論　　文

Effects of Local Physician Concentrations on Physician Labor Supply and Career Trajectories: Evidence from Longitudinal Microdata in Japan*

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Abstract

Incumbent physicians may choose to increase or decrease their labor supply when the concentration of local physicians increases depending on the relative magnitude of income and substitution effects. We study how physicians respond to competition under Japan's mixed FFS and all-payer rate system. Our study suggests that physicians prefer to decrease their labor supply by reducing the number of specialties they practice, limiting career progression, or choosing a job responsibility that does not involve the practice of medicine when local concentrations of physicians increase. Such effects tend to be pronounced among internal medicine physicians residing in rural areas.

JEL Classification Codes: J01, J22, I11

Keywords: Physician labor supply, income effects, substitution effects, spatial competition, machine learning

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「地域における医師密度が医師の診療に対する労働供給とキャリアに及ぼす影響に関する実証分析」

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＜要旨＞

「地域における医師密度が現職医師の労働供給に対して与える影響は、所得効果と代替効果の相対的な大きさに依存する可能性がある。本研究では、日本の国民皆保険制度における診療報酬制度の下、医師が地域内での医師密度を代理変数とする「競争」に対してどのように反応するかについて実証的な検証を行った。結果、地域での医師密度により、専門分野の標ぼう数を減らしたり、キャリアを変更したり、あるいは、現場での診療から離れたりといった選択をして、労働力供給を抑制する傾向にあることが示唆された。こうした傾向は、とりわけ、地方での診療を行う内科医に顕著な傾向であった。」

JEL Classification Codes: J01, J22, I11

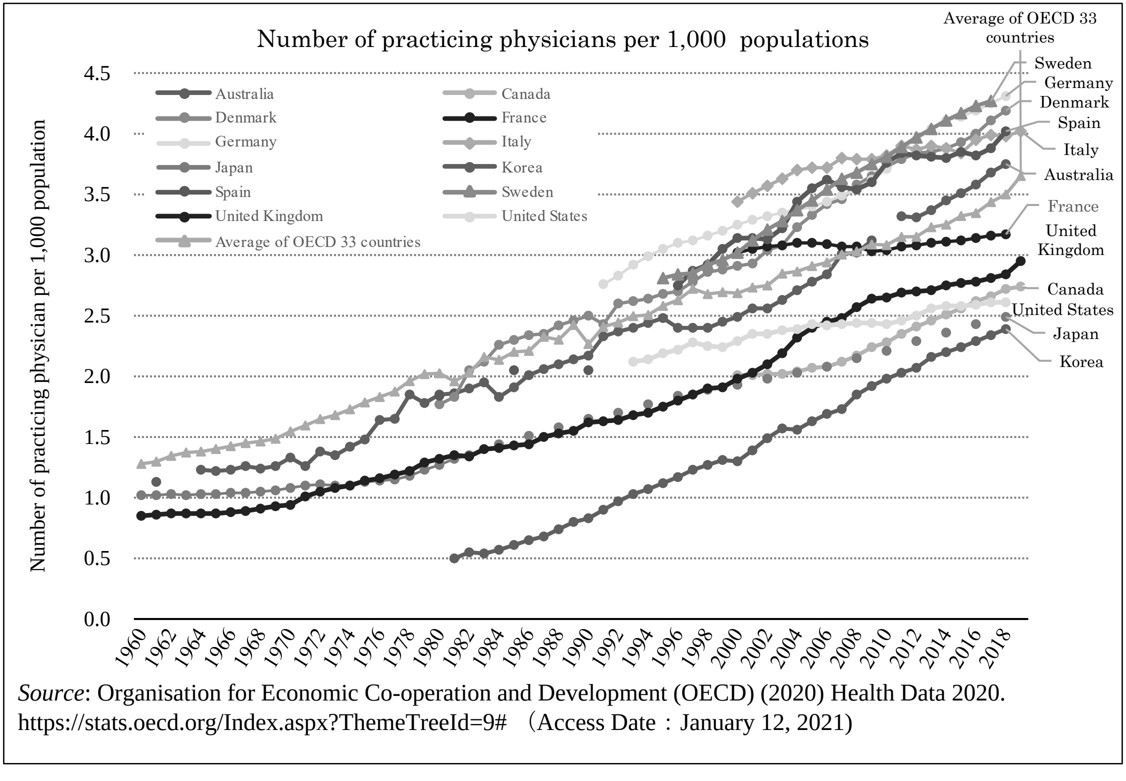
Keywords: 医師の労働供給、所得効果、代替効果、空間的競争、機械学習

1. Introduction

The number of physicians per population in Organization for Economic Co-operation and Development (OECD) countries has gradually been increasing over the past half century (OECD, 2020). An increase in the demand for health care may be one of the most significant drivers behind the rise in the number of physicians in these countries. Rapid population aging due to falling fertility, childbearing, and mortality rates are driven by a global shift in the burden of disease from communicable to non-communicable diseases. These structural changes consequently expand the demand for health care (Stuckler, 2008; Harper, 2014).

In Japan, the number of practicing physicians per 1,000 populations has been increasing from 1.02 in 1960 to 2.49 in 2018 (Figure 1). Compared to other OECD countries, however, the density of practicing physicians in Japan is relatively low. According to the latest available statistics, Japan is fifth from the bottom among 33 OECD countries. Austria has the highest number of doctors at 5.24 per 1,000 population, followed by Norway at 4.93, Lithuania at 4.6, Switzerland at 4.34, and Germany at 4.31. The average number of practicing physicians among the 33 OECD countries is 3.65.

Figure 1: Number of practicing physicians per 1,000 populations



Source: Organisation for Economic Co-operation and Development (OECD) (2020) Health Data 2020. https://stats.oecd.org/Index.aspx?ThemeTreeId=9# （Access Date：January 12, 2021)

A more serious problem in Japan is an uneven regional distribution of hospital beds and physicians (Appendix 1 Figures A1-A2). While regional salaries appear to adjust to supply-side factors, as observed by the weak negative association between physician density and average salaries, supply-side responses to changes in salaries appear to be inadequate (Appendix 1 Figures A2 and A3). To combat these regional inequalities in healthcare supply, the "New Comprehensive Measures for Securing Doctors *(Shin Ishi Kakuho Sogo Taisaku* in Japanese)" and the "Emergency measures to secure physicians (*Kinkyu Ishi Kakuho Taisaku* in Japanese)" were implemented in 2006 and 2007, respectively. The Subcommittee on the Supply and Demand of Medical Personnel, established by the Ministry of Health, Labor and Welfare (MHLW), highlighted the importance of an evidence-based approach to efficiently alleviate regional inequalities in access to care. For instance, supply-side policies should predict and accommodate changes in the local demand for health care using metrics such as population aging or in- and out-migration of patients across regions. Forecasts of the number of physicians required are to be tailored not only at the regional level, but also by physician specialty.[1] Despite efforts by the Japanese government to predict and characterize demand for health care across regions, there has been little attention paid to whether supply-side policies and factors are effective in the first place. There is also a lack of a basic understanding of which factors are most associated with regional variations in physician labor supply.

Therefore, the objective and contribution of our paper is twofold. We begin by characterizing local physician density across municipalities in Japan using machine learning methods – random forests (Breiman, 2001) and the classification and regression tree (CART) (Breiman et al., 1984; Morgan and Sonquist, 1963). These methods give a descriptive understanding of which area-level factors are most strongly correlated with local physician density in high-dimensional settings. It also gives a descriptive picture of the area-level amenities (and hence, opportunity costs) that physicians face across physician densities, which helps us interpret our second and main objective. Our second objective is to examine how incumbent physicians' labor supply and career trajectories respond to changes in the local concentration of physicians using an individual-level panel of the universe of physicians in Japan. This second objective intends to reveal the latent preferences of Japanese physicians' labor supply provision when the concentration of physicians change. A deeper understanding of physicians' response to it will also assist policy makers design policy in the healthcare industry. This may involve subsidies or regulations for incumbent physicians when aggregate supply-side policies are being implemented.

An increase in physician density may increase or decrease incumbent physicians' labor supply depending on the relative magnitude of income and substitution effects. Classical economic theory predicts that competition decreases incumbent physicians' income, which would cause a physician to induce more services at the intensive margin, especially for high-income jobs. However, physicians'

[1] Subcommittee on the Supply and Demand of Medical Personnel, the MHLW. (2019). "Fourth Interim Report (in Japanese)". chrome-extension://oemmndcbldboiebfnladdacbdfmadadm/https://www.mhlw.go.jp/content/10801000/000491569.pdf (Access Date: Jan 13, 2021)

propensity to induce demand are constrained by a professional code of ethics and altruistic preferences (Allard, Jelovac, & Leger, 2011; Chone & Ma, 2011; Mcguire, 2000; Chalkey & Malcomson, 1998; Ellis & McGuire, 1986, 1990; Farley, 1986; Woodward and Warren-Boulton, 1984; Evans, 1974; Newhouse, 1970). Experimental evidence supports the nuance and heterogeneity predicted by these models of utility-maximizing physicians (Brosig-Koch et al., 2017, 2016; Hennig-Schmidt and Wiesen, 2014; Godager and Wiesen, 2013; Hennig-Schmidt et al., 2011). Most observational studies find that physicians tend to induce more demand at the intensive margins under competitive environments when income effects are sufficiently large, especially under fee-for-service payment systems (Chone, Coudin, and Pla, 2019; Dunn and Shapiro, 2018), while a few observational studies find suggestive evidence of physician altruism and downward-sloping reaction functions (Sloan, 1975).

Our study primarily makes two major contributions to the literature. First, we examine physician labor supply responses at the intensive and extensive margins across his/her occupations within health care industry (i.e., practicing medicine, educating or training other physicians, or administrative position of clinic/hospital) when physician density increases, using physician-level panel data. This enables us to control for all sources of physician-level time invariant characteristics. Second, we examine not only labor supply provision, but also physicians' career trajectories, which is an important labor supply outcome that has been understudied in the literature.

Two major findings can be drawn from our study. First, we find that physicians tend to reside in municipalities with a high concentration of neighborhood amenities. Namely, we find that municipality characteristics which reflect quality of life (QOL) such as the density of high schools, sales per business, and the quantity of restaurants and supermarkets per capita accurately predict physician density out-of-sample. Second, we find that physicians tend to either reduce their labor supply or select into less competitive or more fee-regulated environments when physician concentrations increase, with magnitudes varying by age, gender, urban/rural residence, and specialty. This decrease in labor supply or changes in career trajectory coincide with a decrease in physician wages.

The remainder of the paper is organized as follows. Section 2 describes the data and measurement. Section 3 outlines our econometric specification. In Section 4, we present our results, and in Section 5 we conclude.

2. Data and Measurement

We utilize data primarily from the Survey of Medical Institutions (SMI-Static) and the Survey of Physicians, Dentists, and Pharmacists (SPDP). SMI-Static is a tri-annual facility-level panel of the universe of hospitals and clinics in Japan. The survey includes a comprehensive set of information, including the total number of physicians and patients within each facility, by department. The SPDP is bi-annual individual-level panel of all registered medical practitioners in Japan and contains information such as the medical departments a physician is engaged in, occupation, employment status, type of work place, age, sex, and municipality of residence.

Our main explanatory variable of interest is the one-year lag of physician density within a physicians' municipality of residence, defined as the lag of the total number of physicians working in either hospitals or clinics divided by the lag of the total population in a municipality. To obtain the one-year lag of physician density, we merged the 2005 wave of the SMI-Static with the 2006 wave of the SPDP, and the 2011 wave of the SMI-Static with the 2012 wave of the SPDP. Hence, our study utilizes two years of data – 2006 and 2012.

Our first group of outcomes measure physician labor supply, captured using the following variables: (1) whether a physician is practicing medicine as their main job, (2) whether a physician is educating or training other physicians as their main occupation, (3) the log number of specialties a physician is engaged in, and (4) physicians' labor force participation status. Physicians' labor force participation status is further decomposed into whether a physician was employed at a clinic or whether a physician was employed at a hospital.[2]

Our second group of outcomes measure physicians' career trajectories and entrepreneurship. To measure this, we use (1) whether a physician chooses to work in a clinic or hospital, (2) whether a physician establishes/becomes a representative of a clinic, and (3) whether a physician establishes/becomes a representative of a hospital.

Our supplementary group of outcomes measure physician hourly wages (contract and total), using data from the Basic Survey on Wage Structure (BSWS, 2005-2015, odd years only). To obtain the one-year lag of physician density for wage regressions, we merged aggregated data from the 2004 wave of the SPDP with physician-level data from the 2005 BSWS and so on.

We also test for heterogeneous effects across demographic characteristics: physicians younger than 40, physicians aged 40-59, and physicians over 60, by gender. We consider physicians aged 40-59 as those in their prime. The opportunity cost of labor is likely different across age and gender, so we believe this to be an important source of heterogeneity. When feasible, we further study heterogeneous effects by whether a physician resides in a rural or urban municipality, and whether a physician is in internal medicine or surgery, also disaggregated by rural and urban municipality of residence.

[2] An alternative measure of retirement was defined using physicians' "permanent" attrition from the SPDP. However, this measure of retirement is problematic because it is nearly impossible to determine whether a physician has permanently left the survey. This way of defining unemployment/retirement hence contains a large degree of measurement error. It is also difficult to ascertain whether this is classical measurement error (i.e., not correlated with physician density). We thus take a conservative approach and use a question in the survey asking whether a physician is unemployed to measure employment.

Table 1. Description of variables

Variable	Variable Description
Variables employed in main analysis	
Practicing medicine	1 if practicing medicine as main job, 0 otherwise
Educating	1 if education / training young doctors is main job, 0 otherwise
Specialties	No. of medical departments a doctor is engaged in
Retired	1 if retired or unemployed, 0 if working
Retired from hospital	1 if retired or unemployed, 0 if working in a hospital
Retired from clinic	1 if retired or unemployed, 0 if working in a clinic
Works in clinic	1 if working in a clinic, 0 if working in a hospital
Ownership of clinic	1 if established own clinic or became its representative, 0 otherwise
Ownership of hospital	1 if established own hospital or became its representative, 0 otherwise
Male	1 if physician is male, 0 if physician is female
Age	Physician age in years
Urban residence	1 if physician is residing in a municipality with a population size >= 200000, 0 otherwise
Internal medicine	1 if physician is practicing internal medicine, 0 otherwise
Surgery	1 if physician is practicing surgery, 0 otherwise
Other departments	1 if physician is practicing in other medical specialties, 0 otherwise
Lagged physician density	(No. of physicians in a municipality at t-1 / population size of municipality at t-1) *1000
Waves	No. of survey waves observed
Variables employed in wage analysis	
Hourly total wages	(Monthly contractual cash earnings, including overtime and other benefits)/Total scheduled hours worked in a month, including overtime
Hourly contract wages	(Monthly contractual cash earnings, excluding overtime and other benefits)/Scheduled hours worked in a month
Variables employed to characterize physician density in 2010	
High	No. of high schools per 100km of residential land, 2010
Middle	No. of middle schools per 100km of residential land, 2010
Primary	No. of primary schools per 100km of residential land, 2010
Under 15	Proportion of population under the age of 15, 2010
Over 65	Proportion of population over the age of 65, 2010
Nuclear family	Proportion of households that are nuclear families, 2010
Seniors	Proportion of households that are senior citizen couples, 2010
Single seniors	Proportion of households that are single senior citizens, 2010
Business sales	Sales per business (wholesale + retail), 2006
Community centers	No. of community centers per 1,000,000 population, 2008
Restaurants	No. of eateries per 1000 population, 2009
Stores	No. of department stores and supermarkets per 100,000 population, 2009
Senior care centers	No. of senior care centers per population over 65, 2008
Car accidents	No. of car accidents per 100,000 population, 2005
Births	No. of births per 1000 population, 2010
Mortality	No. of deaths per 1000 population, 2010
Pop density	Population per hectare of residential land, 2010

Source: e-Stat at https://www.e-stat.go.jp/en (Access Date: Feb 19, 2021)

For our descriptive analysis of physician density, we collected a large number of municipality variables from e-Stat, which is a portal Site of official statistics of Japanese government statistics.[3] A description of all physician- and municipality-level variables are described in Table 1.

[3] Please see e-Stat at https://www.e-stat.go.jp/en (Access Date: Feb 19, 2021).

3. Empirical Specification

To begin with, we utilize machine learning methods for characterizing local physician density across municipalities, which is shown in Appendix 2.

Then, our main empirical specification is given as follows:

$$y_{i,j,t} = \beta_0 + \beta_1 \log\left(Density_{j,t-1}\right) + X'_{i,j,t}\Omega + \xi_{\mathrm{i}} + \tau_t + \epsilon_{i,j,t} \quad (1)$$

where $y_{i,j,t}$ is an outcome for physician i in municipality j at time t. $log\ (Density_{j,t-1})$ is the log of local physician density in municipality j at time $t-1$. ξ_{i} are individual (physician)-specific fixed effects, and τ_t are year fixed effects. Physician fixed effects control for all physician-specific time invariant endogeneity, such as selection into high or low productive occupations. Year fixed effects control for all year-specific but unit invariant factors, such as national macroeconomic conditions or mortality. $X'_{i,j,t}$ is a vector of controls. In all specifications, this includes year of birth-by year fixed effects, which controls for effects of aging on labor supply decisions. In all specifications excluding subgroup analyses by urban/rural residence, we include an indicator for whether a physician resides in an urban or rural municipality. This controls for whether a physician migrates when the local density of physicians changes. In specifications for occupational choice and entrepreneurship/promotion, we include an indicator for whether a physician is associated with internal medicine, surgery, or other departments. Finally, $\epsilon_{i,j,t}$ is the time-varying physician-specific idiosyncratic error.

4. Results

4.1 Descriptive statistics

The mean and number of observations of the variables used in our main analysis are presented in Table 2. The total number of observations employed in our main analysis, with 2006 and 2012 combined, is 581,195. Male physicians are more likely to engage in education/training, be involved in more medical departments, and own or establish a medical facility compared to that of female physicians. Registered male physicians also tend to be older and retire later than female physicians. A detailed breakdown of mean values by age and gender are presented in Appendix 1 Figures A4-A8. The total number of observations employed in our wage regressions is 17,648, with male physicians exhibiting a higher mean wage than female physicians.

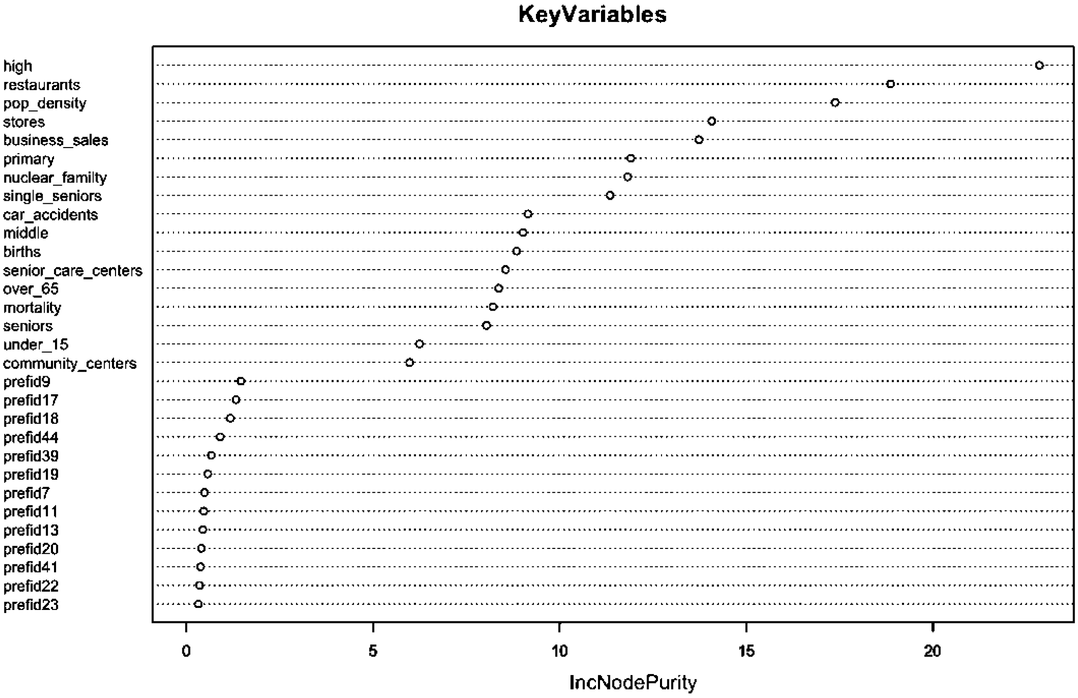
Table 2: Descriptive statistics

	All		Men		Women	
	Obs	Mean	Obs	Mean	Obs	Mean
Variables employed in main analysis						
Practicing medicine	576209	0.921	470040	0.920	106169	0.927
Educating	581193	0.085	473624	0.090	107569	0.062
Specialties	581195	1.351	473625	1.413	107570	1.077
Retired	581193	0.007	473624	0.006	107569	0.011
Retired from hospital	315105	0.014	259788	0.012	55317	0.022
Retired from clinic	200021	0.021	166468	0.018	33553	0.037
Works in Clinic	506598	0.386	420180	0.389	86418	0.374
Ownership of clinic	581193	0.247	473624	0.272	107569	0.134
Ownership of hospital	581193	0.019	473624	0.022	107569	0.004
Age	581195	48.515	473625	49.908	107570	42.382
Urban residence	581195	0.597	473625	0.587	107570	0.644
Internal medicine	581195	0.549	473625	0.553	107570	0.532
Surgery	581195	0.355	473625	0.377	107570	0.261
Other departments	581195	0.149	473625	0.146	107570	0.162
Lagged physician density	581195	268.880	473625	259.713	107570	309.240
Waves	581195	2	473625	2	107570	2
Variables employed in wage analysis						
Hourly contract wage (thousands JPY)	17483	72.339	13318	75.693	4165	61.615
Total hourly wage (thousands JPY)	17483	73.758	13318	77.177	4165	62.825
Waves	17648	7	13434	7	4214	7

Source: All values are estimated by the authors, based on data from the SPDP, SMI-Static, BSWS, and population census.

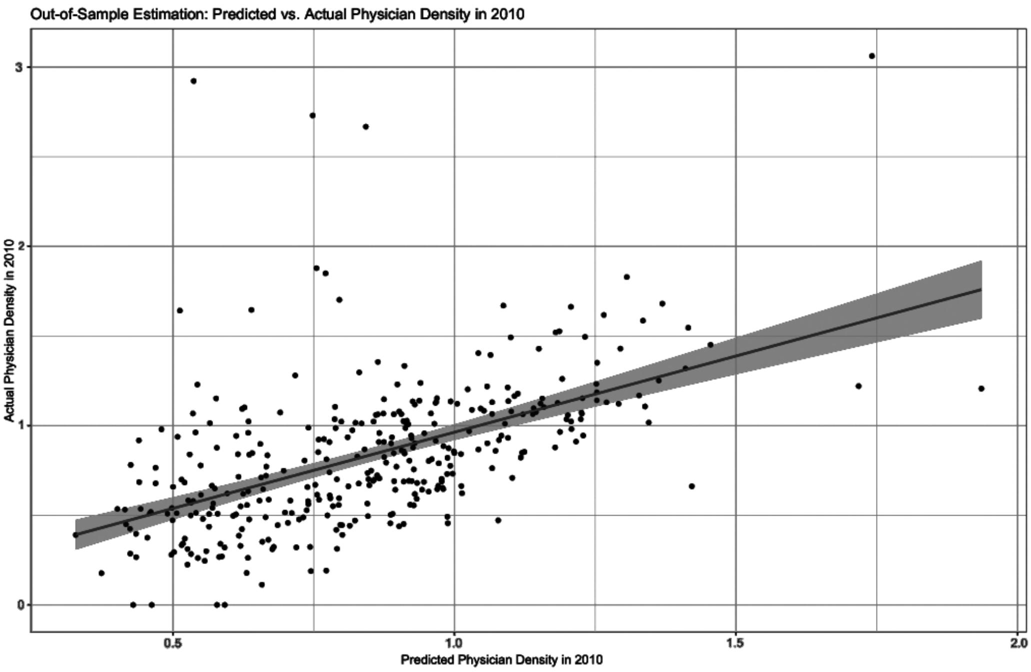
To characterize municipalities with a high density of physicians as of 2010, we utilize nonparametric methods – random forest and classification and regression trees – on 17 municipality level factors and 47 prefecture indicators, all extracted from e-Stat (see https://www.e-stat.go.jp/regional-statistics/ssdsview). Such nonparametric methods are beneficial when describing a variable of interest, especially in high dimensional settings. In Figure 2, random forest finds that a high density of high schools is the best predictor, followed by restaurants, economic activity (business sales), and the density of residential housing per kilometer. Population density and the proportion of households that are single senior citizens are also important indicators. The pseudo out-of-sample predictive accuracy of random forest is measured using the root mean squared error (RMSE). The RMSE on a randomly sampled hold-out sample of 20% of the observations is 0.1 (Figure 3), which suggests a very high accuracy. Employing CART, in Figure 4, we find again that municipalities with a high concentration of high schools, business sales, and availability of restaurants are likely to have the highest concentration of physicians.

Figure 2. Variable importance plot from random forest.



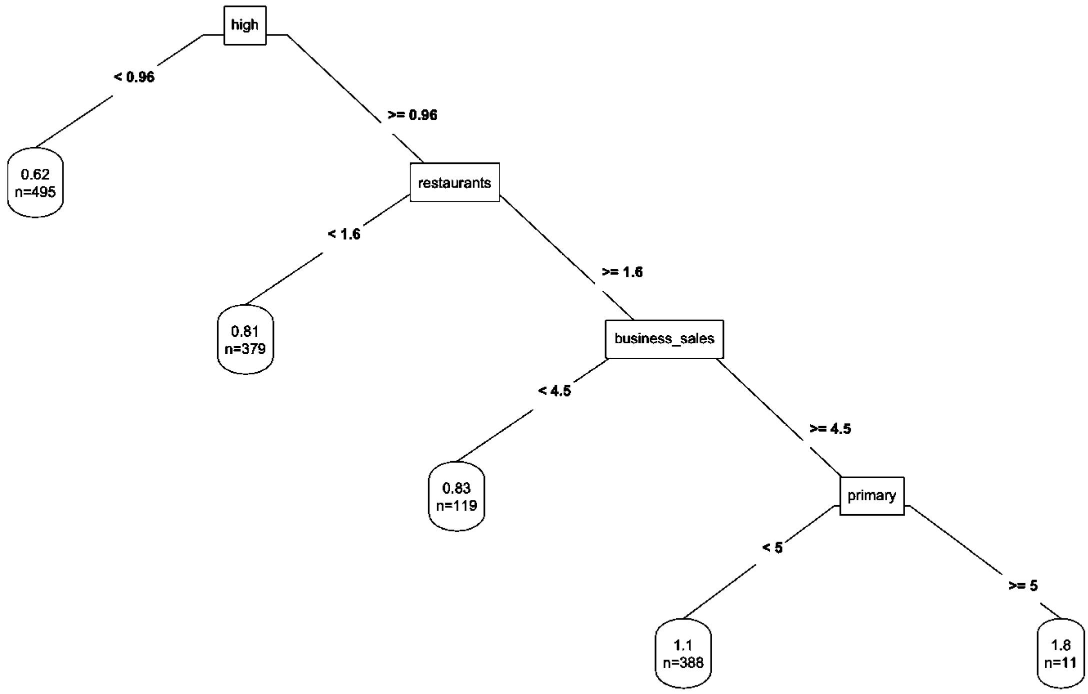
Notes: See Table 1 for a description of variables. “pref#” indicates prefecture codes.

Figure 3. Accuracy of the random forest on the test set (20% of sample).



Notes: The root mean squared error (RMSE) is 0.1.

Figure 4. A regression tree



Notes: All variables are in logarithmic form. See Table 1 for a description of variables. Values at the top of each terminal node denote physician density at an optimal split for a given value of a selected covariate x_k, while vales at the bottom of each node denote the number of observations in a given terminal node.

4.2 Baseline results

We first examine the effect of physician density on physicians' provision of medical services, regardless of place of residence or specialty in Table 3. We find that an increase in physician density significantly decreases physicians' probability of practicing medicine as a main occupation. A 10% increase in physician density leads to a decrease in the likelihood that physicians practice medicine as their main occupation by a magnitude ranging from -0.1 % points ($p<0.1$) to -0.56 % points ($p<0.01$), depending on physicians' age and gender. The effects are particularly pronounced among physicians younger than 40 for both men and women, but significant effects ($p<0.01$) are also observed for prime-aged men.

Next, we examine how physician density affects physicians' propensity to partake in education or training of other physicians as an occupation in the second panel of Table 3. A 10% increase in local physician density increases the probability of training as a main occupation by a magnitude ranging from 0.09 % points ($p<0.1$) to 0.94 % points ($p<0.01$), depending on physicians' age and gender. The effects are particularly pronounced among male physicians in their prime age, but significant effects ($p<0.01$) are also observed among prime-aged women.

Third, we examine how physician density affects the number of specialties/departments a physician is involved in Panel 3 of Table 3, which we use as a measure of labor supply at the intensive margin. Depending on the age and sex groups, we find an elasticity ranging from -0.019 to -0.035, with the effects pronounced particularly among younger male physicians.

Table 3. Effects on provision of medical services

	Male			Female		
	Age < 40	Age 40-59	Age > 60	Age < 40	Age 40-59	Age > 60
	Practice medicine as main occupation					
$Log(Density_{j,t-1})$	-0.056***	-0.018***	-0.013**	-0.044***	-0.010*	0.010
	(0.002)	(0.002)	(0.006)	(0.003)	(0.005)	(0.017)
Observations	131138	226838	112064	54949	39396	11824
Adjusted R^2	0.067	0.007	0.018	0.042	0.011	0.024
	Education or training as main occupation					
$Log(Density_{j,t-1})$	0.080***	0.094***	0.043***	0.061***	0.033***	0.009*
	(0.003)	(0.003)	(0.004)	(0.004)	(0.005)	(0.005)
Observations	131362	227191	115071	55397	39616	12556
Adjusted R2	0.122	0.060	0.054	0.063	0.013	0.017
	Log(1+number of specialties/departments involved in)					
$Log(Density_{j,t-1})$	-0.035***	-0.024***	0.001	-0.019***	-0.007	-0.006
	(0.003)	(0.003)	(0.007)	(0.004)	(0.007)	(0.018)
Observations	131362	227191	115072	55398	39616	12556
Adjusted R2	0.181	0.063	0.125	0.234	0.021	0.075

Notes: All regressions include physician fixed effects, year fixed effects, birth cohort-by-year fixed effects, an urban residency indicator, and indicators for physicians' affiliation with departments of internal medicine, surgery, and other. Data are from the SPDP, SMI Static, and population census. Robust standard errors clustered at the physician level in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

In Table 4, we examine how physician density affects the propensity of unemployment/retirement. We find mixed results for this outcome when ignoring area level heterogeneity — a 10% increase in the density of physicians increases the probability of retirement/unemployment for older men working in clinics by 0.1 % points (p<0.05), but decreases unemployment for female physicians young than 40 by -0.02 % points (p<0.05). A more detailed breakdown of these results are presented in the next section.

Table 4. Effects on unemployment/retirement

	Male			Female		
	Age < 40	Age 40-59	Age > 60	Age < 40	Age 40-59	Age > 60
	Unemployed/retired					
$Log(Density_{j,t-1})$	-0.000	-0.000	0.003*	-0.002**	-0.003*	0.004
	(0.000)	(0.000)	(0.002)	(0.001)	(0.001)	(0.010)
Observations	131362	227191	115071	55397	39616	12556
Adjusted R2	0.000	0.000	0.042	0.001	0.001	0.079
	Unemployed/retired from hospital					
$Log(Density_{j,t-1})$	(1)	(2)	(3)	(4)	(5)	(6)
	0.000	-0.001*	0.002	-0.001	0.001	0.015
	(0.000)	(0.000)	(0.003)	(0.002)	(0.002)	(0.041)
Observations	91930	130521	37337	34412	17815	3090
Adjusted R2	0.000	0.000	0.016	0.001	0.003	0.058
	Unemployed/retired from clinic					
$Log(Density_{j,t-1})$	0.003	0.001	0.011**	0.016	-0.003	0.011
	(0.002)	(0.002)	(0.005)	(0.015)	(0.004)	(0.016)
Observations	7874	85926	72668	5377	18737	9439
Adjusted R2	0.033	0.003	0.054	0.040	0.001	0.092

Notes: All regressions include physician fixed effects, year fixed effects, birth cohort-by-year fixed effects, and an urban residency indicator. Data are from the SPDP, SMI Static, and population census. Robust standard errors clustered at the physician level in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

In Table 5, we examine how physician density affects physicians' career progression and career trajectories. We find that an increase in physician density by 10% decreases the likelihood that a physician will move to a clinic by a magnitude ranging from -0.34 % points to -0.55 % points (p<0.01), depending on physician age and gender. The effects of this career transition are pronounced among younger physicians, especially younger male physicians. A large and significant magnitude (p<0.01) is still observed among primed-aged physicians and older men.

Table 5. Effects on career progression

	Male			Female		
	Age < 40	Age 40-59	Age > 60	Age < 40	Age 40-59	Age > 60
	Choice of clinic over hospital					
$Log(Density_{j,t-1})$	-0.055***	-0.048***	-0.038***	-0.045***	-0.034***	-0.038
	(0.003)	(0.003)	(0.008)	(0.006)	(0.010)	(0.025)
Observations	99644	216161	104375	39081	36216	11121
Adjusted R^2	0.082	0.066	0.014	0.099	0.038	0.015
	Establish/representative of clinic					
$Log(Density_{j,t-1})$	-0.012***	-0.021***	-0.005	-0.005***	-0.014**	-0.008
	(0.001)	(0.002)	(0.005)	(0.001)	(0.006)	(0.016)
Observations	131362	227191	115071	55397	39616	12556
Adjusted R2	0.039	0.068	0.073	0.014	0.033	0.037
	Establish/representative of hospital					
$Log(Density_{j,t-1})$	-0.001***	-0.000	-0.003	-0.000	0.001	0.004
	(0.000)	(0.001)	(0.002)	(0.000)	(0.001)	(0.006)
Observations	131362	227191	115071	55397	39616	12556
Adjusted R2	0.002	0.003	0.004	0.001	0.002	0.001

Notes: All regressions include physician fixed effects, year fixed effects, birth cohort-by-year fixed effects, an urban residency indicator, and indicators for physicians' affiliation with departments of internal medicine, surgery, and other. Data are from the SPDP, SMI Static, and population census. Robust standard errors clustered at the physician level in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

We then examine the effect of physician concentrations on the likelihood of establishing a clinic or becoming its representative. We find that a 10% increase in physician density decreases the probability that a physician will establish their own clinic / become its representative by a magnitude ranging from -0.05 % points to -0.21 % points, depending on the age and gender of physician. The effect is most pronounced among prime-aged male physicians, although we also observe large magnitudes among prime-aged female physicians and young male physicians. Next, we study the likelihood of establishing/becoming a representative of a hospital. The probability of establishing a new hospital is very low, so this measure likely represents the probability of becoming a representative of a hospital. We find the young male physicians are 0.001 % points ($p<0.01$) less likely to become representatives in hospitals when physician competition increases by 10%.

4.3 Geographical heterogeneity by area of residence

In this section, we study how the effects of physician density on the provision of physician labor supply changes depending on whether a physician resides in an urban or rural municipality, with the former defined as having a population greater than or equal to 200,000. According to Table 6, a 10% increase in physician density deceases the probability that a physician practices medicine as their main occupation by a magnitude ranging from -0.16 % points ($p<0.01$) to -0.62 % points ($p<0.01$), depending on age, sex, and also physicians' residence. Compared to the results in Table 3, decomposing our analysis by plan of residence was masking important heterogeneity—the magnitude is slightly greater among physicians residing in urban municipalities.

Table 6. Practice medicine as main occupation, urban/rural

	Male			Female		
	Age < 40	Age 40-59	Age > 60	Age < 40	Age 40-59	Age > 60
			Urban			
$Log(Density_{j,t-1})$	-0.062***	-0.017***	-0.025*	-0.038***	-0.011	0.017
	(0.005)	(0.005)	(0.013)	(0.007)	(0.011)	(0.032)
Observations	81584	130890	63241	36112	24758	7378
Adjusted R^2	0.065	0.005	0.017	0.037	0.007	0.024
			Rural			
$Log(Density_{j,t-1})$	-0.055***	-0.016***	-0.001	-0.038***	-0.003	0.025
	(0.004)	(0.003)	(0.008)	(0.007)	(0.010)	(0.029)
Observations	49554	95948	48823	18837	14638	4446
Adjusted R2	0.063	0.005	0.017	0.032	0.011	0.012

Notes: All regressions include physician fixed effects, year fixed effects, birth cohort-by-year fixed effects, and indicators for physicians' affiliation with departments of internal medicine, surgery, and other. Data are from the SPDP, SMI Static, and population census. Robust standard errors clustered at the physician level in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7 decomposes the results on education/training from Table 3 by urban and rural residence. We find that a 10% increase in physician density increases the probability of training by a magnitude ranging from 0.36 % points (p<0.01) to 0.88 % points (p<0.01), and the effect is pronounced among physicians working in rural areas. Although magnitudes are slightly higher among younger physicians residing in rural municipalities, coefficients are equally statistically significant regardless of place of residence.

Table 7. Educating/training other physicians as main occupation, urban/rural

	Male			Female		
	Age < 40	Age 40-59	Age > 60	Age < 40	Age 40-59	Age > 60
			Urban			
$Log(Density_{j,t-1})$	0.055***	0.084***	0.037***	0.040***	0.042***	-0.002
	(0.005)	(0.006)	(0.009)	(0.007)	(0.011)	(0.014)
Observations	81730	131120	65160	36443	24917	7875
Adjusted R^2	0.128	0.025	0.030	0.056	0.009	0.015
			Rural			
$Log(Density_{j,t-1})$	0.088***	0.088***	0.036***	0.066***	0.046***	0.006
	(0.005)	(0.004)	(0.005)	(0.007)	(0.009)	(0.006)
Observations	49632	96071	49911	18954	14699	4681
Adjusted R^2	0.154	0.085	0.056	0.080	0.034	0.013

Notes: All regressions include physician fixed effects, year fixed effects, birth cohort-by-year fixed effects, and indicators for physicians' affiliation with departments of internal medicine, surgery, and other. Data are from the SPDP, SMI Static, and population census. Robust standard errors clustered at the physician level in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8 decomposes the results on the log (1+number of specialties) from Table 3 by physicians' area of residence. We find that a 10% increase in physician density decreases the log number of specialties by a magnitude ranging from -0.23 % points (p<0.1) to -0.61 % points (p<0.01). The results reveal that the effects of physician density on labor supply at the intensive margin is concentrated among physicians residing in rural areas. Not only are the magnitudes larger among physicians in rural areas, but the coefficients on density among most demographic groups are more statistically significant if they reside in rural municipalities. This may be interpreted as suggestive evidence that physicians were supply constrained in areas with a low physician density.

Table 8. Log (1+number of specialties), urban/rural

	Male			Female		
	Age < 40	Age 40-59	Age > 60	Age < 40	Age 40-59	Age > 60
			Urban			
$Log(Density_{j,t-1})$	-0.013**	-0.014**	-0.023*	-0.008	0.006	0.032
	(0.005)	(0.006)	(0.013)	(0.007)	(0.012)	(0.039)
Observations	81730	131120	65161	36444	24917	7875
Adjusted R^2	0.180	0.074	0.128	0.245	0.021	0.075
			Rural			
$Log(Density_{j,t-1})$	-0.054***	-0.025***	0.007	-0.021***	-0.016	-0.061***
	(0.005)	(0.005)	(0.010)	(0.008)	(0.012)	(0.023)
Observations	49632	96071	49911	18954	14699	4681
Adjusted R^2	0.175	0.077	0.138	0.213	0.034	0.096

Notes: All regressions include physician fixed effects, year fixed effects, birth cohort-by-year fixed effects, and indicators for affiliation with departments of internal medicine, surgery, and other. Data are from the SPDP, SMI Static, and population census. Robust standard errors clustered at the physician level in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 9 decomposes the results on the probability of being unemployed/retired from Table 4 by physicians' area of residence. We find that whether a physician resides in an urban or rural municipality is a crucial source of heterogeneity for labor supply responses at the extensive margin and that the results from Table 4 were masking this important source of heterogeneity. For physicians residing in urban municipalities, we find that physician density decreases the likelihood of unemployment/retirement (i.e., increases labor supply at the extensive margin), while for physicians residing in rural areas, physician density increases the likelihood of unemployment/retirement (i.e., decreases labor supply at the extensive margin). This heterogeneity is pronounced among older female physicians working in clinics: when physician concentration increases by 10%, female physicians over the age of 60 decrease their likelihood of unemployment/retirement by -0.52 % points ($p<0.05$) if they reside in urban neighborhoods, while the female physicians in rural neighborhoods increase their probability of retirement by 0.32 % points ($p<0.05$). In Section 4.4, we further decompose these results and examine whether these labor supply responses vary depending on physicians' medical specialty.

Table 9. Unemployment/retirement, urban/rural

	Male			Female		
	Age < 40	Age 40-59	Age > 60	Age < 40	Age 40-59	Age > 60
	Unemployed/retirement from all facilities					
	Urban					
$Log(Density_{i,t-1})$	-0.001*	-0.001	0.004	-0.004**	-0.003	-0.042*
	(0.001)	(0.000)	(0.006)	(0.002)	(0.003)	(0.022)
Observations	81730	131120	65160	36443	24917	7875
Adjusted R^2	0.001	0.000	0.042	0.002	0.001	0.071
	Rural					
$Log(Density_{i,t-1})$	-0.000	-0.000	0.001	-0.001	-0.004	0.017*
	(0.000)	(0.001)	(0.003)	(0.002)	(0.003)	(0.009)
Observations	49632	96071	49911	18954	14699	4681
Adjusted R^2	0.001	0.000	0.042	0.000	0.003	0.097
	(1)	(2)	(3)	(4)	(5)	(6)
	Unemployed/retirement from hospital					
	Urban					
$Log(Density_{i,t-1})$	-0.000	-0.001	-0.003	-0.002	-0.000	0.059
	(0.001)	(0.001)	(0.006)	(0.003)	(0.003)	(0.066)
Observations	54307	75787	20627	22085	11019	1818
Adjusted R^2	0.000	0.001	0.010	0.002	0.002	0.013
	Rural					
$Log(Density_{i,t-1})$	0.000	-0.001	0.002	-0.003	0.000	0.001
	(0.000)	(0.000)	(0.005)	(0.007)	(0.006)	(0.014)
Observations	37623	54734	16710	12327	6796	1272
Adjusted R2	0.001	0.000	0.015	0.000	0.000	0.025
	Unemployed/retirement from clinics					
	Urban					
$Log(Density_{i,t-1})$	0.000	-0.001	0.006	0.037	-0.006	-0.052**
	(.)	(0.001)	(0.011)	(0.026)	(0.009)	(0.025)
Observations	4478	48427	41950	3475	11885	6075
Adjusted R2	.	0.000	0.051	0.022	0.001	0.081
	Rural					
$Log(Density_{i,t-1})$	0.000	0.001	0.004	0.007	-0.006	0.032**
	(.)	(0.003)	(0.005)	(0.009)	(0.005)	(0.016)
Observations	3396	37499	30718	1902	6852	3364
Adjusted R^2	.	0.001	0.054	0.017	0.004	0.120

Notes: All regressions include physician fixed effects, year fixed effects, and birth cohort-by-year fixed effects. Data are from the SPDP, SMI Static, and population census. Robust standard errors clustered at the physician level in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

In Table 10, we decompose the results on career choice/entrepreneurship from Table 5 by whether physicians reside in an urban or rural municipality. We find that the effects on the probability of moving from a hospital to a clinic, and the probability of establishing a clinic are concentrated primarily among physicians residing in rural municipalities. In particular, these effects are concentrated among male physicians who are either young or in their prime age. The effect of a 10% increase in physician density decreases the probability of establishing/becoming a representative of a clinic by a magnitude ranging from -0.05 % points ($p<0.1$) to -0.13 % points ($p<0.05$) for physicians in urban municipalities, while the magnitude ranges from -0.16 % points ($p<0.01$) to -0.6 % points ($p<0.05$) for physicians residing in rural municipalities.

Table 10. Career choice, urban/rural

	Male			Female		
	Age < 40	Age 40-59	Age > 60	Age < 40	Age 40-59	Age > 60
	Moving from a hospital to a clinic					
	Urban					
$Log(Density_{j,t-1})$	-0.014**	-0.015**	-0.003	-0.003	-0.012	0.077*
	(0.006)	(0.007)	(0.014)	(0.011)	(0.019)	(0.044)
Observations	58671	124016	58967	25044	22652	6937
Adjusted R^2	0.069	0.054	0.007	0.085	0.026	0.016
	Rural					
$Log(Density_{j,t-1})$	-0.084***	-0.066***	-0.054***	-0.080***	-0.061***	-0.057
	(0.006)	(0.005)	(0.010)	(0.013)	(0.018)	(0.036)
Observations	40973	92145	45408	14037	13564	4184
Adjusted R2	0.117	0.063	0.016	0.107	0.041	0.032
	Establishing/representative of a clinic					
	Urban					
$Log(Density_{j,t-1})$	-0.007***	-0.013**	-0.010	-0.005*	-0.019	0.042
	(0.002)	(0.005)	(0.011)	(0.003)	(0.014)	(0.032)
Observations	81730	131120	65160	36443	24917	7875
Adjusted R2	0.030	0.062	0.075	0.010	0.031	0.044
	Rural					
$Log(Density_{j,t-1})$	-0.016***	-0.026***	-0.008	-0.003	-0.015	-0.060**
	(0.002)	(0.004)	(0.007)	(0.003)	(0.011)	(0.026)
Observations	49632	96071	49911	18954	14699	4681
Adjusted R^2	0.043	0.059	0.072	0.011	0.026	0.035
	Establishing or becoming representative of a hospital					
	Urban					
$Log(Density_{j,t-1})$	-0.001	-0.002	-0.011**	0.000	0.001	0.004*
	(0.000)	(0.001)	(0.005)	(0.000)	(0.001)	(0.002)
Observations	81730	131120	65160	36443	24917	7875
Adjusted R^2	0.002	0.003	0.004	0.001	0.001	-0.000
	Rural					
$Log(Density_{j,t-1})$	-0.001	0.002	-0.002	0.000	0.001	0.009
	(0.000)	(0.001)	(0.003)	(0.000)	(0.001)	(0.015)
Observations	49632	96071	49911	18954	14699	4681
Adjusted R^2	0.002	0.004	0.005	0.002	0.006	0.007

Notes: All regressions include physician fixed effects, year fixed effects, birth cohort-by-year fixed effects, and indicators for affiliation with departments of internal medicine, surgery, and other. Data are from the SPDP, SMI Static, and population census. Robust standard errors clustered at the physician level in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

4.4 Effects on physicians in internal medicine versus surgery

The effects of physician density on labor supply may depend not only on physicians' place of residence, but also their specialty. The provision of some forms of medicine or treatment are not determined at a patients' discretion, and so the ease of inducing the provision of physician services may vary by medical specialty. For instance, surgical procedures for acute myocardial infarction (AMI) are largely decided by physicians. In this section, we thus decompose our results by two major categories of physician specialty: internal medicine and surgery.

Table 11 shows that physician density decreases the probability of practicing medicine among internal medicine physicians by a large magnitude, with effects being driven by younger physicians from both genders and prime-aged male physicians who reside in rural municipalities. For physicians in surgery (Table 12), prime-aged and older male physicians in surgery who reside in rural municipalities are not sensitive to physician concentrations.

Table 11. Practice medicine as main occupation among internal medicine physicians, urban/rural

	Male			Female		
	Age < 40	Age 40-59	Age > 60	Age < 40	Age 40-59	Age > 60
			Urban			
$Log(Density_{j,t-1})$	-0.071***	-0.015*	-0.013	-0.065***	0.001	-0.010
	(0.011)	(0.008)	(0.016)	(0.016)	(0.016)	(0.050)
Observations	27355	69775	39743	12298	13616	4432
Adjusted R^2	0.045	0.001	0.016	0.037	-0.000	0.020
			Rural			
$Log(Density_{j,t-1})$	-0.046***	-0.016***	-0.003	-0.056***	0.007	0.063*
	(0.006)	(0.004)	(0.011)	(0.012)	(0.006)	(0.033)
Observations	17764	54946	32719	7014	8677	2914
Adjusted R^2	0.058	0.003	0.012	0.049	0.001	0.027

Notes: All regressions include physician fixed effects, year fixed effects, and birth cohort-by-year fixed effects. Data are from the SPDP, SMI Static, and population census. Robust standard errors clustered at the physician level in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 12. Practicing medicine as main occupation among surgery physicians, urban/rural

	Male			Female		
	Age < 40	Age 40-59	Age > 60	Age < 40	Age 40-59	Age > 60
			Urban			
$Log(Density_{j,t-1})$	-0.054***	-0.008	-0.020	-0.087***	-0.006	0.037
	(0.010)	(0.006)	(0.018)	(0.020)	(0.010)	(0.031)
Observations	22358	50239	23905	6804	6351	2282
Adjusted R^2	0.072	0.002	0.020	0.038	-0.000	0.024
			Rural			
$Log(Density_{j,t-1})$	-0.076***	-0.004	0.000	0.003	-0.004	-0.092
	(0.009)	(0.003)	(0.013)	(0.019)	(0.009)	(0.070)
Observations	14278	38229	18910	3758	3682	1207
Adjusted R^2	0.092	0.001	0.018	0.016	0.004	0.047

Notes: All regressions include physician fixed effects, year fixed effects, and birth cohort-by-year fixed effects. Data are from the SPDP, SMI Static, and population census. Robust standard errors clustered at the physician level in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 13 reports the effect of physician density on education/training of other physicians for internal medicine physicians while Table 14 shows the same regressions for physicians in surgery. There do not appear to be any systematic differences between the two physician specialties, although the coefficient for older male physicians is significant for internal medicine physicians in urban areas (10% increase leads to 0.36 % points increase, p<0.01), but is no longer statistically significant for physicians in surgery. Furthermore, while the coefficient for prime-aged female physicians in urban areas is significant (10% increase leads to 0.52 % points increase, p<0.01), the coefficient for this age group is no longer significant for physicians in surgery.

Table 13. Educating/training other physicians as main occupation among internal medicine physicians, urban/rural

	Male			Female		
	Age < 40	Age 40-59	Age > 60	Age < 40	Age 40-59	Age > 60
			Urban			
$Log(Density_{j,t-1})$	0.069***	0.054***	0.036***	0.028	0.052***	0.028
	(0.012)	(0.010)	(0.012)	(0.018)	(0.014)	(0.026)
Observations	27385	69879	40225	12395	13651	4517
Adjusted R^2	0.135	0.015	0.022	0.034	0.016	0.017
			Rural			
$Log(Density_{j,t-1})$	0.105***	0.072***	0.015***	0.096***	0.049***	-0.000
	(0.010)	(0.006)	(0.004)	(0.015)	(0.015)	(0.000)
Observations	17784	54996	33018	7048	8698	2965
Adjusted R^2	0.156	0.069	0.020	0.079	0.034	0.001

Notes: All regressions include physician fixed effects, year fixed effects, and birth cohort-by-year fixed effects. Data are from the SPDP, SMI Static, and population census. Robust standard errors clustered at the physician level in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 14. Educating/training other physicians as main occupation among surgery physicians, urban/rural

	Male			Female		
	Age < 40	Age 40-59	Age > 60	Age < 40	Age 40-59	Age > 60
			Urban			
$Log(Density_{j,t-1})$	0.097***	0.097***	0.008	0.120***	0.006	0.000
	(0.013)	(0.012)	(0.019)	(0.023)	(0.024)	(.)
Observations	22394	50299	24163	6850	6369	2339
Adjusted R^2	0.144	0.033	0.020	0.086	0.007	.
			Rural			
$Log(Density_{j,t-1})$	0.125***	0.088***	0.053***	0.096***	0.045**	0.000
	(0.012)	(0.008)	(0.011)	(0.027)	(0.021)	(.)
Observations	14295	38264	19080	3772	3688	1233
Adjusted R^2	0.180	0.098	0.085	0.109	0.053	.

Notes: All regressions include physician fixed effects, year fixed effects, and birth cohort-by-year fixed effects. Data are from the SPDP, SMI Static, and population census. Robust standard errors clustered at the physician level in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 15 reports the effect of physician density on the log number of specialties internal medicine a physician is involved in, while Table 16 reports the same regressions but on a sample of physicians in surgery. We find systematic differences for female physicians who reside in rural neighborhoods. While the effect of physician density is negative and statistically significant for young and prime-aged female physicians in internal medicine, physicians in surgery of the same demographic group are not responsive to changes in physician concentrations.

Table 15. Log (1+ number of specialties) among internal medicine physicians, urban/rural

	Male			Female		
	Age < 40	Age 40-59	Age > 60	Age < 40	Age 40-59	Age > 60
			Urban			
$Log(Density_{j,t-1})$	-0.023**	-0.012	-0.009	-0.022*	0.004	-0.040
	(0.009)	(0.009)	(0.019)	(0.013)	(0.017)	(0.066)
Observations	27385	69879	40226	12396	13651	4517
Adjusted R^2	0.012	0.058	0.119	0.036	0.030	0.078
			Rural			
$Log(Density_{j,t-1})$	-0.051***	-0.019***	-0.007	-0.030***	-0.036**	-0.019
	(0.008)	(0.006)	(0.015)	(0.011)	(0.017)	(0.028)
Observations	17784	54996	33018	7048	8698	2965
Adjusted R^2	0.043	0.063	0.133	0.035	0.048	0.072

Notes: All regressions include physician fixed effects, year fixed effects, and birth cohort-by-year fixed effects. Data are from the SPDP, SMI Static, and population census. Robust standard errors clustered at the physician level in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 16. Log (1+ number of specialties) among surgery physicians, urban/rural

	Male			Female		
	Age < 40	Age 40-59	Age > 60	Age < 40	Age 40-59	Age > 60
			Urban			
$Log(Density_{j,t-1})$	-0.009	-0.017**	0.004	-0.009	0.001	0.083*
	(0.008)	(0.009)	(0.021)	(0.015)	(0.018)	(0.049)
Observations	22394	50299	24163	6850	6369	2339
Adjusted R^2	0.036	0.102	0.186	0.014	0.023	0.049
			Rural			
$Log(Density_{j,t-1})$	-0.042***	-0.029***	-0.019	0.011	0.016	0.027
	(0.007)	(0.007)	(0.019)	(0.015)	(0.030)	(0.026)
Observations	14295	38264	19080	3772	3688	1233
Adjusted R^2	0.056	0.108	0.176	0.047	0.031	0.058

Notes: All regressions include physician fixed effects, year fixed effects, and birth cohort-by-year fixed effects. Data are from the SPDP, SMI Static, and population census. Robust standard errors clustered at the physician level in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 17 reports the effect of physical density on the probability of being unemployed/retired among internal medicine physicians, while Table 18 reports the same regressions but on a sample of physicians in surgery. We find systematic heterogeneity—while the effect of physician density is positive and statistically significant for internal medicine physicians who reside in rural municipalities, the effect is negative and statistically significant for physicians in surgery who reside in urban municipalities. These systematic differences are driven by older female physicians, and partially by older male physicians.

Table 17. Unemployment/retirement among internal medicine physicians, urban/rural

	Male			Female		
	Age < 40	Age 40-59	Age > 60	Age < 40	Age 40-59	Age > 60
	Unemployed/retirement from all facilities					
	Urban					
$Log(Density_{j,t-1})$	-0.001	-0.000	0.001	0.001	-0.003	0.015
	(0.001)	(0.000)	(0.006)	(0.004)	(0.003)	(0.019)
Observations	27385	69879	40225	12395	13651	4517
Adjusted R^2	0.001	0.000	0.018	0.002	0.002	0.035
	Rural					
$Log(Density j,t-1)$	0.000	0.001	0.004*	-0.002	-0.001	0.012**
	(0.000)	(0.001)	(0.002)	(0.006)	(0.004)	(0.006)
Observations	17784	54996	33018	7048	8698	2965
Adjusted R^2	0.001	0.001	0.021	0.002	0.000	0.027
	Unemployed/retirement from hospital					
	Urban					
$Log(Density_{j,t-1})$	-0.001	-0.001	0.001	0.008	0.000	0.147
	(0.001)	(0.001)	(0.002)	(0.011)	(.)	(0.144)
Observations	17847	35231	10835	7540	6138	996
Adjusted R^2	0.002	0.001	0.004	0.005	.	0.029
	Rural					
$Log(Density_{j,t-1})$	0.000	-0.001	0.018	-0.008	0.010	0.026
	(0.000)	(0.001)	(0.012)	(0.016)	(0.010)	(0.027)
Observations	13521	27128	9663	4824	4062	827
Adjusted R^2	0.002	0.000	0.021	0.007	0.005	0.012
	Unemployed/retirement from clinics					
	Urban					
$Log(Density_{j,t-1})$	0.000	-0.000	0.001	0.008	0.000	0.147
	(.)	(0.001)	(0.011)	(0.011)	(.)	(0.144)
Observations	2325	33530	29228	7540	6138	996
Adjusted R^2	.	0.001	0.023	0.005	.	0.029
	Rural					
$Log(Density_{j,t-1})$	0.000	0.003	0.004	0.018	-0.011	0.015*
	(.)	(0.003)	(0.004)	(0.018)	(0.010)	(0.008)
Observations	1883	27261	23083	943	4431	2152
Adjusted R^2	.	0.015	0.025	0.044	0.011	0.031

Notes: All regressions include physician fixed effects, year fixed effects, and birth cohort-by-year fixed effects. Data are from the SPDP, SMI Static, and population census. Robust standard errors clustered at the physician level in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 18. Unemployment/retirement among surgery physicians, urban/rural

	Male			Female		
	Age < 40	Age 40-59	Age > 60	Age < 40	Age 40-59	Age > 60
	Unemployed/retirement from all facilities					
	Urban					
$Log(Density_{j,t-1})$	0.000	-0.000	-0.013	-0.004	-0.014	-0.089*
	(0.000)	(0.001)	(0.012)	(0.004)	(0.010)	(0.049)
Observations	22394	50299	24163	6850	6369	2339
Adjusted R^2	0.001	-0.000	0.012	0.003	0.011	0.052
	Rural					
$Log(Density_{j,t-1})$	0.000	0.000	-0.002	-0.003	-0.007	-0.004
	(.)	(0.000)	(0.003)	(0.002)	(0.007)	(0.009)
Observations	14295	38264	19080	3772	3688	1233
Adjusted R^2	.	0.000	0.018	0.012	0.012	0.027
	Unemployed/retirement from hospital					
	Urban					
$Log(Density_{j,t-1})$	0.000	0.000	-0.007	-0.011	0.001	0.000
	(.)	(0.001)	(0.017)	(0.011)	(0.001)	(.)
Observations	15478	29680	7263	4242	2297	285
Adjusted R^2	.	0.000	0.002	0.019	0.002	.
	Rural					
$Log(Density_{j,t-1})$	0.000	0.000	-0.005	-0.008	0.000	0.000
	(.)	(.)	(0.004)	(0.006)	(.)	(.)
Observations	11471	21617	5920	2636	1424	187
Adjusted R^2	.	.	0.004	0.023	.	.
	Unemployed/retirement from clinics					
	Urban					
$Log(Density_{j,t-1})$	0.000	-0.002	-0.018	0.020	-0.032	-0.112**
	(.)	(0.003)	(0.019)	(0.024)	(0.023)	(0.056)
Observations	1792	20108	16790	957	3902	2090
Adjusted R^2	.	0.001	0.017	0.060	0.040	0.060
	Rural					
$Log(Density_{j,t-1})$	0.000	0.000	-0.001	0.000	-0.016	-0.013
	(.)	(0.000)	(0.005)	(.)	(0.016)	(0.014)
Observations	1297	16374	13031	531	2206	1060
Adjusted R^2	.	0.000	0.022	.	0.028	0.033

Notes: All regressions include physician fixed effects, year fixed effects, and birth cohort-by-year fixed effects. Data are from the SPDP, SMI Static, and population census. Robust standard errors clustered at the physician level in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

We finally turn our attention to comparing the effects of physician concentrations on career choice between physicians in internal medicine and physicians in surgery. We find some suggestive evidence of differences in labor supply responses between physicians of these two specialties. While young and prime-aged female physicians in internal medicine who reside in rural neighborhoods decrease their probability of switching from a hospital to a clinic when the concentration of physicians increases, physicians in surgery of the same demographic groups who also reside in rural areas do not respond to changes in physician density. This may be because the individual labor supply of physicians in surgery is less responsive to changes in the demand for care compared to that of internal medicine physicians. However, regardless of specialty, all physicians who reside in rural areas are less likely to become representatives/establish their own clinic when physician concentrations increase. Hence, as a whole, there are no major differences in career choice responses between physicians in internal medicine and physicians in surgery.

Table 19. Career choice among internal medicine physicians, urban/rural.

	Male			Female		
	Age < 40	Age 40-59	Age > 60	Age < 40	Age 40-59	Age > 60
	Moving from a hospital to a clinic					
	Urban					
$Log(Density_{j,t-1})$	-0.037**	-0.004	0.003	-0.010	-0.005	0.010
	(0.015)	(0.011)	(0.017)	(0.023)	(0.028)	(0.047)
Observations	20150	68699	39189	9028	13194	4388
Adjusted R^2	0.088	0.044	0.004	0.094	0.028	0.006
	Rural					
$Log(Density_{j,t-1})$	-0.094***	-0.061***	-0.049***	-0.081***	-0.084***	-0.058
	(0.012)	(0.008)	(0.013)	(0.022)	(0.025)	(0.037)
Observations	15392	54369	32228	5709	8475	2885
Adjusted R^2	0.110	0.049	0.013	0.082	0.052	0.029
	Establishing or becoming representative of a clinic					
	Urban					
$Log(Density_{j,t-1})$	-0.013**	-0.005	-0.008	-0.008	-0.031*	0.031
	(0.006)	(0.009)	(0.017)	(0.005)	(0.018)	(0.077)
Observations	27385	69879	40225	12395	13651	4517
Adjusted R^2	0.038	0.065	0.056	0.009	0.041	0.009
	Rural					
$Log(Density_{j,t-1})$	-0.016***	-0.020***	-0.012	-0.005	-0.032*	-0.023
	(0.005)	(0.006)	(0.012)	(0.007)	(0.018)	(0.035)
Observations	17784	54996	33018	7048	8698	2965
Adjusted R^2	0.040	0.059	0.053	0.007	0.032	0.016
	Establishing or becoming representative of a hospital					
	Urban					
$Log(Density_{j,t-1})$	-0.001	0.001	-0.018*	-0.001	-0.000	0.012*
	(0.001)	(0.002)	(0.009)	(0.001)	(0.002)	(0.007)
Observations	27385	69879	40225	12395	13651	4517
Adjusted R^2	0.004	0.003	0.004	0.001	0.000	0.001
	Rural					
$Log(Density_{j,t-1})$	-0.002	0.003	0.002	0.000	0.001	-0.009
	(0.001)	(0.002)	(0.005)	(0.000)	(0.002)	(0.009)
Observations	17784	54996	33018	7048	8698	2965
Adjusted R^2	0.004	0.005	0.004	0.001	0.006	0.004

Notes: All regressions include physician fixed effects, year fixed effects, and birth cohort-by-year fixed effects. Data are from the SPDP, SMI Static, and population census. Robust standard errors clustered at the physician level in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 20. Career choice among surgery physicians, urban/rural.

	Male			Female		
	Age < 40	Age 40-59	Age > 60	Age < 40	Age 40-59	Age > 60
			Moving from a hospital to a clinic			
			Urban			
$Log(Density_{j,t-1})$	-0.010	-0.015	0.020	-0.054	-0.012	0.067
	(0.014)	(0.010)	(0.020)	(0.036)	(0.044)	(0.053)
Observations	17256	49760	23633	5141	6179	2271
Adjusted R^2	0.070	0.048	0.005	0.079	0.035	0.013
			Rural			
$Log(Density_{j,t-1})$	-0.058***	-0.084***	-0.041***	-0.019	-0.028	-0.112*
	(0.012)	(0.009)	(0.015)	(0.034)	(0.034)	(0.059)
Observations	12762	37975	18665	3149	3620	1199
Adjusted R^2	0.107	0.068	0.010	0.136	0.039	0.094
			Establishing or becoming representative of a clinic			
			Urban			
$Log(Density_{j,t-1})$	-0.001	-0.010	-0.011	-0.006	-0.039	0.124*
	(0.007)	(0.010)	(0.021)	(0.008)	(0.044)	(0.070)
Observations	22394	50299	24163	6850	6369	2339
Adjusted R^2	0.033	0.056	0.052	0.010	0.029	0.044
			Rural			
$Log(Density_{j,t-1})$	-0.013***	-0.050***	-0.028*	-0.006	0.014	-0.080
	(0.005)	(0.008)	(0.015)	(0.009)	(0.020)	(0.080)
Observations	14295	38264	19080	3772	3688	1233
Adjusted R^2	0.051	0.062	0.047	0.043	0.027	0.031
			Establishing or becoming representative of a hospital			
			Urban			
$Log(Density_{j,t-1})$	-0.000	-0.002	0.002	0.003	0.007	0.003
	(0.000)	(0.002)	(0.009)	(0.003)	(0.004)	(0.003)
Observations	22394	50299	24163	6850	6369	2339
Adjusted R^2	0.001	0.003	0.006	0.004	0.007	0.003
			Rural			
$Log(Density_{j,t-1})$	-0.000	0.004**	-0.003	0.001	0.003	0.093
	(0.000)	(0.002)	(0.005)	(0.001)	(0.002)	(0.064)
Observations	14295	38264	19080	3772	3688	1233
Adjusted R^2	0.001	0.005	0.007	0.009	0.007	0.088

Notes: All regressions include physician fixed effects, year fixed effects, and birth cohort-by-year fixed effects. Data are from the SPDP, SMI Static, and population census. Robust standard errors clustered at the physician level in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

4.5 Effects on physician wages

As a supplementary analysis, we examine effects of physician concentrations on physician hourly wages, with results reported in Table 21. While we are unable to identify whether a physician is working in internal medicine or surgery in the BSWS, we are able to identify respondents' municipality of residence. This allows us to study heterogeneity across urban/rural regions of residence.

We find negative and statistically significant decreases in physician hourly wages with and without prefecture-specific linear time trends.[4] However, our estimates on physician wages should be

[4] We choose to utilize prefecture fixed effects for our analysis of the BSWS as opposed to municipality fixed effects

taken with a grain of salt, as the data we employ is repeated cross-sectional and may suffer from selection bias, especially in the context of our study where the main explanatory variable is physician density.

Table 21: Effects of physician density on physician wages

	Male			Female		
	Age <40	Age 40-59	Age > 60	Age < 40	Age 40-59	Age > 60
Dependent Variable: Log (1+hourly wage, including overtime and benefits)						
Urban						
$Log(Density_{j,t-1})$	-0.631***	-0.444***	-0.189*	-0.591***	-0.421***	-0.151
	(0.107)	(0.041)	(0.101)	(0.071)	(0.031)	(0.139)
Observations	4158	2763	900	1833	713	113
Adjusted R^2	0.276	0.148	0.100	0.287	0.106	-0.027
Rural						
$Log(Density_{j,t-1})$	-0.492***	-0.323***	0.002	-0.420***	-0.261*	0.010
	(0.090)	(0.046)	(0.039)	(0.085)	(0.146)	(0.123)
Observations	2718	2098	681	1014	427	65
Adjusted R^2	0.432	0.197	0.089	0.395	0.099	-0.101
Dependent Variable: Log (1+hourly wage, excluding overtime or benefits)						
Urban						
$Log(Density_{j,t-1})$	-0.685***	-0.445***	-0.206**	-0.637***	-0.379***	-0.111
	(0.124)	(0.041)	(0.086)	(0.058)	(0.040)	(0.161)
Observations	4158	2763	900	1833	713	113
Adjusted R^2	0.306	0.169	0.094	0.302	0.099	0.024
Rural						
$Log(Density_{j,t-1})$	-0.501***	-0.350***	0.020	-0.441***	-0.252	0.046
	(0.096)	(0.047)	(0.049)	(0.093)	(0.185)	(0.124)
Observations	2718	2098	681	1014	427	65
Adjusted R^2	0.447	0.217	0.121	0.418	0.106	-0.212

Notes: Each observation is a physician and treatment is at the municipality level. All regressions include prefecture fixed effects, year fixed effects, and prefecture-specific linear time trends. Log population and respondent age are included as controls. Robust standard errors clustered at the municipality level in parentheses. Data are taken from the BSWS, SPDP, and population census.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

5. Discussion and Conclusion

Utility maximizing physicians may have upward- or downward- sloping reaction functions (physicians react to the existence of competitors by increasing or decreasing their provision of labor) depending on the relative magnitude of income and substitution effects. Aside from inducing demand at the intensive margin, physicians may also opt for a less competitive career path when regional competition increases. Understanding these labor supply responses by incumbent physicians when market competition increases is relevant for policy-makers seeking to regulate the market-level supply of physicians, and for a broader understanding of the desirability of supplier competition in a partially fee regulated environment such as Japan's.

because the number of observations within each municipality is too small, often less than 10, which would lead to attenuation bias.

Our results show downward sloping reaction functions, while several recent studies from the U.S. and France show upward sloping reaction functions among physicians that operate within a fee-for-service (FFS) payment system. Our results suggest that in response to greater competition and lower hourly wages, physicians in Japan prefer to decrease their overall labor supply by means of limiting career progression or choosing an occupation that does not involve the practice of medicine. Such effects tend to be pronounced among internal medicine physicians residing in more rural areas. If we consider leisure and altruism towards patients in need as important elements in a physician's objective function, then our results are somewhat expected. In particular, for physicians residing in rural areas with considerably greater supply-side constraints, an increase in physician concentrations may satisfy physicians' motivation to practice medicine if such supply-side shortages were driving physicians' provision of labor. On the other hand, one may additionally interpret our results as strategic selection away from competitive markets due to a decrease in hourly wages.

The labor supply responses found in our study not only reveal the latent labor supply preferences of physicians in Japan when local physician concentrations increase, but also provides policy implications for countries seeking to implement regional supply-side policies. For instance, if a country is seeking to increase the aggregate labor supply of physicians in specific regions due to labor supply constraints, then regulators could intervene by introducing programs that encourage the continued labor force participation of (incumbent) physicians before implementing large-scale supply-side policies. This may come in the form of higher salaries, more flexible work hours, or higher pensions for delayed retirement.

Our results may also provide some welfare implications for antitrust policy in the healthcare industry. The misdistribution of physicians in Japan from rural to urban municipalities may negatively affect not only the welfare of patients in rural regions, but also the welfare of physicians in these rural regions. This is because the results derived in our study suggest that, when given the opportunity, physicians in such supply-constrained rural cities prefer to reduce their provision of labor. Hence, further incentives for physicians to migrate to supply-constrained areas may be desirable, in addition to additional targeted incentives for incumbent physicians to continue their provision of labor.

One major limitation of our study is in our wage regressions, where wages may be endogenous to changes in labor supply at the intensive margin. In future studies, we hope to employ more sophisticated methods and longitudinal micro data containing an indicator for physician wages. Doing so would enable us to identify the true causal effect of physician competition on incumbent physicians' wages, and how it can potentially mediate physicians' labor supply trajectories.

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Appendix 1

Figure A1. Hospital beds per 1000 population in 2006 and 2012

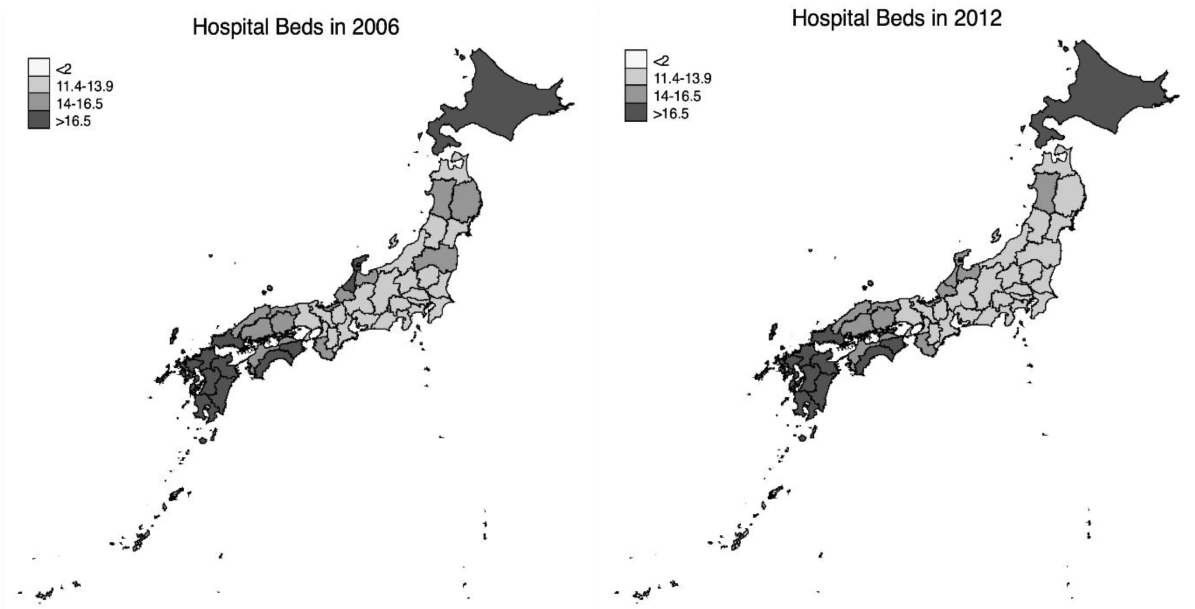


Figure A2. Physicians per 1000 population in 2006 and 2012

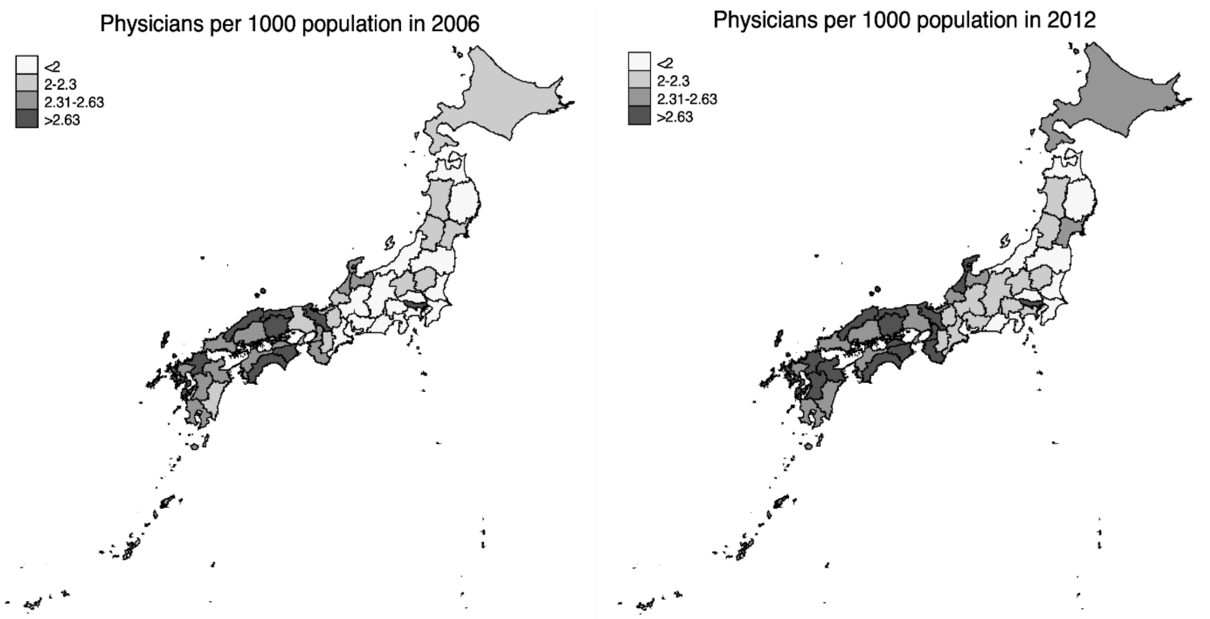
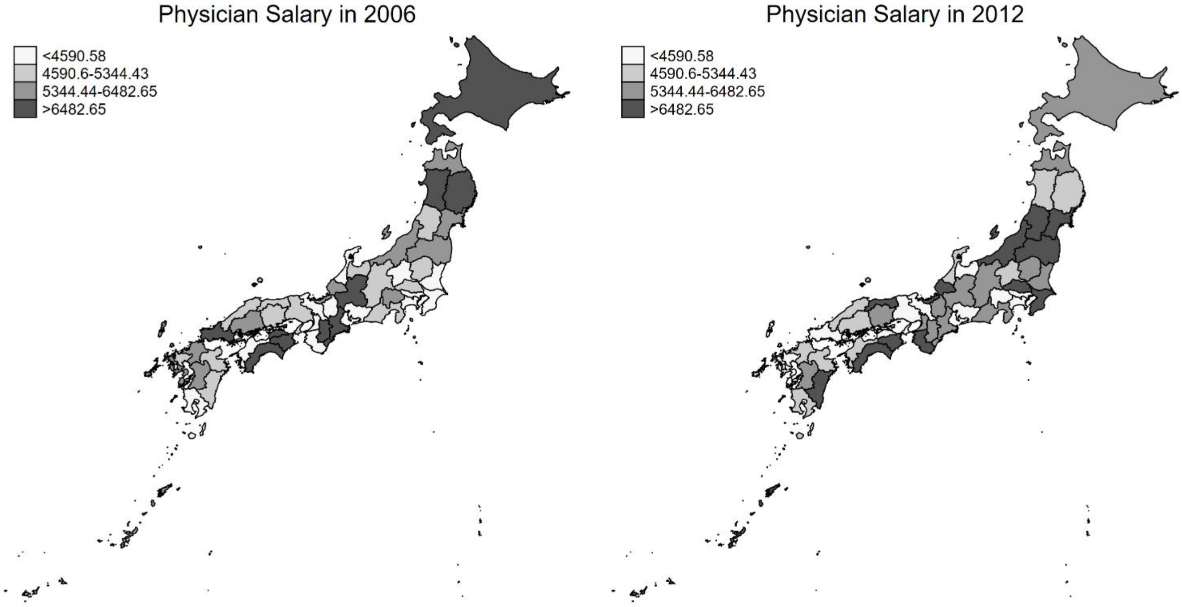


Figure A3. Total physician monthly salary in 2006 and 2012



Notes: Values are in ten thousands JPY

Figure A4: Educating/training other physicians as main occupation, 2010

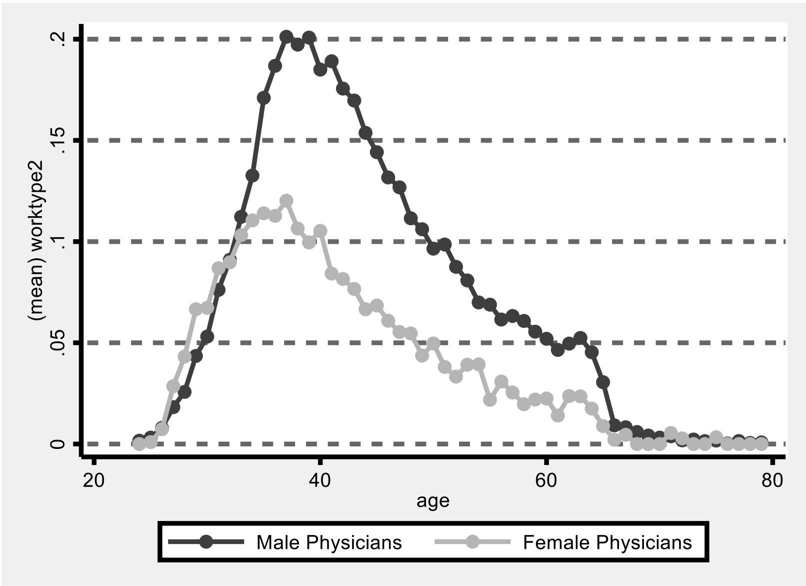


Figure A5: Number of departments/specialties involved in, 2010

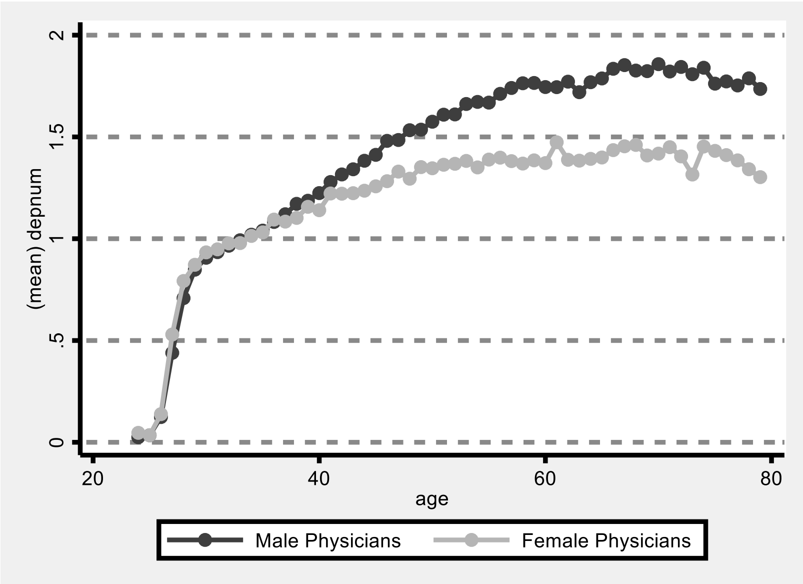


Figure A6: Unemployed/retired, 2010

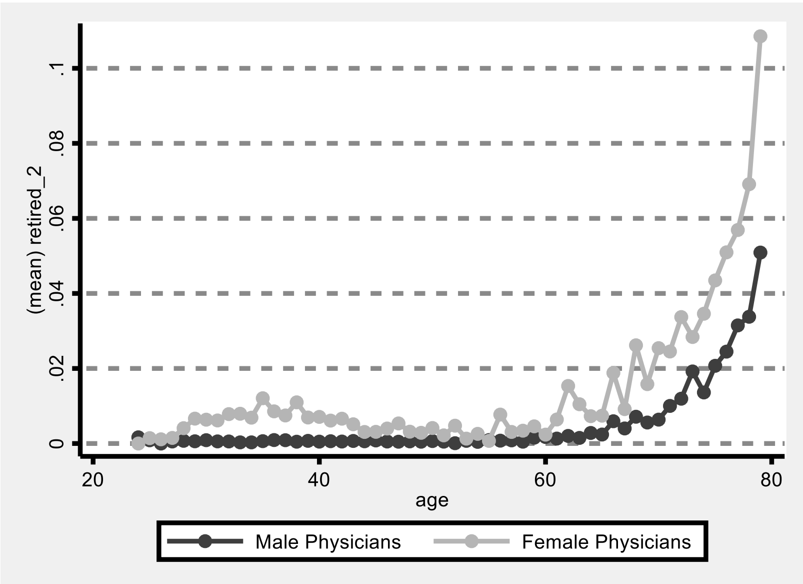


Figure A7: Establish/representative of a clinic, 2010

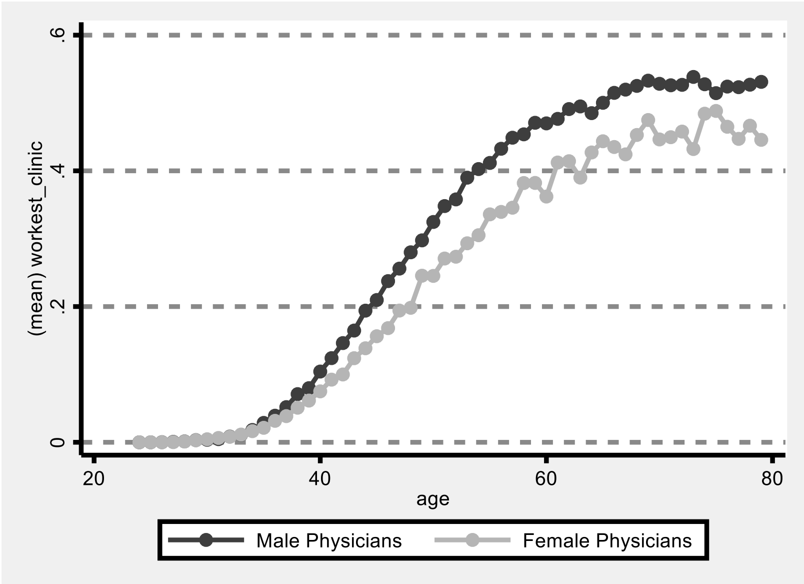
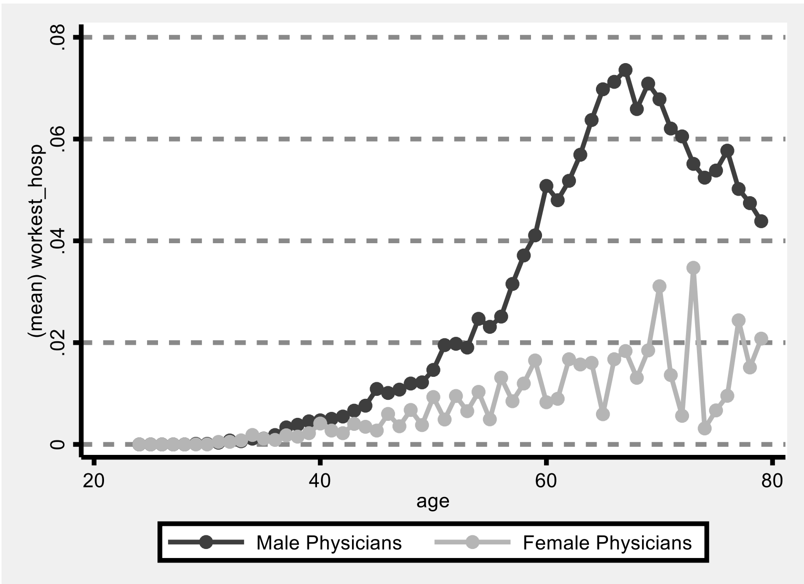


Figure A8: Establish/representative of a hospital, 2010



Appendix 2

When attempting to characterize a variable, which in our case is the density of physicians, one runs into practical issues of functional form misspecification, overfitting, and/or non-identifiability. Overfitting is when a model fits the data too closely and predicts poorly out-of-sample, and non-identifiability is when the number of parameters exceeds the number of data points, and estimation becomes theoretically intractable. One solution that can resolve all three of the above issues is nonparametric estimation with regularization combined with ensemble methods. We use Friedman, Tibshirani, and Hastie (2001) as a key reference for Appendix 2, which describes these methods in more detail.

Ⅰ. Classification and Regression Trees (CART)

CART operates by constructing a large "tree" by means of recursive partitioning to identify the best covariate split combinations within a branch of observations that can best characterize the variation of an outcome of interest. In this section, we describe CART when the outcome is continuous.

We first use Figure 4 as a numerical example to illustrate the basic objective of CART. Let $\mathrm{R_m} = (\mathrm{R_1}, .., \mathrm{R_5})$ denote the number of terminal nodes (leaves) that result from optimal recursive partitioning, and $\mathrm{c_m} = (\mathrm{c_1}, \dots, \mathrm{c_5})$ denote the y values at the end of each terminal node (region). Finally, let $x_k = (x_1, \dots, x_4)$ denote the four covariates selected by CART for characterizing physician density. The tree in Figure 4 characterizes physician density (y) as a linear combination of indicators of the value of physician density observed at region $\mathrm{R_m}$ with constant $\mathrm{c_m}$, summarized as follows:

$$\hat{y} = \sum_{m=1}^{5} c_m I(x_k \in R_m)$$

Where $I(x_k \in R_m)$ is an indicator variable taking a value of 1 if an input variable x_k is contained in a region R_m. In this simple example, a suitable loss function to predict the constant c_m for any given region R_m is the minimization of the sum of squares of all observations contained in the region, or equivalently, the average y_i in region R_m:

$$\widehat{c_m} = \mathrm{ave}\left(y_\mathrm{i} \middle| x_i \in R_m\left(j, s_j\right)\right)$$

To arrive at the partitions observed in Figure 4, CART employed a greedy approach, constructed as follows:

Let $\mathbf{x} = (\mathrm{x_1}, .., x_m)' \in \mathbf{R^m}$ denote a dataset with an m number of variables prior to each split. Let $j \in (1, \dots, 64)$ denote the variables to be considered for splitting, and s_j the possible values at which a variable is split.

Prior to each split and at every sub-region, there will be a pair of half-spaces, denoted:

$$R_{\text{left}}(j, s_j) = (\mathbf{x}|x_j \leq s_j)$$
$$R_{\text{right}}(j, s_j) = (\mathbf{x}|x_j > s_j)$$

Now, to find the optimal variable-split pair (j, s_j), CART solves the following bilevel optimization problem:

$$L(j, s_j) = \min_{j,s_j}\left[\min_{c_{\text{left}}} \sum\nolimits_{x_i \in R_{\text{left}}(j,s_j)} (y_i - c_1)^2 + \min_{c_{\text{right}}} \sum\nolimits_{x_i \in R_{\text{right}}(j,s_j)} (y_i - c_2)^2\right]$$

where for any splitting variable j and splitting point s_j, the solution to the inner minimization is given by

$$\widehat{c_{\text{left}}} = \text{ave}\left(y_{\text{i}}\middle|x_i \in R_{\text{left}}(j, s_j)\right)$$

$$\widehat{c_{\text{right}}} = \text{ave}\left(y_i\middle|x_i \in R_{\text{right}}(j, s_j)\right)$$

Once an optimal variable-split pair $(j, s_j)^*$ is found, CART partitions the data at this point and recursively continues this process for each new subset of data.

To determine how large a tree should grow and to circumvent overfitting, CART employs backward pruning, which involves building a very large tree, followed by penalizing and removing splits that do not increase the R-squared by a certain amount. In our figure, we define the penalty term to 0.01, based on cross-validation results (i.e., we set the complexity parameter to 0.01 in the R package 'rpart').

Ⅱ. Random Forest

Due to the curse of dimensionality of CART, ensemble methods are required to improve predictive performance. One common method is the random forest, which follows the following algorithm.

Random Forest Algorithm:
For $b = 1, \dots, B$:
Draw a bootstrap random sample of size *n* from the training set
Randomly select *m* variables from the *p* set of total variables
Grow a regression tree, and compute the predicted value of y, $\hat{T}^b$
Output the ensemble of trees $\hat{T}^b$

Take the average over all predictors at a new point x:

$$\widehat{f_{rf}}^{B}(x) = \frac{1}{B}\sum_{b=1}^{B} T_b(x)$$