_j' \boldsymbol{\beta}_3\right)}{\sum_{j=1}^{J} \exp\left(\delta_j + \beta_1 \text{State}_{ij} + \beta_2 \text{Region}_{ij} + \text{Female}_i \mathbf{v}_j' \boldsymbol{\beta}_3\right)}.$$

The elasticity of labor supply in location j with respect to the wage of location k is

$$\eta_{jk} = \frac{\partial \hat{s}_j(\cdot)}{\partial w_k} \cdot \frac{w_k}{s_j} = \begin{cases} \dfrac{w_k}{s_j N} \displaystyle\sum_{i=1}^{N} \left[\frac{(\alpha_1 + \beta_3^{w_k} \text{Female}_i)}{w_k} \hat{s}_{ij} \left(1 - \hat{s}_{ij}\right) \right] & \text{if } j = k \\ -\dfrac{w_k}{s_j N} \displaystyle\sum_{i=1}^{N} \left[\frac{(\alpha_1 + \beta_3^{w_k} \text{Female}_i)}{w_k} \hat{s}_{ij} \hat{s}_{ik} \right] & \text{if } j \neq k \end{cases}$$

where N is the number of physicians, $\beta_3^{w_k}$ is the coefficient on log wages in $\mathbf{v}_j' \boldsymbol{\beta}_3$, s_j is the observed share of physicians who choose to practice medicine in location j, and $\hat{s}_j(\cdot)$ is the corresponding predicted share.

[8] As discussed below, we cannot use the ACS or CPS to recover PCP salaries because these surveys report occupational status on too broad a level. The finest level of detail on PCP salaries we would be able to obtain would be salaries for all physicians and surgeons in each location, which would vastly overstate the true salary of a PCP.

[9] We admit that this is indirect, as the literal interpretation of the model is that women have a different marginal utility of income than men.

Finally, we note that the restrictive independence of irrelevant alternatives property (IIA) does not hold in our model. First, the presence of State_{ij} and Region_{ij} allows correlation in preferences within states and regions and breaks the IIA at the state level. Second, the interaction of Female_i with location characteristics such as wages breaks the IIA within states. Thus, our model does not suffer from the restrictive substitution patterns of pure logit or nested logit models and should generate realistic elasticities.

4 Data

In order to estimate our model of physician location decisions, we assemble data from several different sources. The assembled data can be thought of as two distinct datasets. The first dataset, which we refer to hereafter as the PCP dataset, contains demographic information and practice location decisions for individual physicians who bill to Medicare and is used in the first step of estimating the model. The second dataset, which we call the location dataset, contains annual PCP salaries, observed amenities, and other characteristics of each location. The construction of both datasets is described below.

4.1 Sources

Since 2012, the Centers for Medicare & Medicaid Services (CMS) has published the Physician Utilization and Payment Public Use File, which contains data on services provided and payments received by all health professionals who bill Medicare for services. This data contains the street address, gender, primary medical specialty, dollar amounts billed to Medicare, and characteristics of the professional's Medicare patient pool such as the average age of patients and the fraction of patients diagnosed with cancer. Starting in 2014, CMS was also required by a provision in the Affordable Care Act to publish the Physician Compare database, which allows patients to view additional demographics (such as the physician's medical school and graduation year) and performance measures for all physicians who accept Medicare. We merge these two sources to create a dataset of PCPs[10] who graduated from medical school ten years prior to the period 2012–2015 (i.e., physicians who graduated between 2002 and 2005). We use a ten year lag because PCPs typically spend three or four years in a residency program before practicing on their own. Since residency is determined by a matching process, a physician's location just a few years after finishing their degree does not solely reflect a physician's own locational preferences. Furthermore, our model assumes

[10]To be as consistent as possible with the definition from the AMA Physician Masterfile, we define any physician who lists their primary specialty as family practice, general practice, geriatric medicine, internal medicine, and pediatric medicine in the Medicare data as a PCP.

that location decisions are once-and-for-all; physicians tend to be fairly mobile in their late twenties and early thirties but tend to settle down in their late thirties and early forties, roughly 10 years after leaving medical school (see Figure 2).

Though this data gives us quite detailed information on individual physicians, it has some limitations. First, Medicare patients are typically only a fraction of all the patients a physician treats. A physician may also serve patients with private insurance, patients with insurance through another government entity (e.g., Medicaid or the Department of Veterans Affairs), and patients who are uninsured. Because of this, we cannot use the Medicare data to determine physician salaries, as doing so would underestimate a physician's total compensation. Second, not all primary care physicians accept Medicare patients.[11] For this reason, we cannot use the Medicare data to determine the actual number of PCPs in each location.

To address the first issue, we use data from the Occupational Employment Statistics (OES) program of the Bureau of Labor Statistics (BLS) to determine annual salaries for PCPs in each location.[12] This data contains average salaries of workers in narrowly defined occupations in each metropolitan statistical area (MSA), each state, and the nonmetropolitan areas of each state. We use the 2014 average salary for occupation code 29-1062: Family and General Practitioners.[13] Unfortunately, this data does not report salaries by age or gender.

To overcome the second issue with the Medicare data and obtain a more conservative estimate of the number of active PCPs in each location, we use the Area Health Resources File from the Health Resources & Services Administration (HRSA). This file contains data taken from the American Medical Association (AMA) Physician Masterfile, a comprehensive record of all physicians in the United States.[14] In particular, we use the number of physicians in direct primary patient care excluding hospital residents and physicians over the age of 75 as our measure of the number of PCPs.[15] The Area Health Resources File also contains many other statistics on health outcomes in each county as well as amenities such as home prices

[11] According to the Kaiser Family Foundation, the proportion who do accept Medicare patients is approximately 93 percent. See `http://www.kff.org/medicare/issue-brief/primary-care-physicians-accepting-medicare-a-snapshot/`.

[12] We cannot use the ACS or CPS for this purpose because these surveys report occupational status on too broad a level. The finest level of detail on PCP salaries we would be able to obtain would be salaries for all physicians and surgeons, which would vastly overstate the true salary of a PCP.

[13] For some MSAs, there is not enough data for the BLS to report an accurate salary estimate. In these cases, we use the statewide average salary.

[14] We wish we could use the AMA Physician Masterfile itself, as it contains even more detailed information on individual physicians than the Medicare data. Unfortunately, the Masterfile is proprietary and prohibitively expensive.

[15] This should yield a conservative estimate of the true number of PCPs since the Physician Masterfile underestimates the number of physicians who are retired. See Petterson, Rayburn and Liaw (2016) for a thorough explanation.

that physicians may consider important when making location decisions. We use several of these variables as observed amenities in our model.

Diamond (2016) constructs an index of different amenities containing measures of crime, entertainment, public transit, the labor market and environmental factors. We consider similar factors but let them enter the indirect utility function separately. We incorporate data on entertainment amenities from the Census. In particular, we measure entertainment using the number of establishments by county that fall in the categories of "Arts, Entertainment and Recreation" (museums, movie theatres) and "Food Services" (restaurants, bars, etc.). The entertainment index (Entertainment index$_j$) is the average of the county level variable for all counties within a location. We also incorporate data on crime from Segarra (2017), which we obtained from the author. The Uniform Crime Reporting dataset contains the number of violent and non-violent crimes for several thousand law enforcement agencies in the US. We aggregate both types of crimes. Further aggregation at the county level can be achieved through the Law Enforcement Agency Crosswalk available from the National Archive of Criminal Justice. Currently we retain the definition of the crime index as the total number of crimes by county but changing the definition to crimes per capita does not affect the results very much. We obtain data on the remaining amenities (home values, percent of population with a college degree, percent living in poverty) from the Area Health Resources File. All data is for 2014 or for the most recent available year before 2014. The final definition of amenities uses county averages by location.

Most of our amenity data is published at the county level. However, a model in which physicians choose to locate in individual counties would be intractable. We therefore partition the 3,142 counties of the United States into 200 geographic units according to metropolitan status and population. First, MSAs[16] with 500,000 or more people in 2010 are given their own distinct location. Second, all other counties that are part of a MSA within a state are aggregated into a "small metro" location for that state. Finally, all counties within a state that are not part of a MSA are grouped together as the rural areas of that state. This process results in 104 large metro areas, 49 small metro areas, and 47 rural areas.[17]

4.2 Summary Statistics

Table 2 displays summary statistics for the physicians in our PCP dataset. Overall, 47 percent are female; though female physicians disproportionately choose primary care as their

[16] An MSA is defined by the Office of Management and Budget (OMB) as one or more adjacent counties that contain a city of at least 50,000 people

[17] Some states on the east coast and Washington, D.C. do not have any counties in the small metro or rural categories. We also note that several large MSAs overlap multiple states (e.g., New York-Newark-Jersey City, NY-NJ-PA MSA and Washington-Arlington-Alexandria, DC-VA-MD-WV MSA).

specialty, the medical profession overall has become less dominated by males in recent years. A somewhat smaller proportion of PCPs in rural areas are female (40 percent). Preferences for living near one's native state (proxied by medical school state) are strong. Overall, 26 percent of PCPs practice medicine in the same state as their medical school, and 34 percent practice in the same region. These patterns are even stronger in rural areas, as 32 percent of rural physicians practice in their home state and 41 percent practice in their home region.

Table 3 summarizes the characteristics and amenities of rural, small metro, and large metro locations. On average, the annual salaries of PCPs are $10,000 higher in rural areas than in urban areas. Although home prices and crime rates tend to be higher, urban areas tend to have more desirable amenities than rural areas. This suggests that physicians in rural areas are being paid a small compensating differential for the lack of amenities, which may be a result of current incentive programs. Despite this difference in pay, PCPs disproportionately practice medicine in urban areas; the average population-to-PCP ratio is 1,787 to one in rural areas but 1,319 to one in large metro areas. Furthermore, compensating differentials do not appear to be uniformly applied across the United States. Figure 3 shows a heat map of PCP salaries; comparing this to the heat map of shortage areas in Figure 1 shows that some rural areas with shortages actually pay physicians far less than the national average (e.g., New Mexico).

4.3 Shortage Areas

The Health Resources & Services Administration (HRSA) defines a list of shortage areas and gives them a score according to the severity of the shortage (see Figure 1). Their shortage calculations are based on a very simple premise that takes into account mostly population. In a population that is distributed according to the national average of gender and age groups, the medical literature is in agreement that one primary care physician can handle the healthcare demand of around 1,500 people (Goodman et al., 1996; Ricketts III et al., 2007). Consequently, in an average location the desired population-to-PCP ratio is 1,500 to 1. Areas that exceed this ratio would then be defined as shortage areas. To get a conservative estimate of shortage, the HRSA doesn't actually define an area as having a shortage until it reaches a ratio of 3,000 to 1. One PCP cannot deliver adequate care to 3,000 people. In our first set of estimates we define a shortage area as any location with a population-to-PCP ratio greater than 1,500 to one.

An improved approach would attempt to model the demand for health care a little more carefully. One way to do this is described in a report of the Department of Health and Human Services (Ricketts III et al. (2007)). The basic idea is to adjust the raw population in a given area in two steps to create an "effective population" that better reflects healthcare needs; the healthcare demand of a mostly young and wealthy population will be very different from the healthcare demand of an ageing or poorer population. The DHHS report suggests adjusting the raw population by age and sex in the first stage. They propose using the healthcare utilization data from the Medicare Expenditure Panel Survey (MEPS) for a "barrier-free" population (employed, non-poor and non-minority) as a measure of true demand for health services. After adjusting for age and sex in this way, they argue that several other factors (minority status, poverty, population density) also matter for the healthiness and consequently the healthcare demand of a population. In future versions of this paper, we plan to have a simple model for healthcare demand along the lines just described.

Table 4 shows information about the shortage areas that we find using the population-to-PCP ratio of 1,500 to one. Rural areas (which constitute over half of all shortage areas) have the greatest disparities in health outcomes. The means for preventable hospitalizations, percent readmitted to a hospital within 30 days of release, and the number of cardiovascular and diabetes deaths are statistically significantly higher in shortage than in non-shortage areas. Differences are much less pronounced for metro areas, especially large metro areas. Overall, this evidence suggests that shortage areas have worse health outcomes than non-shortage areas.

5 Estimation

This section describes our estimation procedure, which closely follows the two-step procedure in Berry, Levinsohn and Pakes (2004).

5.1 Step One: Maximum Likelihood

In the first step of estimation, we recover the vector of common utility components for each location $\boldsymbol{\delta} = (\delta_1, \delta_2, \ldots, \delta_J)'$ and the idiosyncratic preference parameters $\boldsymbol{\beta} = (\beta_1, \beta_2, \boldsymbol{\beta}_3')'$ via maximum likelihood.

Let d_{ij} be an indicator that takes the value one if physician i practices in location j. The log-likelihood function could be formulated as

$$L\left(\boldsymbol{\delta}, \boldsymbol{\beta}\right) = \frac{1}{N} \sum_{i=1}^{N} \sum_{j=1}^{J} d_{ij} \ln \left[\hat{s}_{ij} \left(\boldsymbol{\delta}, \boldsymbol{\beta}; \text{State}_{ij}, \text{Region}_{ij}, \text{Female}_i, \mathbf{v}_j \right) \right]. \tag{1}$$

However, we do not maximize (1) directly because it would require a search over $J-1+K_1$ parameters (where $K_1 = \dim(\boldsymbol{\beta})$), which is infeasible for $J = 200$. Instead, we use a strategy first proposed by Berry (1994), who showed that for every value of $\boldsymbol{\beta}$ there exists a unique vector $\boldsymbol{\delta}$ that matches the estimated aggregate location shares $\hat{s}_j(\boldsymbol{\delta}, \boldsymbol{\beta}) = \frac{1}{N}\sum_{i=1}^{N} \hat{s}_{ij}(\cdot)$ to the observed shares s_j. Berry, Levinsohn and Pakes (1995) show that $\boldsymbol{\delta}$ can be characterized as the unique fixed point of the contraction mapping

$$T\left(\delta_j\right) = \delta_j + \left[\ln\left(s_j\right) - \ln\left(\hat{s}_j\left(\boldsymbol{\delta}, \boldsymbol{\beta}\right)\right)\right] \tag{2}$$

for $j = 2, 3, \ldots, J$. (Recall that δ_1 is normalized to zero.) This convenient contraction mapping allows us to reformulate the log-likelihood function as

$$L\left(\boldsymbol{\delta}(\boldsymbol{\beta}), \boldsymbol{\beta}\right) = \frac{1}{N}\sum_{i=1}^{N}\sum_{j=1}^{J} d_{ij} \ln\left[\hat{s}_{ij}\left(\boldsymbol{\delta}(\boldsymbol{\beta}), \boldsymbol{\beta}; \text{State}_{ij}, \text{Region}_{ij}, \text{Female}_i, \mathbf{v}_j\right)\right], \tag{3}$$

which allows us to search for just K_1 parameters rather than $J - 1 + K_1$ parameters.[18]

5.2 Step Two: Two-Stage Least Squares

Having recovered the common component of utility for each location $\boldsymbol{\delta} = (\delta_1, \delta_2, \ldots, \delta_J)$ and the idiosyncratic preference parameters $\boldsymbol{\beta} = (\beta_1, \beta_2, \boldsymbol{\beta}_3')'$ in step one, we now estimate $\boldsymbol{\alpha} = (\alpha_1, \boldsymbol{\alpha}_2')'$, the parameters of mean utility. By definition, we have

$$\delta_j \equiv \alpha_1 \ln(w_j) + \mathbf{x}_j'\boldsymbol{\alpha}_2 + \xi_j.$$

Estimation of this equation is relatively straightforward, with one exception: wages are likely to be correlated with unobserved amenities, creating an endogeneity problem between $\ln(w_j)$ and ξ_j. Ordinary least squares estimation would therefore give us biased estimates of α_1, our key parameter.

To address this problem, we exploit exogenous geographic variation in Medicare's compensation scheme to create an instrument for wages. Any instrument z_j must be uncorrelated with unobserved amenities but correlated with wages. Formally, such an instrument z_j must satisfy

$$\mathbb{E}\left[z_j \xi_j\right] = 0$$
$$\mathbb{E}\left[z_j \ln(w_j)\right] \neq 0.$$

[18] In practice, finding the fixed point of the contraction mapping in equation (2) is computationally expensive, which is exacerbated by the fact that it must be evaluated at each candidate value of $\boldsymbol{\beta}$. To speed up the algorithm, we augment the contraction mapping with a modified Newton-Raphson method suggested by Wong (2015) and Li (2012). Another alternative is to use the mathematical programming with equilibrium constraints (MPEC) approach of Dube, Fox and Su (2012), but we do not pursue this here.

The evidence suggests that there already exists some degree of compensating differentials in wages for rural and non-rural PCPs (i.e., the mean annual salary is slightly higher in rural areas).[19] In this case, we can conclude that unobserved amenities in a location are likely to be negatively correlated with wages ($\mathbb{E}\left[\ln(w_j)\xi_j\right] < 0$) in that location — the more desirable a place is, the lower the local wage. This implies that OLS estimates of α_1 would be biased downward.

Medicare reimbursements by service are calculated based on three different components: the relative time and intensity associated with providing that service, costs of maintaining a practice (for example renting space, staff costs, equipment) and costs of malpractice insurance. For each component, Medicare defines a baseline value by procedure. Each component is adjusted by a separate geographic adjustment factor called Geographic Practice Cost Index (GPCI). The purpose of these factors is to capture geographic cost differences in practicing medicine. As discussed previously, this method adjusts reimbursement rates for rural areas downward due to lower price levels. Thus, instead of being compensated for the lack of amenities, rural physicians are paid lower salaries than the theory of compensating differentials would predict. To partially avoid these perverse incentives, the lower bound on the GPCI for the first component (Work GPCI) is equal to one.[20] There is no lower bound for the other two components.

Figure 4 shows the areas defined by Medicare for the first component, the Work GPCI. Medicare's Work GPCI floor binds for most states in the the Midwest and Mountain census divisions (all states labelled as "State-wide areas" are given a work GPCI of one throughout). All states labelled as "Rest-of-state areas" contain higher-GPCI areas (big metropolitan areas) and a Work GPCI of one in the remaining regions. The Medicare GPCI generates a high correlation among physician wages in places with a similar adjustment factor. By construction, wages for the same procedure will be very close in those areas, espcially for regions with a large proportion of Medicare patients.[21] This forms a good institutional basis for a relevant instrument.

We define a set of regions broadly based on the Census Divisions but adapted for the slightly different boundaries that the GPCIs suggest. For example, the Census Division "East North Central" is defined as the states of Illinois, Indiana, Michigan, Ohio and Wisconsin. However, the Medicare GPCIs define no high-cost area in Wisconsin, and reimbursement

[19]Comparing Figure 3 and Figure 1 further illustrates this. Wages are higher in shortage states like Mississippi and Georgia but there are also many rural areas with both a large physician shortage as well as a comparatively low mean wage (i.e. New Mexico, Arizona, Idaho).

[20]The Work GPCI adjusts for the time and intensity of labor for each procedure.

[21]According to Sommers, Paradise and Miller (2011) 19 percent of PCPs are considered 'high-share Medicare' PCPs, meaning that more than 26 percent of their practice revenue comes from Medicare.

rates should be more similar across urban areas in the other four states. We instead group Wisconsin with Iowa, Minnesota and Missouri. Proceeding in this way yields 12 regions.[22]

Let R_j be the set of locations in j's Medicare pay schedule region, and let M_j be the set of locations with the same metropolitan status (rural/small metro/large metro) as j. Our instrument is

$$z_j = \ln\left(\frac{1}{|R_j \cap M_j| - 1} \sum_{k \in (R_j \cap M_j) \setminus j} w_k\right).$$

Hence we instrument for wages at each location with an average of wages of all other locations in a PFS region of the same metropolitan status. Due to similar labor market conditions and work GPCI in locations in the same region with the same metropolitan status, the instrument should be positively correlated with wages ($\mathbb{E}[z_j \ln(w_j)] > 0$). On the other hand, the average wage in surrounding locations is unlikely to be correlated with unobserved amenities in location j due to Medicare's other geographic adjustment factors (i.e., the Practice Expense GPCI and Malpractice GPCI), which are ultimately determined by government bureaucrats and are highly variable across locations. As a result, we believe that our instrument satisfies the conditions for exogeneity ($\mathbb{E}[z_j \xi_j] = 0$) and relevance ($\mathbb{E}[z_j \ln(w_j)] > 0$). The first-stage results are reported in Table 5. As expected, our instrument is highly correlated with log wages.

6 Results

Table 6 reports parameter estimates and standard errors from the full model as well as ordinary least squares estimates that ignore the endogeneity of wages. Standard errors are preliminary and do not adjust for the inefficiency of two-step estimation.[23] When we address the endogeneity problem using our Medicare adjustment instrument, the coefficient on log wages in the indirect utility function becomes larger, changing from 0.619 to 0.783. This is as expected; if wages reflect compensating differentials for living in unattractive locations, wages should be negatively correlated with unobserved amenities. When the endogeneity is ignored, this negative correlation causes the marginal utility of income to be underestimated (as can be seen from the OLS results).

Salaries, home prices, population density, and proximity to one's medical school seem to be the most important factors in physician location decisions. As is commonly found in

[22] Currently, Alaska and Hawaii constitute one region of their own and there seems to be a strong correlation between wages in those two areas. Due to the remoteness of both, we might consider different specifications in the future. We may also use the original definitions of Census Regions as a robustness check.

[23] Currently, the standard errors for the first step are obtained from the inverse of the Fisher information matrix and from a heteroskedasticity-robust sandwich estimator in the second step.

the migration literature, distance from one's home location (here proxied by the distance from one's medical school) is particularly important. However, relative to estimates of high- and low-skilled workers' responsiveness to wages in the migration literature, we find that primary care physicians respond very weakly to differences in salaries across locations. For example, Colas and Hutchinson (2017) find that the average location's elasticity with respect to wages for high-skilled workers is 12.05. In our model, the average wage elasticity is 0.68, meaning a 1% increase in salaries at a location will only increase the number of physicians who choose that location by 0.68%. Though somewhat smaller, this estimate is consistent with the results from other papers that estimate models of physician location decisions. For example, Hurley (1991) finds an average income elasticity of 1.05 and Bolduc, Fortin and Fournier (1996) report an average income elasticity of 1.11, both of which are contained in the 95 percent confidence interval for our estimate. However, we note that the locations in our model are much more heterogeneous than in either Hurley (1991) or Bolduc, Fortin and Fournier (1996) and are not particularly close substitutes for each other. Given this, it is not surprising that our estimate of the average income elasticity is smaller than in the previous literature.

Figure 6 shows a histogram of all 200 own wage elasticities. Most locations have own-wage elasticities around 0.7. Since large cities tend to have the fewest close substitutes, they also tend to have the most inelastic wage elasticities. Table 7 lists the locations with the ten smallest own wage elasticities.

To facilitate the understanding of the substitution patterns generated by our model, Table 8 displays the own- and cross-wage elasticity matrix for locations in Illinois, Iowa, and Wisconsin. As expected, locations within the same state are the closest substitutes for each other. Though we think that large cities ought to be closer substitutes for each other than reflected here, our model seems to produce reasonable substitution patterns, especially within states.

7 Policy Counterfactuals

In this section, we simulate several policies intended to reduce physician shortages. There are a fairly large number of monetary and non-monetary policies already in place to make rural areas more attractive for physicians. Table 1 shows an overview of these policies. The most popular program by far is the J-1 visa initiative which has been implemented in all 50 states. In this program, international medical school graduates who practice in rural areas enter an accelerated process to become U.S. permanent residents. Thirty-nine states offer student debt repayment schemes for physicians who complete residency or commit to practice medicine in an underserved area for a certain number of years. These programs are promising because they are targeted directly at medical graduates from underserved states and rural areas; due to home preferences, these physicians are more likely to return to live there. However, these policies are difficult for us to simulate with our model given that they are typically lump sum payments. Finally, six states (Georgia, Oregon, New Mexico, Louisiana, Alabama and Montana) have implemented a rural physician tax credit of $5,000 a year, and another 14 states give additional payments or grants. While some states have limited this credit to a maximum of five years, we simulate the policy as though its time horizon were unlimited.

In all cases, we begin our policy counterfactual in 2014 and report the results of the policy as of 2024. To do so, we use the population growth rate of each location in 2014 to obtain an estimate of the population in 2024. We also assume that all PCPs who are between the ages of 65 and 74 in 2014 retire by 2024. We then allow 4,668 new PCPs per year (the average number of new PCPs in the four years of our PCP dataset) to choose a location and begin practicing medicine. To be consistent with our model, we do not allow current PCPs to switch locations upon implementation of the policy; all decisions are once-and-for-all.

Of the 68 locations with a shortage of any magnitude in 2014, 13 no longer have a shortage in 2024 when no additional policy is implemented. This is a result of population growth and the location choice of new physicians; locations with declining populations relative to the number of PCPs will naturally have less severe shortages as time passes. All results below should be interpreted with this fact in mind.

7.1 Tax credits for new PCPs in shortage areas

In our first counterfactual, we simulate the effects of a program that gives tax credits to new PCPs who practice in shortage areas. The typical tax credit is $5,000 per year; we use this amount as a baseline and then increase the amount to $100,000 per year.[24]

Figure 7 displays PCP shortages in 2024 for all locations with a shortage of at least 100 PCPs in 2014. Along with the 2014 shortage, it displays the shortages in 2024 under three scenarios: without any policy intervention, with $5,000 tax credits, and with $100,000 tax credits. Providing $5,000 tax credits barely changes the shortage relative to the case with no intervention; no further 2014 shortage areas become non-shortage areas in 2024 as a result of the policy. Increasing the amount of the tax credit to $100,000 does somewhat better, as most shortages are visibly alleviated; only 48 locations still face a physician shortage in 2024 under this scenario. However, this program is quite expensive; the cost over the

[24] However, it is important to note that our model assumes that any wage increase is permanent, whereas most of the tax credit programs currently in force end after a few years.

first 10 years is approximately \$7.32 billion.[25] These results indicate that current policies are unable to eliminate shortages. Given how unresponsive physicians are to differences in wages across locations, the magnitudes of the current tax credit and loan forgiveness incentives are hopelessly small to entice enough PCPs to move to shortage areas.

7.2 Revenue-neutral policies

We now simulate the effects of a revenue-neutral policy that taxes new PCPs who choose to practice in non-shortage areas and subsidizes those who practice in shortage areas.[26] Figure 8 displays the nationwide shortage of PCPs in 2024 as a function of the tax rate for PCPs in non-shortage areas and the corresponding revenue-neutral subsidy rate in shortage areas. Because our elasticities are only accurate for small percentage changes in wages, we caution against taking our results for tax rates above 50 percent too seriously. However, it is clear from our results that these policies, no matter the tax rate, do not come close to eliminating shortages. For example, a 30 percent tax rate and the corresponding 59.36 percent revenue-neutral subsidy rate reduces the overall shortage of PCPs by less than one third.

8 Conclusion

We estimate a model of physician location decisions and use it to simulate the effects of incentive programs intended to eliminate shortages of primary care physicians. Physicians appear to be unresponsive to small differences in salaries across locations and prefer to live in their home state; a one percent increase in salaries at the average location results in just a 0.68 percent increase in the fraction of physicians who choose to practice medicine in that location. As a result, we find that current incentive programs intended to reduce physician shortages are too small to entice enough physicians to move to shortage areas. A twentyfold increase in the payment size generates a modest improvement but still does not go far enough. We also find that simple revenue-neutral policies with reasonable tax rates do slightly better but only reduce the shortage by approximately one third over ten years.

In light of these results, we suggest that policymakers who desire to reduce shortages of primary care physicians recruit more physicians who were raised in shortage areas to stay

[25] As a reference, the budget for the entire University of Wisconsin System for the 2015-2016 academic year was \$6.19 billion.

[26] We also simulated the effects of a policy in which the government was allowed to discriminate by rural, small metro, and large metro status when determining the subsidy and tax rates. The results were qualitatively similar to those reported here.

and practice medicine there. Given the strength of physicians' preferences for living close to their home location, attracting physicians from out-of-state to move to shortage areas in another state appears to be extremely difficult. Current rural residency programs and student debt relief programs for rural physicians often target medical school graduates who were raised in rural areas. Our results suggest that programs that leverage home preferences in this way should be more effective than those that attempt to attract physicians from out-of-state.

There are a few other possible alternatives that might improve access to healthcare in areas with physician shortages. One option is to entice more medical school graduates to choose a career in primary care rather than another specialty; as Schwartz et al. (2005) notes, more physicians might choose primary care if the pay gap between it and other specialties was narrowed. Another option is to allow other well-qualified but less-educated medical professionals such as nurse practitioners perform more tasks usually completed by physicians. Traczynski and Udalova (2014) find that increasing the total number of primary care providers in this way improves health outcomes and decreases administrative costs. Finally, telemedicine (the use of remote communications technology to diagnose, monitor, and treat patients) may alleviate primary care shortages (Kvedar, Coye and Everett, 2014; Weinstein et al., 2014). However, there is a lack of research on the accuracy of diagnoses using such methods (Armfield et al., 2014), and many physicians seem reluctant to practice remotely. While there seems to be great potential for telemedicine for some medical procedures, there is also evidence that care provided through telemedicine is of lower quality than traditional care (Uscher-Pines et al., 2016).

This study has several weaknesses. While our model is static, migration is certainly a dynamic decision; physicians may choose to relocate many times over their careers for a variety of reasons. At the present time, we do not have a long enough panel of physicians to estimate a dynamic model of migration as in Kennan and Walker (2011).[27] Furthermore, we do not model occupational choice; shortages may also be reduced or eliminated by policies that increase the number of workers who chose to be physicians or entice more physicians to choose primary care over other specialties. This may be an important omission from our model if monetary incentives affect physicians' choice of speciality more than their choice of location; if this were the case, government policies would be much more effective than what is reported here. In the future, we may expand our model to incorporate specialty choice.

Finally, we note that our measure of the demand for physicians (and hence the shortage of physicians) is simplistic and only accounts for differences in population. In the future,

[27]This dynamic approach may be possible in the future if CMS continues to release the Physician Compare and Utilization and Payment datasets or if we somehow obtain access to the AMA Physician Masterfile.

we hope to model the demand for primary care physicians more explicitly by accounting for differences in income, age, insurance status, and other factors across locations. Changes in healthcare demand in different locations over time may drastically change the magnitude of shortages. For example, population decline may be so rapid in some areas that physician shortages may disappear without any further policy changes. On the other hand, an area with a rising proportion of elderly residents may see an increase in demand for healthcare in the short term but a decline over a longer time horizon as these residents die. Other factors such as competition in the insurance marketplace and idiosyncratic characteristics such as the population's lifestyle and overall attitudes toward healthcare may also play a role in demand. As a result, modeling physician demand will require a great deal of thought, which we postpone until a later draft.

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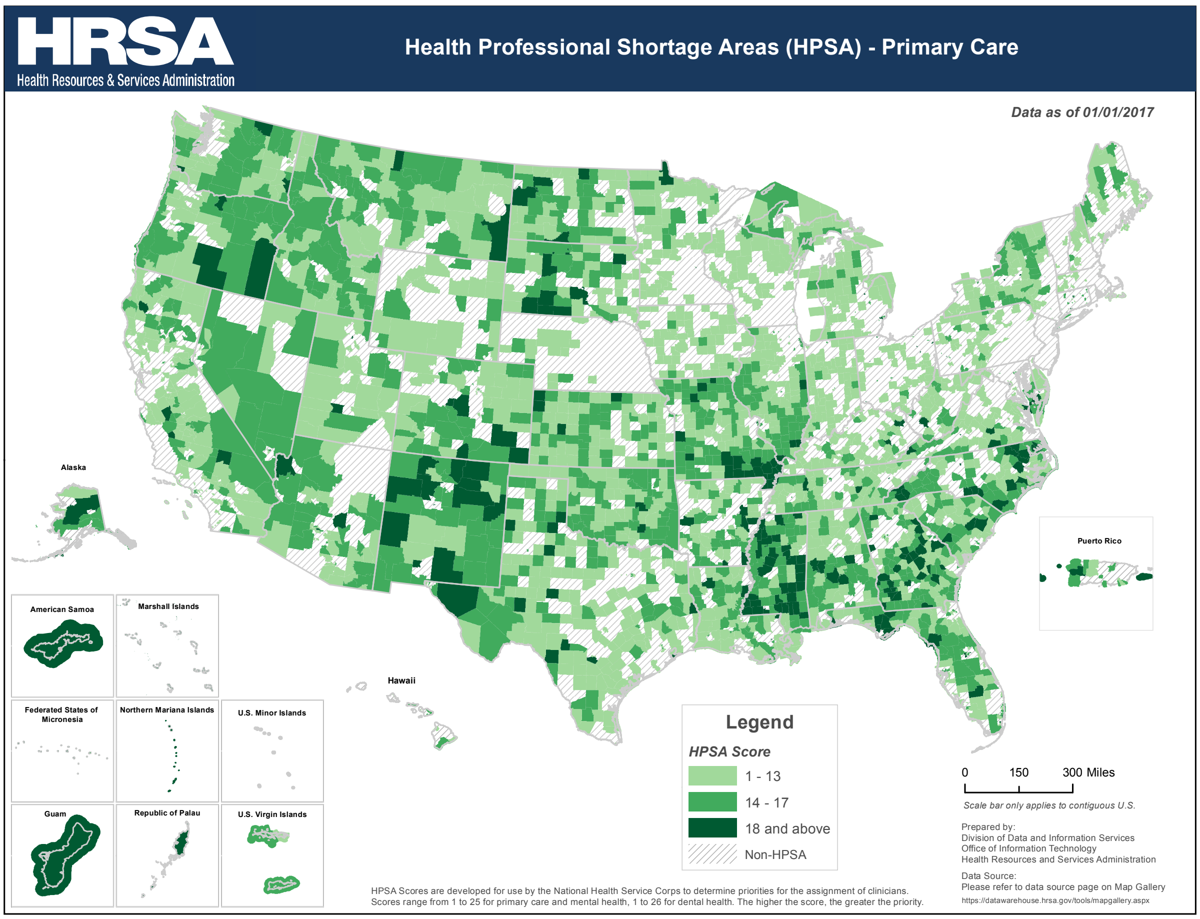

Figure 1: Shortages of primary care physicians across the United States

Table 1: Current rural physician initiatives

Type of program	Number of states	Average payment amount
Rural physician tax credit	6	\$5,000 p.a. [a]
Student loan repayment	39	\$92,088
J-1 visa initiative[b]	50	-
Other monetary rural initiative[c]	14	\$46,500

Source: National Organization of State Offices of Rural Health

[a] In Georgia, Alabama and Louisiana receipt of the tax credit is limited to 5 years (4 years in Montana). Oregon and New Mexico place no restrictions on the number of years.

[b] State and federal partnership sponsoring (by waiving the two-year home residence requirement) international medical graduates who agree to practice in an underserved area for at least 3 years after completing their residency.

[c] These include additional debt relief (Louisiana, Colorado, Missouri, North Carolina, Oklahoma, Oregon, Wisconsin, Kansas, Rhode Island) as well as small income boosts and grants (Maine, Wyoming, Connecticut, Arkansas, South Carolina, South Dakota)

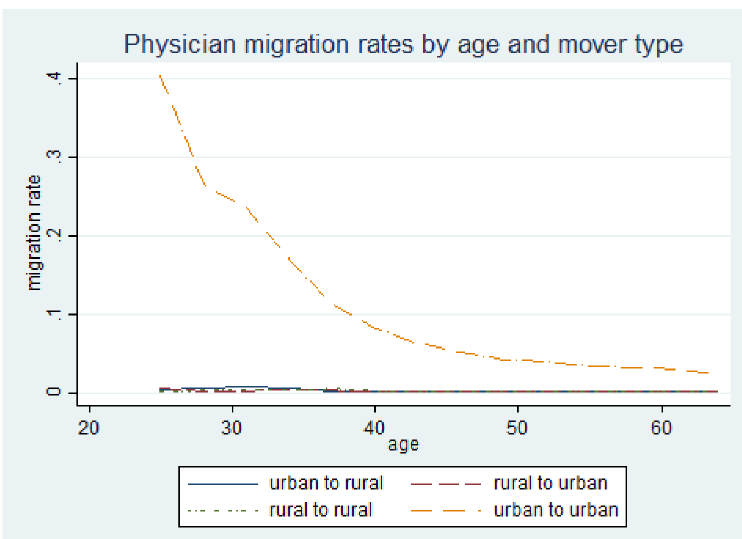

Figure 2: Migration rates for physicians by age (Source: ACS)

Table 2: Sample physician characteristics

	Mean	(Std. Dev.)
Rural areas (47 locations):		
Fraction female	0.4008	(0.0835)
Fraction living in med school state (State_{ij})	0.3221	(0.1858)
Fraction living in med school census division (Region_{ij})	0.4074	(0.1892)
Small metro areas (49 locations):		
Fraction female	0.4319	(0.0802)
Fraction in med school state (State_{ij})	0.2425	(0.1377)
Fraction in med school census division (Region_{ij})	0.3285	(0.1441)
Large metro areas (104 locations):		
Fraction female	0.4929	(0.0738)
Fraction in med school state (State_{ij})	0.2530	(0.1241)
Fraction in med school census division (Region_{ij})	0.3327	(0.1629)
Overall (200 locations):		
Fraction female	0.4703	(0.0837)
Fraction in med school state (State_{ij})	0.2588	(0.1371)
Fraction in med school census division (Region_{ij})	0.3403	(0.1643)

Table 3: Summary statistics for locations

	Mean	(Std. Dev.)	5%	Median	95%
Rural areas (47 locations):					
Annual salary (w_j)	\$195,335	(\$21,988)	\$164,902	\$194,508	\$232,092
Home value$_j$	\$144,189	(\$91,156)	\$79,500	\$110,460	\$259,800
Percent w/college degree$_j$	19.34%	(5.88%)	13.04%	18.37%	30.20%
Percent in poverty$_j$	17.12%	(4.72%)	10.80%	16.59%	25.46%
ln(Crime index$_j$)	6.81	(1.15)	6.07	6.99	7.82
ln(Entertainment index$_j$)	4.11	(0.68)	3.20	3.95	5.40
Population density$_j$	40.77	(37.05)	4.56	37.39	100.40
Persons per PCP$_j$	1,787	(412)	1,049	1,803	2,397
Small metro areas (49 locations):					
Annual salary (w_j)	\$185,398	(\$24,466)	\$136,848	\$184,412	\$217,360
Home value$_j$	\$169,289	(\$71,593)	\$101,892	\$149,227	\$282,093
Percent w/college degree$_j$	24.36%	(5.30%)	16.69%	23.19%	34.96%
Percent in poverty$_j$	15.45%	(3.51%)	8.88%	15.65%	20.38%
ln(Crime index$_j$)	8.15	(1.26)	7.50	8.42	8.90
ln(Entertainment index$_j$)	5.55	(0.60)	4.71	5.51	6.63
Population density$_j$	152.83	(114.81)	22.18	131.86	411.62
Persons per PCP$_j$	1,343	(254)	903	1,343	1,778
Large metro areas (104 locations):					
Annual salary (w_j)	\$186,854	(\$27,196)	\$139,690	\$187,085	\$234,060
Home value$_j$	\$194,512	(\$101,824)	\$111,857	\$161,750	\$422,400
Percent w/college degree$_j$	26.57%	(6.57%)	17.58%	25.62%	38.00%
Percent in poverty$_j$	14.65%	(4.52%)	9.16%	13.94%	21.83%
ln(Crime index$_j$)	9.36	(0.81)	8.32%	9.25	11.17
ln(Entertainment index$_j$)	6.60	(0.90)	5.24	6.45	8.16
Population density$_j$	546.78	(472.40)	107.55	383.76	1,424.75
Persons per PCP$_j$	1,319	(285)	991	1,266	2,039

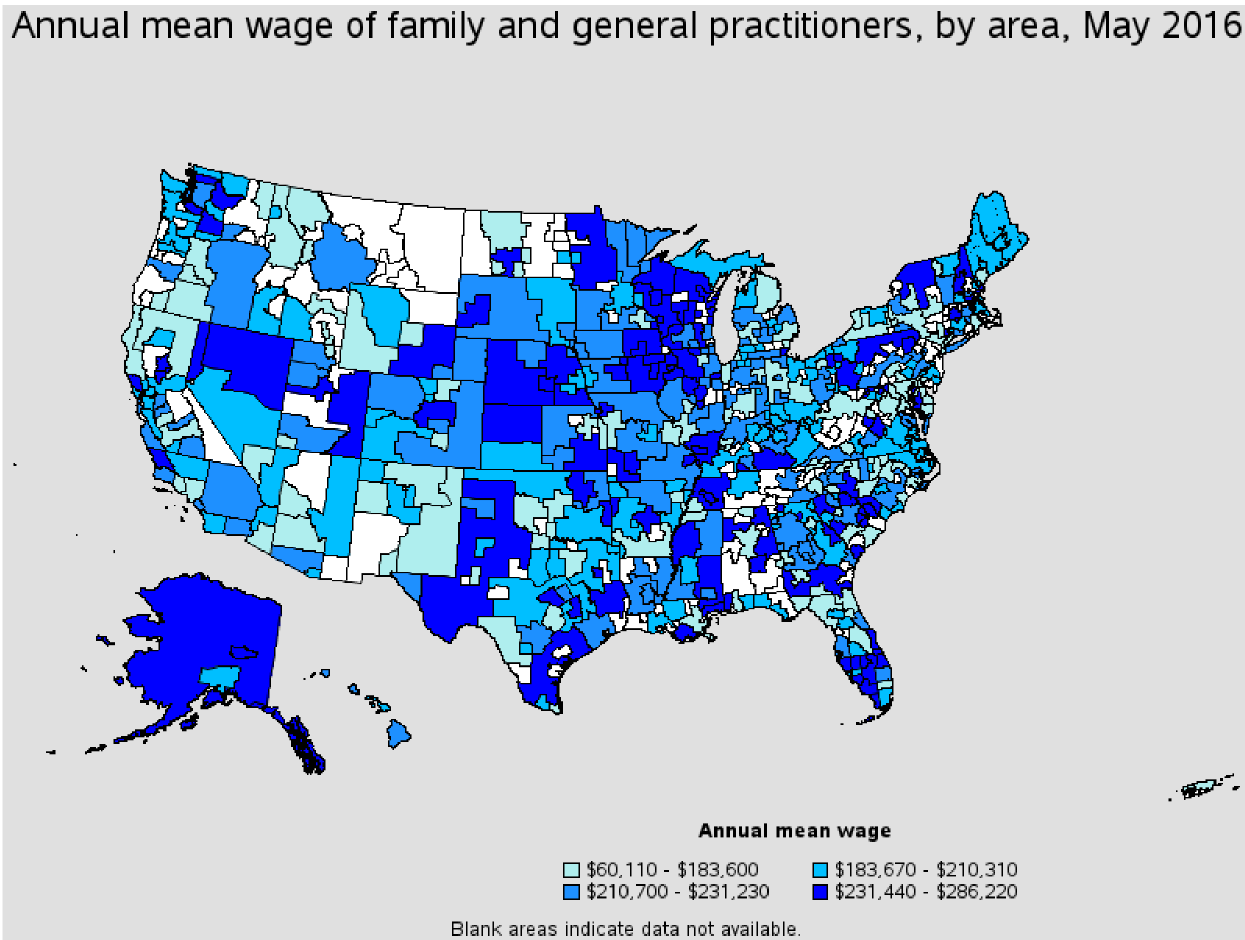

Figure 3: Annual salaries for PCPs by location (Source: OES)

Table 4: Statistics for shortage areas

	Non-shortage areas Mean	(Std. Dev.)	Shortage areas Mean	(Std. Dev.)
Rural areas (47 locations):	(12 locations)		(35 locations)	
Prev. hosp. per 1000	45.47	(9.42)	62.82†	(16.13)
% readmitted within 30 days	13.19	(1.1)	14.52†	(0.93)
% ER visit within 30 days	19.93	(1.44)	20.08	(1.71)
Nurses per 1000	2.58	(0.83)	2.31	(0.61)
Cardiovascular deaths per 1000	1.11	(0.17)	1.32†	(0.31)
Influenza deaths per 1000	0.26	(0.07)	0.3	(0.07)
Diabetes deaths per 1000	0.30	(0.07)	0.40†	(0.09)
Pop. in mental hospital per 1000	0.066	(0.107)	0.100	(0.154)
Small metro areas (49 locations):	(37 locations)		(12 locations)	
Prev. hosp. per 1000	47.18	(11.36)	53.56	(13.56)
% readmitted within 30 days	14.2	(0.78)	14.08	(1.52)
% ER visit within 30 days	19.99	(1.28)	19.63	(1.86)
Nurses per 1000	3.34	(1.47)	3.24	(0.94)
Cardiovascular deaths per 1000	1.02	(0.23)	1.11	(0.28)
Influenza deaths per 1000	0.18	(0.06)	0.19	(0.06)
Diabetes deaths per 1000	0.26	(0.07)	0.29	(0.07)
Pop. in mental hospital per 1000	0.129	(0.201)	0.050†	(0.056)
Large metro areas (104 locations):	(83 locations)		(21 locations)	
Prev. hosp. per 1000	49.43	(11.66)	49.41	(12.34)
% readmitted within 30 days	14.47	(0.97)	14.66	(1.33)
% ER visit within 30 days	19.77	(1.27)	19.96	(1.40)
Nurses per 1000	2.76	(1.01)	2.31	(0.8)
Cardiovascular deaths per 1000	0.98	(0.22)	0.90	(0.29)
Influenza deaths per 1000	0.17	(0.06)	0.15†	(0.05)
Diabetes deaths per 1000	0.25	(0.07)	0.25	(0.10)
Pop. in mental hospital per 1000	0.095	(0.159)	0.186	(0.631)
Overall (200 locations):	(132 locations)		(68 locations)	
Prev. hosp. per 1000	48.44	(11.4)	57.05†	(15.67)
% readmitted within 30 days	14.28	(0.99)	14.49	(1.17)
% ER visit within 30 days	19.84	(1.28)	19.96	(1.63)
Nurses per 1000	2.9	(1.17)	2.47†	(0.81)
Cardiovascular deaths per 1000	1.00	(0.22)	1.16†	(0.35)
Influenza deaths per 1000	0.18	(0.06)	0.23†	(0.09)
Diabetes deaths per 1000	0.25	(0.07)	0.33†	(0.11)
Pop. in mental hospital per 1000	0.102	(0.168)	0.118	(0.366)

† Shortage area mean statistically different from non-shortage area mean at 5% level.

Sources: Dartmouth Atlas and Area Health Resources File (HRSA)

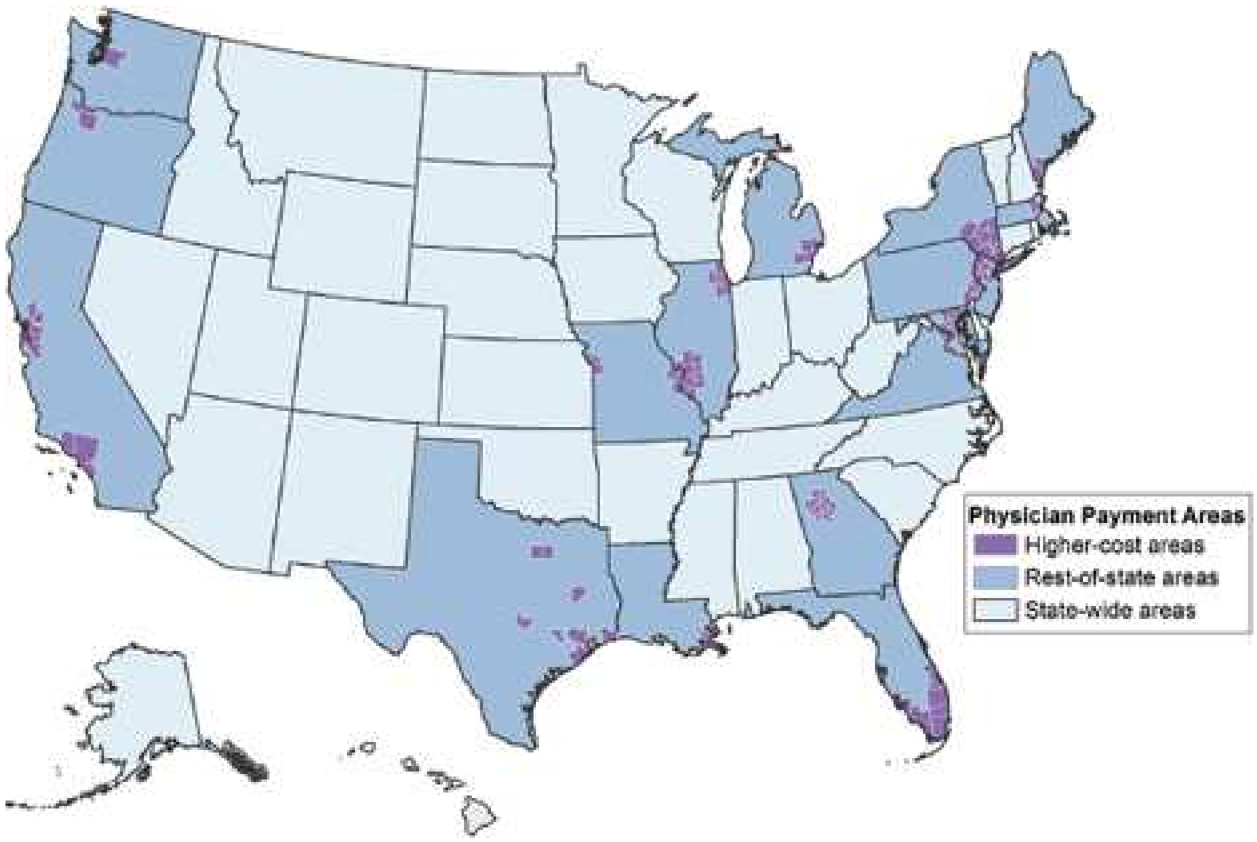

Figure 4: Medicare Work Geographic Practice Cost Index (GPCI) areas

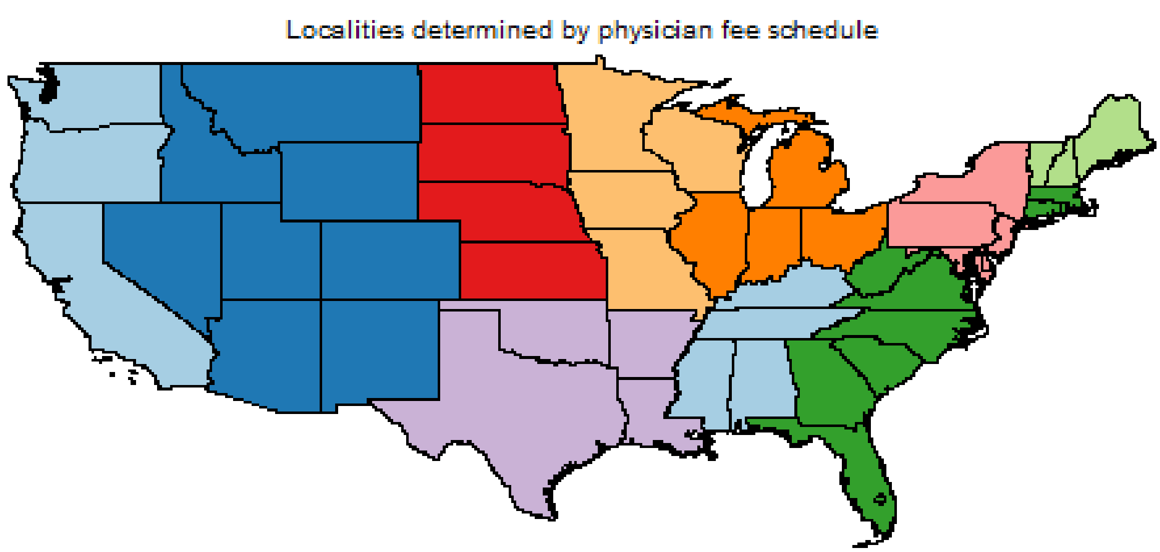

Figure 5: Self-constructed regions defined by Medicare's physician pay schedule

Table 5: First-stage IV results

$\ln(w_j)$	Estimate	(Std. Error)
$\ln(\text{Medicare adjustment instrument}_j)$	0.957^{***}	(0.037)
$\ln(\text{Home value}_j)$	0.043	(0.043)
Percent w/college degree$_j$	0.001	(0.004)
Poverty rate$_j$	0.000	(0.002)
$\ln(\text{Crime index}_j)$	0.008	(0.008)
$\ln(\text{Entertainment index}_j)$	-0.017	(0.016)
Population density$_j$	0.000	(0.000)
Observations (locations)	200	
F-statistic	240,917	

Note: Standard errors are robust to heteroskedasticity.
* Statistically significant at 10% level
** Statistically significant at 5% level
*** Statistically significant at 1% level

Table 6: Parameter Estimates

	IV Estimates		OLS Estimates	
	Estimate	(Std. Error)	Estimate	(Std. Error)
$\boldsymbol{\alpha}$:				
$\ln(w_j)$	0.783^{***}	(0.252)	0.619^{***}	(0.204)
$\ln(\text{Home value}_j)$	-0.839^{***}	(0.275)	-0.662^{***}	(0.225)
Percent w/college degree$_j$	-0.010	(0.018)	-0.016	(0.018)
Percent in poverty$_j$	-0.019	(0.019)	-0.016	(0.019)
$\ln(\text{Crime index}_j)$	0.022	(0.070)	0.031	(0.075)
$\ln(\text{Entertainment index}_j)$	0.166	(0.105)	0.146	(0.105)
Population density$_j$	0.001^{***}	(0.000)	0.001^{***}	(0.000)
$\boldsymbol{\beta}$:				
State$_{ij}$	2.792	(4.429)	2.792	(4.429)
Region$_{ij}$	0.746	(3.873)	0.746	(3.873)
$\text{Female}_i \times \ln(w_j)$	-0.181	(10.821)	-0.181	(10.821)
Number of locations (J)	200		200	
Number of PCPs (N)	18,674		18,674	

Note: Standard errors are preliminary and do not adjust for the inefficiency of two-step estimation.
* Statistically significant at 10% level
** Statistically significant at 5% level
*** Statistically significant at 1% level

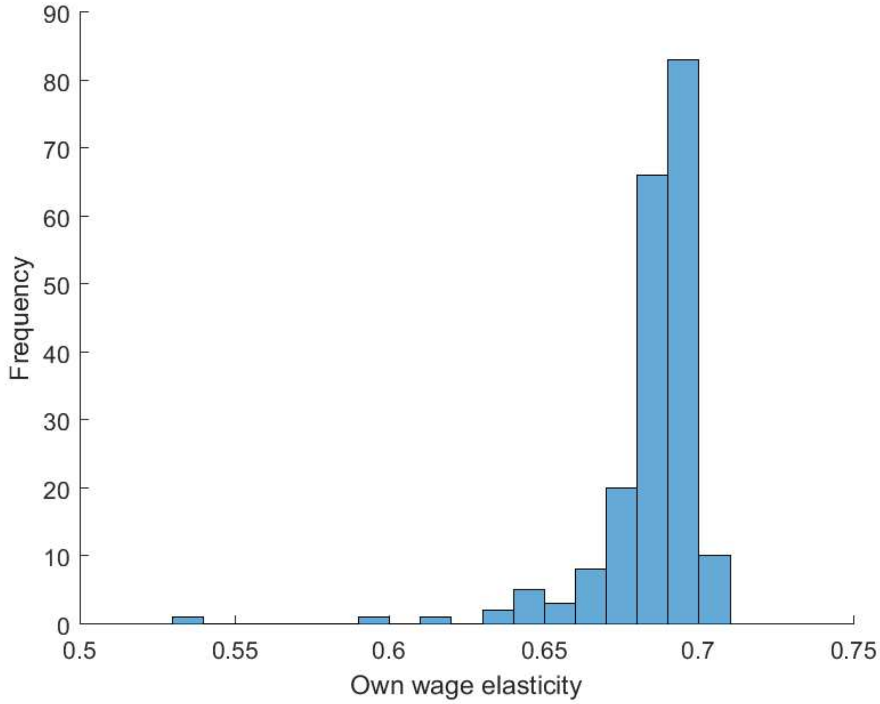

Figure 6: Frequency histogram of own wage elasticities

Table 7: Locations with smallest own wage elasticities

Rank	Location name	Own wage elasticity (η_{jj})
1	New York-Newark-Jersey City, NY-NJ-PA	0.522
2	Chicago-Naperville-Elgin, IL-IN-WI	0.590
3	Washington-Arlington-Alexandria, DC-VA-MD-WV	0.618
4	Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	0.634
5	Minneapolis-St. Paul-Bloomington, MN-WI	0.640
6	Detroit-Warren-Dearborn, MI	0.641
7	Dallas-Fort Worth-Arlington, TX	0.645
8	Los Angeles-Long Beach-Anaheim, CA	0.646
9	St. Louis, MO-IL	0.646
10	Houston-The Woodlands-Sugar Land, TX	0.649

Note: All elasticities above represent the percentage change in the share of PCPs choosing the location that would result from a 1% increase in salaries at that location.

Table 8: Wage elasticity matrix for locations in Illinois, Iowa, and Wisconsin

	Rural areas of IL	Rural areas of IA	Rural areas of WI	Small metro areas of IL	Small metro areas of IA	Small metro areas of WI	Chicago-Naperville-Elgin, IL-IN-WI	Des Moines-West Des Moines, IA	Madison, WI	Milwaukee-Waukesha-West Allis, WI	Minneapolis-St. Paul-Bloomington, MN-WI	Omaha-Council Bluffs, NE-IA	St. Louis, MO-IL
Rural areas of IL	0.686	-0.002	-0.002	-0.009	-0.002	-0.002	-0.008	-0.002	-0.002	-0.002	-0.002	-0.002	-0.006
Rural areas of IA	-0.002	0.685	-0.003	-0.002	-0.017	-0.003	-0.002	-0.017	-0.003	-0.003	-0.003	-0.015	-0.003
Rural areas of WI	-0.004	-0.004	0.690	-0.004	-0.004	-0.010	-0.008	-0.004	-0.010	-0.010	-0.008	-0.004	-0.003
Small metro areas of IL	-0.029	-0.006	-0.007	0.665	-0.006	-0.007	-0.024	-0.006	-0.007	-0.007	-0.006	-0.006	-0.020
Small metro areas of IA	-0.003	-0.021	-0.003	-0.003	0.681	-0.003	-0.003	-0.021	-0.003	-0.003	-0.004	-0.019	-0.004
Small metro areas of WI	-0.005	-0.005	-0.013	-0.005	-0.005	0.687	-0.010	-0.005	-0.013	-0.013	-0.010	-0.005	-0.004
Chicago-Naperville-Elgin, IL-IN-WI	-0.083	-0.018	-0.048	-0.083	-0.018	-0.048	0.590	-0.018	-0.048	-0.048	-0.038	-0.017	-0.056
Des Moines-West Des Moines, IA	-0.002	-0.011	-0.002	-0.002	-0.011	-0.002	-0.001	0.691	-0.002	-0.002	-0.002	-0.010	-0.002
Madison, WI	-0.003	-0.003	-0.008	-0.003	-0.003	-0.008	-0.006	-0.003	0.690	-0.008	-0.007	-0.003	-0.003
Milwaukee-Waukesha-West Allis, WI	-0.005	-0.005	-0.014	-0.005	-0.005	-0.014	-0.011	-0.005	-0.014	0.686	-0.011	-0.005	-0.005
Minneapolis-St. Paul-Bloomington, MN-WI	-0.010	-0.013	-0.024	-0.010	-0.013	-0.024	-0.019	-0.013	-0.024	-0.024	0.640	-0.013	-0.012
Omaha-Council Bluffs, NE-IA	-0.002	-0.014	-0.003	-0.002	-0.014	-0.003	-0.002	-0.014	-0.003	-0.003	-0.003	0.678	-0.003
St. Louis, MO-IL	-0.020	-0.008	-0.006	-0.020	-0.008	-0.006	-0.017	-0.008	-0.006	-0.006	-0.008	-0.008	0.646

Note: All elasticities above represent the percentage change in the share of PCPs in the row location that would result from a 1% increase in salaries at the column location. Also note that Illinois and Wisconsin are in the same Census Division, but Iowa is not.

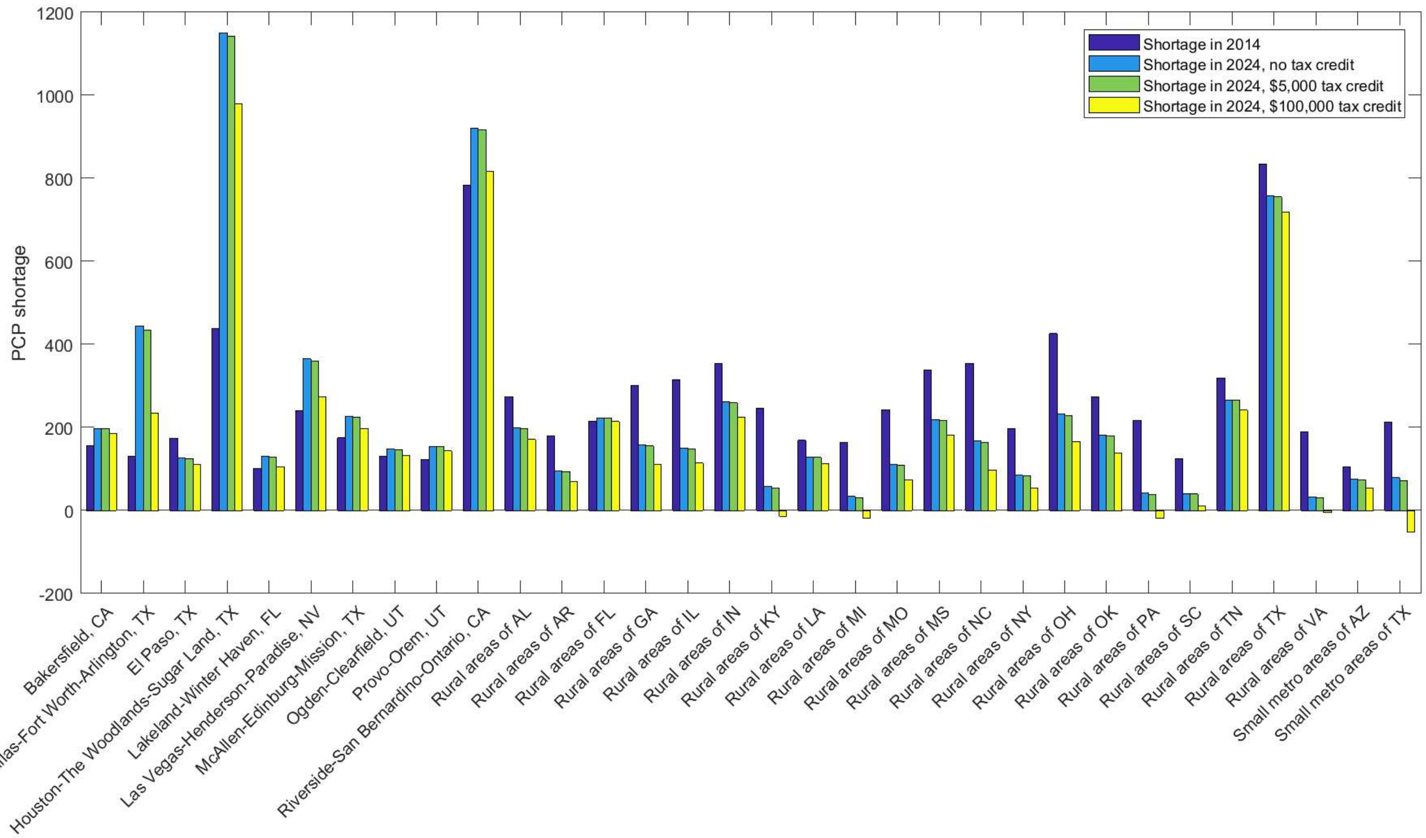

Figure 7: Effects of tax credits in areas with a shortage of at least 100 PCPs

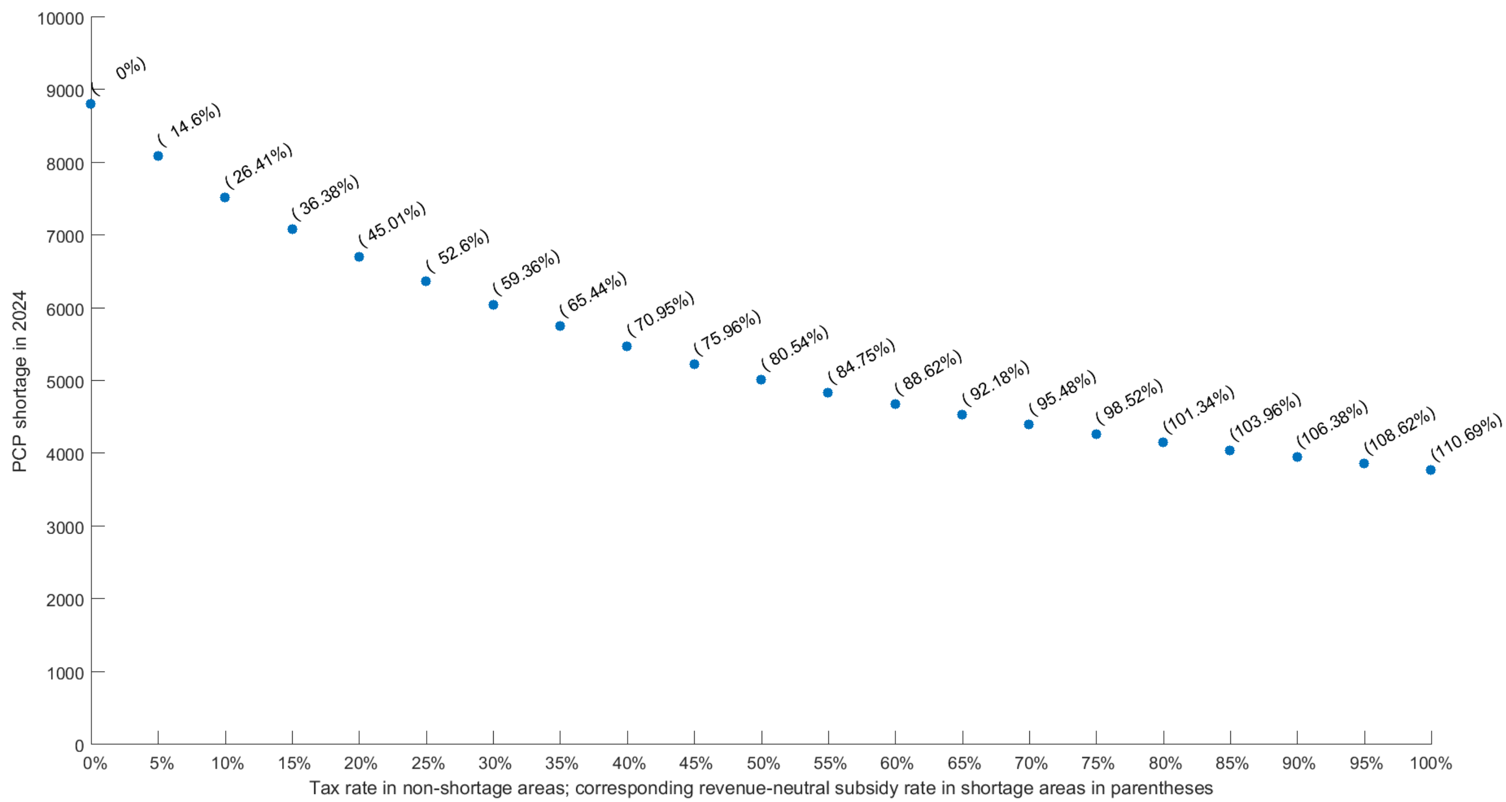

Figure 8: Overall PCP shortage as a function of tax rates and corresponding revenue-neutral subsidy rates