Online Appendix to: The Earnings and Labor Supply of U.S. Physicians

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A NORC AmeriSpeak Survey

Summary

The broader public is not well-informed about physicians' incomes, as we observed in a nationally-representative survey of 1,071 respondents conducted via both internet and telephone in June 2021.[62] Respondents had dispersed views about physician earnings: 19% believed that the average physician earned above $300,000; another 33% believed the number was $200,000 to $300,000, leaving nearly half of the respondents believing that physicians earned under $200,000. 36% considered physicians overpaid, while 50% said they were paid "the right amount" and 11% chose underpaid.

Respondents broadly understood that physicians have substantially higher earnings than nurses, with 8% stating that average nurse earnings exceed $125,000, 31% answering $75,000 to $125,000, and 40% reporting that nurses earn $50,000 to $75,000. The BLS reports average registered nurse earnings of $89,010,[63] though it is not clear whether respondents were thinking of registered nurses or also including other categories such as licensed practical nurses. In general, respondents tend to underreport pay for both types of health care workers, perhaps reflecting earnings growth in healthcare over time, leaving the general public with an outdated view of earnings in the sector.

Methodological Notes

Our survey questions were added to NORC's AmeriSpeak Omnibus survey, conducted monthly using a sampling frame that captures 97% of the U.S. population. The survey was conducted among adults 18 and over from all 50 states plus D.C. from June 10 to 14, 2021. 1,036 responded via the internet and 35 via telephone. Among other questions, we asked:

- "What do you think is the average annual income of people in each of the following jobs?"
  - Answers were reported for doctors, nurses, and other selected occupations.
  - The response grid included the following options: less than $25,000; $25,000 to $50,000; $50,001 to $75,000; $75,001 to $125,000; $125,001 to $200,000; $200,001 to $300,000; or more than $300,000.

[62] This survey was conducted jointly by the University of Chicago Harris School of Public Policy and The Associated Press-NORC Center for Public Affairs Research with funding from NORC at the University of Chicago.

[63] https://www.bls.gov/oes/current/oes291141.htm

  - For doctors, 3% of respondents skipped this question and 1% answered "don't know."
  - For nurses, 4% skipped and 1% did not know.

- "Thinking about the different types of health care professionals, would you say each of the following is overpaid, underpaid[64] or gets paid the right amount?"
  - Answers were reported for doctors, nurses, and other selected occupations.
  - The response grid included the following options: very overpaid, somewhat overpaid, the right amount, somewhat underpaid, very underpaid.
  - For doctors, 3% of respondents skipped this question and 1% answered "don't know."
  - For nurses, 3% skipped and 1% did not know.

This survey was deemed exempt by the NORC Institutional Review Board.

[64] The order of these two options was chosen randomly.

B Data and Measurement Appendix

B.1 Data Sources

Tax Data

Tax data available to us contain the universe of filers, but a limited number of variables. From Form 1040, we observe the tax unit's filing status, adjusted gross income (AGI), taxable dividend and interest amounts, social security income, as well as indicators for filing schedules C, S, and SE. In addition, we observe wage income on Form W-2 and receipt of Social Security benefits on Form 1099-SSA, which are both information returns filed by third parties.

We follow the Chetty et al. (2014) approach for harmonizing raw Form 1040, 1099-SSA, and W-2 data. In case of multiple W-2s from different employers, we add earnings across all W-2s and consider the EIN with the largest amount of earnings to be the primary EIN. We use address information on Form 1040 to assign a commuting zone to the individual. If no address is available on Form 1040, we use information returns, and if those are not available either, we rely on other survey and administrative sources of the Census Bureau to determine an individual's address.

Physician Registry

Individuals and organizations that provide healthcare services in the U.S. must use their unique 10-digit National Provider Identifier (NPI) to identify themselves throughout the healthcare system, including in submitting claims for payment. These NPIs are recorded in the National Plan and Provider Enumeration System (NPPES) file maintained by the Centers for Medicare and Medicaid Services (CMS). We define an individual as a physician if we observe them in the April 2018 vintage of NPPES and if their associated primary provider taxonomy code starts with 20 ("physicians"). The data also includes all NPIs deactivated prior to April 2018, such as would occur due a physician's retirement or death. We merge tax data with this physician list using the Census Bureau's Protected Identification Key (PIK)-based data linkage infrastructure, which Wagner and Layne (2014) describe in detail.

Although the brief discussion in Section 1.2 does not describe every path a physician can take, such as obtaining the Doctor of Osteopathic Medicine (DO) degree or an MD abroad, all physicians who practice in the U.S. and have an NPI are included in our income data.

Specialty Taxonomy

The NPPES file provides a granular provider taxonomy code for each physician.[65] We crosswalk these codes to a more aggregated specialty classifications: 60 Medicare Specialty Codes.[66] We then create a crosswalk of Medicare Specialty Codes to nine aggregate *specialty categories*, defined in Table E.1. We also crosswalk Medicare Specialty Codes to the specialty

[65] Provider taxonomy codes and their description can be found at https://taxonomy.nucc.org).

[66] The crosswalk is available from http://www.cms.gov/Medicare/Provider-Enrollment-and-Certification/MedicareProviderSupEnroll/Downloads/TaxonomyCrosswalk.pdf.

taxonomy used by the National Resident Matching Program, which we use in Sections 2.2 and 3.3.

Medical School

Medical school name and graduation year comes from the Doctors and Clinicians National Downloadable File, available from CMS for years 2014 to 2018. We add information on the U.S. News and World Report medical school ranking for years 2005 to 2018, collected from online sources. The report ranks 50 schools each year. Across years 2005-2018, 58 unique medical schools were ranked. We define a school to be top-5 if it was ranked among the top-5 schools in at least one year between 2005 and 2017.

American Community Survey

The ACS surveys repeated cross-sections of approximately 1% of the U.S. population per year. ACS full implementation happened in 2005. Prior to 2005, sample sizes were much smaller. We retain the following self-reported ACS variables: wages, indicator for being self-employed and self-employment income, spousal income, and the number of hours per week and the number of weeks per year an individual reports working.

We consider an ACS respondent to be a lawyer if they have an occupational code for a legal profession. This includes lawyers, judges, magistrates, judicial law clerks, and other judicial workers. Similarly to physicians, we use PIKs to merge this list of lawyers with their 2005–2017 tax returns.

Medicare Data

Since 2012, CMS has released the Physician and Other Supplier Public Use File of the Physician Medicare Provider Utilization and Payment Data (MPUPD) for each provider who treated fee-for-service Medicare patients. The file is publicly available on cms.gov.[67] The data exclude procedure codes that a physician provides to Medicare patients ten or fewer times in a given year. Subject to these restrictions, the file reports the list of services performed, the number of times each service was offered, the place of service, the number of unique patients for each service, and Medicare payment. The term "service" here refers to a Healthcare Common Procedure Coding System (HCPCS) code, treated as distinct when performed in a facility and in a non-facility setting.

B.2 Measurement

Defining Income

We observe individual wage earnings (including pre-tax deferrals) and household AGI directly in tax data.

Measuring individual total income and business income is more challenging for two reasons. First, our tax data do not fully record the amount of business or self-employment

[67] https://data.cms.gov/provider-summary-by-type-of-service/medicare-physician-other-practitioners/medicare-physician-other-practitioners-by-provider-and-service.

income on Schedules E and C. Second, non-wage income on Form 1040 is reported at the tax unit rather than individual level. We follow Bell et al. (2019), who use similar data to study incomes of inventors for whom non-wage earnings may also play an important role. As in Bell et al. (2019), we define total individual income as the sum of individual total wage income and the household AGI net of all wage earnings and taxable retirement distributions (for those aged 60 or older), but gross of tax-exempt interest and Social Security payments. For non-filers, we only use individual wage earnings as a measure of total individual income. The idea is that AGI net of wages and retirement cash flows captures current business income as well as financial returns and capital gains on previous earnings. For those physicians who file joint returns with a spouse, this object technically captures business and financial income of both spouses. We examined various approaches to approximating the income attributable to the index individual of interest (versus the spouse). The results are not qualitatively sensitive to the approach we use, so we focus on the measure that attributes all of imputed business income to the index physician for simplicity. We make one exception. If a physician is filing jointly with a spouse and the spouse is *also* a physician in our data, then we attribute 50% of the implied business and financial earnings of the household to each spouse.

We define individual total business income as the Total Money Income (TMI) of the household net of wages, taxable dividends, taxable interest, social security, partially observed profit and loss from Schedule E, and distributions from pre-tax deferral accounts irrespective of age. For physicians married filing jointly with a physician spouse, we take 50% of this amount. TMI is a measure of income used by the U.S. Census Bureau and is pre-computed in the tax data extract available to us. Its main advantage for the purpose of inferring business income is that TMI excludes capital gains. The U.S. Census Bureau defines TMI as income received on a regular basis (exclusive of certain money receipts such as capital gains) before payments for personal income taxes, social security, union dues, Medicare deductions, etc.

Following the literature on income inequality, we use the tax unit's AGI when characterizing physicians' position in the national income distribution.

We construct the self-reported analogues of all income objects using ACS income variables.

Measuring the length of training

We use the tax data to construct estimates of average training length by specialty by measuring the number of years for which physician incomes are fixed after medical school completion before they discontinuously jump. There is relatively little variation in physicians' earnings during residency. While earnings may increase somewhat as resident progress into fellowships, earnings reliably increase dramatically when physicians start their first post-training jobs. These two facts about physicians' early-career income levels and changes allow us to use panel income data to estimate the average duration of training by specialty.

For this exercise, we use all physicians in our data who were between 20 and 28 years old (inclusive) in 2005 and have W-2 wage income information available every year from 2005 through 2017. Since residencies begin halfway through the year, we can identify new residents as those who earn about half the typical resident's wage income in year t (assuming they do not have meaningful wage income while in their last semester of medical school) and then see their wage income increase to a typical resident's income in year $t+1$. We identify a person as starting their residency when we observe year t wage income between \$15,000 and \$35,000 (roughly half the wage income range in which we observe a large share of the mass in the distribution of physicians at typical residency ages) followed by an increase in wage income of at least 30% (constructed as the change in income between the first and second year divided by the average income over the two years). We use a percent change requirement rather than specifying the level of income for the second year to allow for some variation in salaries across programs, plus the possibility that residents might have wage income from other sources. We identify a person as completing their training in the first year that they experience another 30% increase in their wage income from the prior year, and that year's income is at least \$80,000. Variations on these parameters produce similar results. We take the mean of the resulting person-level estimates of residency duration by each level of residency taxonomy that we use throughout the paper.

Measuring hourly earnings

We construct hourly earnings in specialty s in year t by dividing the average annual earnings in specialty s in year t among 40-to-55-year-old physicians by 52 times the average of weekly hours worked as reported in the ACS by 40-to-55-year-old physicians in specialty s in year t.

Measuring tuition costs

We calculate the average tuition cost for a medical education—which we define as the tuition and fees for both an undergraduate and graduate degree—from a variety of sources. These include undergraduate tuition from the National Center for Education Statistics and medical school tuition from the Association of American Medical Colleges (AAMC) surveys. These datasets report both public and private school tuition. Using data for 2016-2017 academic year, we compute (i) average tuition and fees for attending a public (in-state) college and a public medical (or law) school, and (ii) average tuition and fees for attending a private college and a private medical (or law) school. For a medical career in public universities this yields: \$32,351 per year times four years for medical school and \$9,003 per year times four years for college, for a total of \$165,416. For a medical career via private universities, we get \$53,850 per year for four years of medical school and \$30,139 per year for four years of college, for a total tuition and fees cost of \$335,956. In Appendix D, we use a simple average of this range as the measure of tuition.

The underlying sources are:

- American Association of Medical Colleges, Tuition and Student Fees Report, October 2018 (https://www.aamc.org/data/tuitionandstudentfees/)
- National Center for Education Statistics, 2018 Digest of Education Statistics, Table 330.10. This reports average undergraduate tuition and fees and room and board rates charged for full-time students in degree-granting postsecondary institutions. (https://nces.ed.gov/programs/digest/d17/tables/dt17_330.10.asp).
- American Bar Association, Tuition Fee Expenses, ABA 509 required disclosures (http://abarequireddisclosures.org/Disclosure509.aspx)

Our estimate of $250,688 in aggregate tuition costs for a medical degree is consistent with reports of debt levels among medical students. For example, Harvard Medical School reports that the average graduating debt in 2022 at HMS was $108,382, compared to the national averages of $179,679 at public medical schools and $187,229 at private medical schools.[68] Our estimates use older data, but are not weighted by the share attending private versus public schools, and include tuition and fees overall rather than only portions that resulted in debt.

Present discounted value of earnings

We use the panel structure of our data to estimate the present discounted value (PDV) of income earned over a physician's (or a lawyer's) career for analysis in Appendix D. The data allow us to incorporate variability across individuals and over time, accounting for actual income dynamics over the career. We start by grouping observations with physicians (lawyers) of the same age. To minimize noise, we pool data from all years 2005 to 2017 and adjust income observed in different calendar years for inflation. For each age cohort, we divide individuals into thirteen income bins: top 1% of income within each age cohort, next 4%, next 5%, each of the bottom nine deciles, and zero income. We estimate empirical transition probabilities between income bins from age a to age $a+1$. In practice, to improve precision, we use individuals within a five-year age window centered on each age; that is, to calculate transition probabilities between ages 50 and 51, we actually use people who had age a between 48 and 52 in any year t between 2005 and 2016. We link these respondents to their incomes at age $a+1$ in year $t+1$, and use the transition probabilities from a to $a+1$ to estimate the transition probabilities between 50 and 51. We estimate one-year transition probabilities across income bins for each year of age beginning at age 20 and ending at age 70. We use the empirical distribution of income levels at the starting age and age-specific transition probabilities to simulate 50,000 careers for physicians and lawyers, which gives us the distribution of income paths in each occupation. We discount the value of these incomes back to age 20 using a discount factor of 0.97.

B.3 Additional Descriptive Patterns

Table 1 shows that the average physician in 2017 is 49 years old, 38% of physicians are women, 22% were not U.S. citizens at birth (record of ever being an "alien" in Census Numident), and 80% are married. Older cohorts of physicians are substantially less likely to be female or not U.S. citizens at birth. The most common specialty category in all samples is primary care, accounting for a bit more than 40% of physicians.

In Table 2 we observe that top-earning physicians work in smaller firms, are a year older than the sample average, and work similar hours as the average physician, but more than physicians in the top half of the distribution. They are 1.5 to 2 times more likely to live in New York or New Jersey, Florida, Arizona, or Texas. Only 24% of top earners are women, as compared to 40% in the full sample. Top earners are also 5 percentage points less likely than the median physician to have had any immigration history and are ten percentage

[68] https://meded.hms.harvard.edu/admissions-at-a-glance

points more likely to be married. 7% of all physicians in 2017 were retired according to our measure, with almost all of these individuals in the 56 to 70 age sample, for a retirement rate of 19% in that sample.

Figures E.3A and E.3B plot the time series of real earnings and of the share of physician households in top 1% of the national income distribution. We plot raw and regression-adjusted values to capture the evolution of mean real income for a comparable physician over time. We regression-adjust the time series for age fixed effects, sex, state of residence fixed effects, and Medicare Specialty Code fixed effects. The rate of real income growth among physicians from 2005 to 2017 is around 1% annually—or half of the inflation-adjusted growth rate in per capita national healthcare expenditures over the same time period.

The median physician in 2017 works 50 hours per week in a firm with 85 physicians. Firm size is very skewed, as employers vary from single-person practices to large hospitals. Firm size increased substantially over time, with a median firm having 52 physicians in the full panel and only 20 physicians among older cohorts. The share of single-person firms fell from 26% to 20% over our time period; see Figure E.3C.[69] This pattern is not driven by a change in the share of physicians not having any W-2 earnings (who would hence would have a missing EIN) as we see in Figure E.3D.

Figure E.4 shows lifecycle patterns of labor supply. Physician peak work hours are in their early late 20s and early 30s, consistent with the time in residency. Hours start declining after age 55. Physicians start retiring at age 65, with a significant jump in retirement rate between 69 and 70.

[69]Since our measure of firm relies on the EIN in W-2 records, we only observe those single-physician practices that are either structured as S-corporations that pay the physician some portion of income with a W-2. If the physician is only practicing as a solo proprietor, there will be no W-2. We could also be capturing as single physician firm a practice where one physician is an owner and has no W-2 income, while another physician works as a W-2 employee.

B.4 Comparison of Tax and Survey Data

We use 2017 American Community Survey (ACS) to compare physicians' self-reported income to income measures constructed from the administrative tax data. In the ACS, we define individual total income as the sum of individual wage and self-employment income of the index individual plus self-employment income of the spouse (or 50% of the latter if the spouse is also a physician according to NPPES). ACS defines self-employment income to include both farm or non-farm self-employment income. The non-farm self-employment income includes all sources of business income that we also capture in the tax data, including one's own business, professional enterprise, or partnership income. We start with our baseline sample of 848,000 physicians in 2017 cross-section and restrict it to 14,000 individuals who are also observed in 2017 ACS (Table E.3). Among these individuals, 11,500 also report being a physician in ACS, while 2,500 report other occupations. We observe a large difference in average individual total income between the tax data and ACS for both subsamples.

In the sample of 11,500 individuals who are physicians in NPPES and also report being physicians in ACS, average individual total income in the tax data is \$365,400, while ACS income is \$258,100—a more than \$100,000 (29%) difference in annual income between the tax and survey data. We zoom onto this sample to examine this large discrepancy in average tax-based and survey-based income of physicians. Table E.4 separates average individual total income into wage income and business income. Average wages, conditional on reporting strictly positive wages, differ by \$32,100. The number of individuals reporting positive wages is similar. This difference implies that wage reporting is quite accurate in ACS data, as the difference of \$32,100 is close to allowed pre-tax contributions that we added in our measure of wages in the tax data. It is reasonable to assume that in survey questions, individuals report their wages after pre-tax retirement contributions.

Columns (3)-(6) of Table E.4 report average business income, for the full sample, and conditional on business income being strictly positive. We use self-employment income as the measure of business income in ACS. Business income is \$58,000 lower in ACS data in the full sample. The difference shrinks to \$41,000 when we condition on business income having to be positive. In relative terms, average business income in the tax data goes from being 3.7 to being 1.4 times average business income in ACS data when we move from the full subsample to conditioning on business income being strictly positive. Only 19% of individuals report positive business income in ACS, compared to 60% in the tax data. Overall, we find that about a third of the total \$100,000 difference in income between tax and survey data is attributable to differences in wage reporting that likely stems from the difference in attribution of pre-tax deductions in survey responses. More than 85% of the remaining difference is due to differences in business income reporting (primarily on the extensive margin), and the remainder are other types of income that we capture in the tax data, but not in ACS data.

C Details of Empirical Methods and Further Results

C.1 Changes in Medicare Reimbursement

RVU Example and Definitions. In 2017, a standard office visit was worth 2.06 RVUs, while inserting a cardiac stent (code 92928) was worth 17.24 RVUs (CMS, 2017). Each service's RVUs are adjusted across geographies using geographic practice cost indices and converted to dollars using a "conversion factor"—$35.89 per RVU in 2017.

Since Medicare has separate RVU allocations for many codes depending on whether they are performed in a *facility* (such as hospital) or *non-facility* (such as physician's office) setting, we treat "service" throughout as a pair of billing code (Healthcare Common Procedure Coding System, which differentiates across 13,000 unique codes) and place of service (facility or non-facility).

IV Framework for Earnings. Our instrumental variable setup builds on equation (5) in the text, repeated here for convenience:

$$\ln Y_{i,t} = \alpha_i + \beta \ln P_{i,t} + \theta_{a(i,t)} + \eta_{t,s(i)} + \varepsilon_{i,t}. \tag{C.1}$$

where $\ln Y_{i,t}$ denotes log income, $P_{i,t}$ is the Medicare price instrument driven by RVU changes, α_i are physician fixed effects, $\theta_{a(i,t)}$ are age fixed effects, and $\eta_{t,s(i)}$ are year-by-specialty fixed effects. The instrument is defined by equation (4), repeated here for convenience:

$$P_{i,t} = \sum_{k \in K} \overline{q_{i,k}} \times RVU_{k,t}. \tag{C.2}$$

We use $Q_{i,t}$ to denote the total number of RVUs a physician bills in year t, formally:

$$Q_{i,t} = \sum_{k \in K} q_{i,k,t} \times RVU_{k,t}. \tag{C.3}$$

The difference from equation (C.2) is that $q_{i,k,t}$ denotes the actual number of times physician i provides service k in year t, rather than the average number of times physician i provides service k across all years. Thus $Q_{i,t}$ incorporates endogenous supply responses in $q_{i,k,t}$ and changes in RVUs, while $P_{i,t}$ only reflects the latter.

We estimate the following two-stage least squares (2SLS) model:

$$\begin{aligned} &\text{First stage: Total RVUs billed} \\ &\qquad \ln Q_{i,t} = \pi \ln P_{i,t} + \alpha_i + \theta_{a(i,t)} + \eta_{t,s(i)} + u_{i,t} && \text{(C.4)} \\ &\text{Second stage: Income} \\ &\qquad \ln Y_{i,t} = \beta \widehat{\ln Q_{i,t}} + \alpha_i + \theta_{a(i,t)} + \eta_{t,s(i)} + \varepsilon_{i,t} && \text{(C.5)} \end{aligned}$$

The first-stage regression reveals changes in billing that include both the mechanical impact of RVU changes along with the supply responses. A coefficient of $\pi = 1$ must be interpreted as no supply response; the supply elasticity is $\pi - 1$.

IV Framework for Retirement Decision. We also estimate a supply response of retirement to earnings. To do this, we treat income as the endogenous variable in the following 2SLS setup:

$$\begin{aligned}\text{First stage: Income}&\\ \ln Y_{i,t} &= \pi \ln P_{i,t} + \alpha_i + \theta_{a(i,t)} + \eta_{t,s(i)} + \varepsilon_{i,t} \qquad \text{(C.6)}\\ \text{Second stage: Retirement}&\\ R_{i,t} &= \beta \ln Y_{i,t} + \alpha_i + \theta_{a(i,t)} + \eta_{t,s(i)} + \varepsilon_{i,t} \qquad \text{(C.7)}\end{aligned}$$

where $R_{i,t}$ is a dummy for the retirement decision.

Baseline Pass-Through Calculation. Suppose a physician's Medicare reimbursements were to increase by 1%, as measured by our Medicare price instrument $P_{i,t}$. Our reduced-form estimate of the elasticity of earnings to the Medicare price instrument is 0.236 (column 1 of Table 3), so a 1% increase in reimbursements would increase earnings by 0.236% or $955 for the mean physician (=0.236% × $404,500, which is the mean income in the age 40 to 55 sample). The mean physician in our sample provides 4,079 RVUs (mean of $P_{i,t}$), and Medicare's Conversion Factor was $37.89 at the beginning of our sample, for total Medicare billing of $154,553. The extra spending from this hypothetical 1% reimbursement increase would thus be $1,545, for a pass-through of 62% (=$955/$1,545).

Accounting for Private Insurance Spillovers. Clemens and Gottlieb (2017) find that a $1 increase in Medicare reimbursements increases private insurance reimbursements by $1.16, or 83% of the baseline private/public payment difference (a factor of 1.39 in their data). Private insurance is 1.7 times as large as Medicare (CMS, 2019), so 83% as large a response in a market 1.7 times the scale of Medicare implies 1.4 times the extra spending, or $2,192. The total increase in Medicare-attributable spending is then $3,737, implying a pass-through of 25%.

C.2 ACA Insurance Expansions

Based on Medicaid expansion dates (listed below in parentheses) obtained from the Kaiser Family Foundation we include the following states in our analysis: AZ (1/2014), AR (1/2014), CA (1/2014), CO (1/2014), CT (1/2014), HI (1/2014), IL (1/2014), IN (2/2015), IA (1/2014), KY (1/2014), MD (1/2014), MI (4/2014), MN (1/2014), NV (2/2014), NH (8/2014), NJ (1/2014), NM (1/2014), ND (1/2014), OH (1/2014), OR (1/2014), PA (1/2015), RI (1/2014), WA (1/2014), WV (1/2014). Following the literature on Medicaid expansion (Ghosh et al., 2019; Miller and Wherry, 2019; Miller et al., 2021; McInerney et al., 2020), we exclude DE, DC, MA, NY, and VT from our analysis, as ACA insurance expansions in these states either took place earlier than 2014 or were not binding in practice, as the states had more generous coverage rules already prior to the ACA.

County-level insurance rates are from the Census Bureau Small Area Health Insurance Estimates (SAHIE) data at https://www.census.gov/data/datasets/time-series/demo/sahie/estimates-acs.html.

D Extensive Margin Choice: Medicine vs. Law

We use our data to compare physicians earnings to the next-most-common high-earning career in the U.S.: lawyers. This calculation provides loose guidance about how much scope there realistically is for policy to reduce physicians' incomes before alternative career options would dominate financially. Law is also a profession with high human capital investments, expensive specialized training, and licensure requirements. Yet barriers to entry are lower. Anecdotally, there is no shortage of law school spots, no analogue to limited residency slots, and no shortage of lawyers (Murphy et al., 1991). So it seems plausible that most people who become a physician could have become a lawyer, and lawyers' income provides a useful measure of outside options available to potential physicians.

Physicians and lawyers have very different lifecycle earnings patterns, so simple comparisons of mean earnings between working physicians and working lawyers would be misleading. We use the panel dimension of our data to estimate the distribution of total career earnings, reported in Table E.15. Appendix B.2 describes our method of computing the present discounted value of earnings. With 3% annual discounting, we estimate that physicians' average PDV of earnings at age 20 is \$10.1 million (equivalent to a \$386,000 annuity payment). The analogous estimate for lawyers is \$7.1 million (equivalent to a \$274,300 annuity payment). Notably, our estimates of annual earnings and resulting PDVs for both physicians and lawyers are 2 to 5 times higher than in Altonji and Zhong (2021), consistent with the substantial underreporting of non-wage earnings in survey data documented in Section 2. Against these discounted earnings we must count the cost of undergraduate and professional training, which we estimate to be \$250,500 for physicians and \$187,000 for lawyers, each corresponding to 2.5% of average lifetime earnings. (Appendix B.2 provides the sources for this estimate.) Once we account for difference in tuition, an average physician earns 42% more over their lifetime than an average lawyer.[70]

We next consider differences in working hours. We include a premium for hours beyond a 40-hour work week, since labor supply slopes up and the skilled labor market offers a premium for working long hours (Goldin, 2014). If physicians and lawyers had the same base hourly income, physicians would earn 12% more based purely on the difference in hours. This leaves a 30 percentage point difference in earnings attributable to forces beyond hours worked. For the lowest-paid specialty, primary care, we estimate the average lifetime earnings at \$6.5 million. The total cost of tuition with debt is around 5% of these lifetime earnings. This implies that an average PCP earns \$0.6 million less than an average lawyer and, with interest,

[70]To make the calculation as conservative as possible, we can also consider borrowing costs. It is not obvious that these should matter—after all, future debt payments should be discounted. But, for argument's sake, suppose students have to pay a risk premium entirely due to financial market frictions and their pure rate of time preference is zero. Medical students might borrow an extra \$115,000 relative to lawyers to cover the additional year of schooling (tuition of \$63,000 and approximately \$50,000 for living expenses) (Stanford, 2020). Suppose students borrow this at an average interest rate of 6.6% for 10 years (Bhole, 2017). This results in total (undiscounted) debt payment of around \$160,000 over 10 years. Assuming a 40% marginal tax rate, but ignoring any beneficial tax treatment of student loans, physicians would need to earn \$267,000 in undiscounted income to repay this extra loan. Under this extremely conservative calculation, the extra debt constitutes 9% of the extra \$3 million in discounted income that an average physician earns relative to an average lawyer.

pays about 1.5 percentage points more of lifetime earnings for their training.[71] Another way to see this is that lawyers would be very close to the regression line in Figure 2A; physicians have outside options that offer a similar hours-earnings tradeoff.

Overall, the evidence on relative incomes along with our estimates of meaningful labor supply responses suggest that policies aiming to cut physician earnings across the board could encounter serious problems. Section 3 shows the government has the power to make these sorts of changes. But income cuts may push lower-paid primary care physicians further below realistic outside options available to them within the U.S.

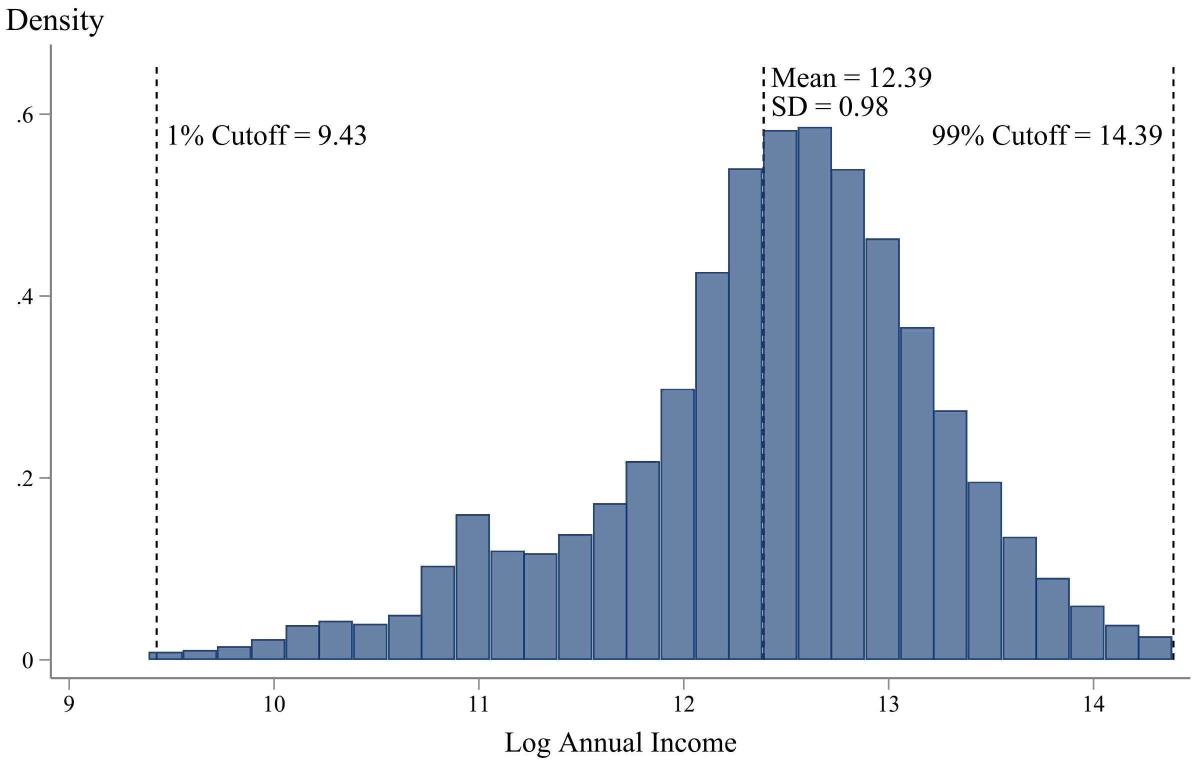
These results also highlight that the comparison of physician earnings in the U.S. to physician earnings in other OECD countries is not necessarily helpful for domestic policy debates. These comparisons miss the point that U.S. physicians could alternatively have been other high-skilled professionals in the U.S., who also command high incomes. Indeed, while U.S. physicians clearly earn more than their counterparts in other countries in absolute terms, their position in their respective national income distribution is not necessarily as different (Fadlon et al., 2020; Chen et al., 2022; Ketel et al., 2016).[72]

[71] Note that, even for PCPs, average tuition accounts for a modest share of earnings. This casts doubt on the importance of efforts to reduce or eliminate tuition for medical education (Supiano, 2018) as a way of reallocating talent towards PCPs.

[72] Using Swedish administrative earning records, Chen et al. (2022) found that 10% of physicians are in the top two and 42% of physicians are in the top five percentiles of the Swedish income distribution, thus resembling the U.S. in relative terms.

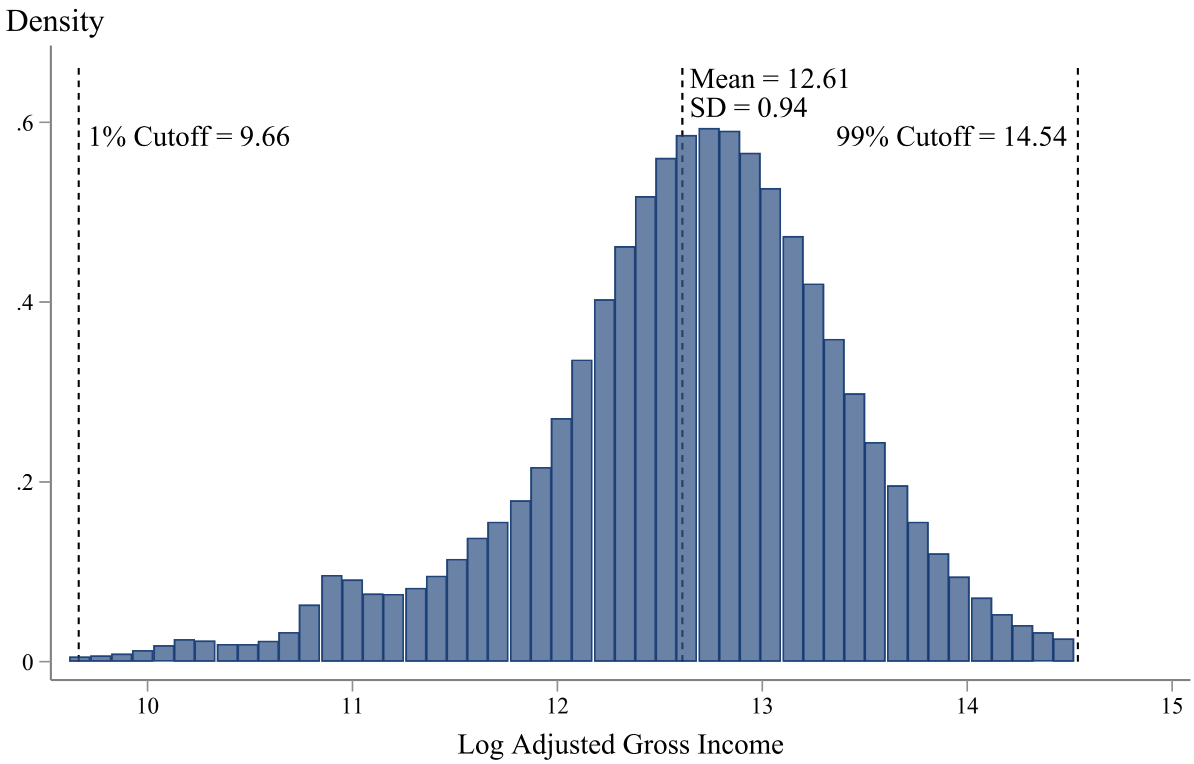
E Appendix Tables and Figures

Figure E.1: **Distribution of Physician Income**



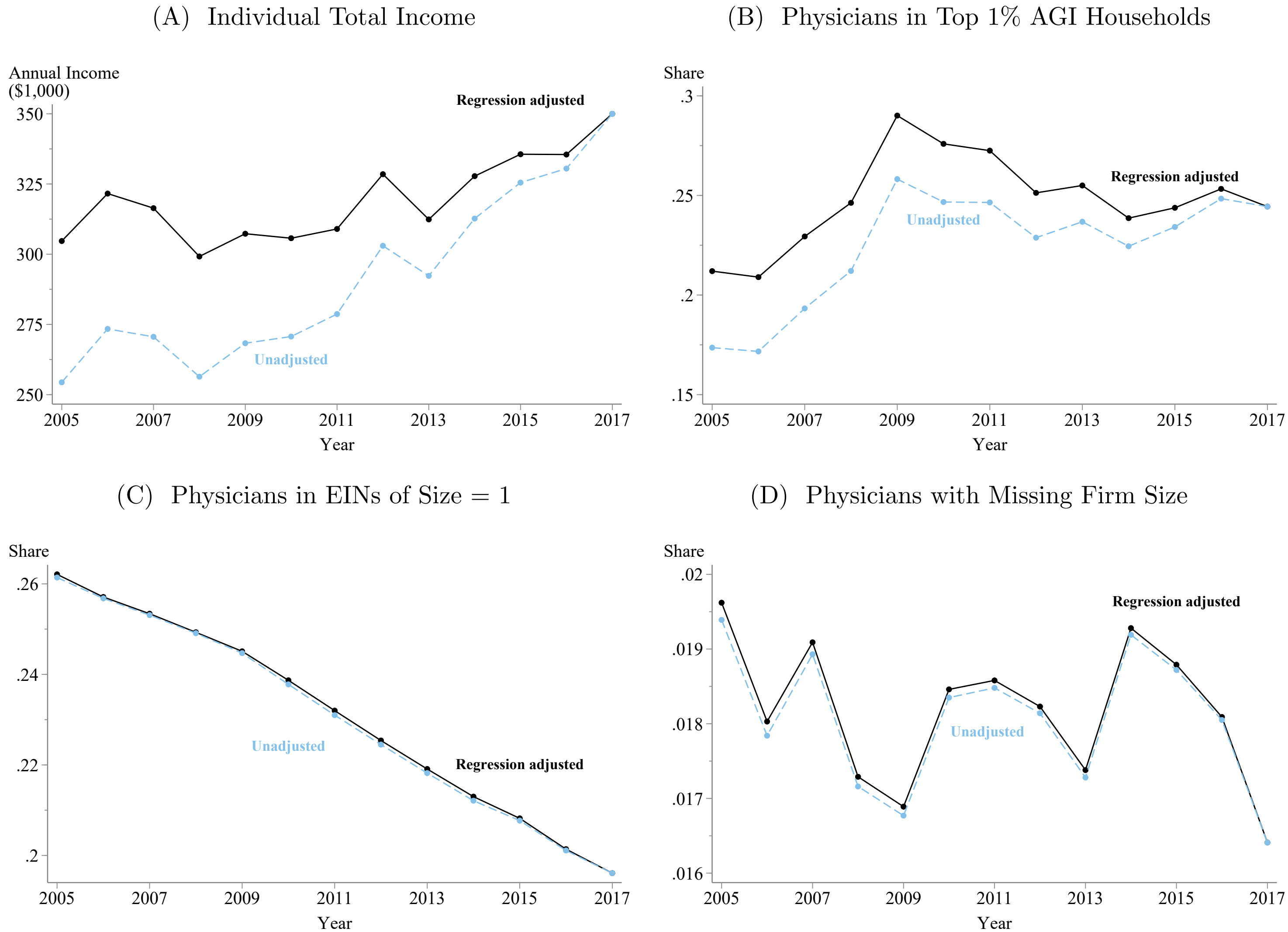
Notes: This figure plots the distribution of log individual total income among 20- to 70-year-old U.S. physicians in year 2017. The sample includes all physicians who were listed in the 2017 vintage of the National Plan and Provider Enumeration System (NPPES) for whom a record was observed in the universe of 2017 U.S. individual income tax return data. Individual total income is measured using individual tax returns data and is defined as the sum of individual total wage income and the household AGI net of all wage earnings and taxable retirement distributions (for those aged 60 or older), but gross of tax-exempt interest and Social Security payments. Section 1 and Appendix B.2 provide measurement details. Disclosure Review Board approval CBDRB-FY23-0319, CBDRB-FY2023-CES005-024.

Figure E.2: **Distribution of Physician Adjusted Gross Income**



Notes: This figure plots the distribution of log Adjusted Gross Income (AGI) among 20- to 70-year-old U.S. physicians in year 2017. The sample includes all physicians who were listed in the 2017 vintage of the National Plan and Provider Enumeration System (NPPES) for whom a record was observed in the universe of 2017 U.S. individual income tax return data. AGI is directly reported in the individual tax data and is a household-level measure of income. Appendix B.2 provides details of all income measures. Disclosure Review Board approval CBDRB-FY23-0319, CBDRB-FY2023-CES005-024.

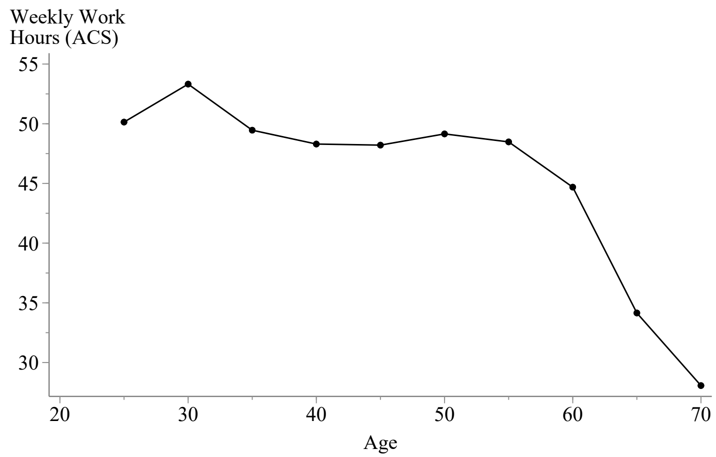
Figure E.3: **Time Series of Earnings and Firm Size**



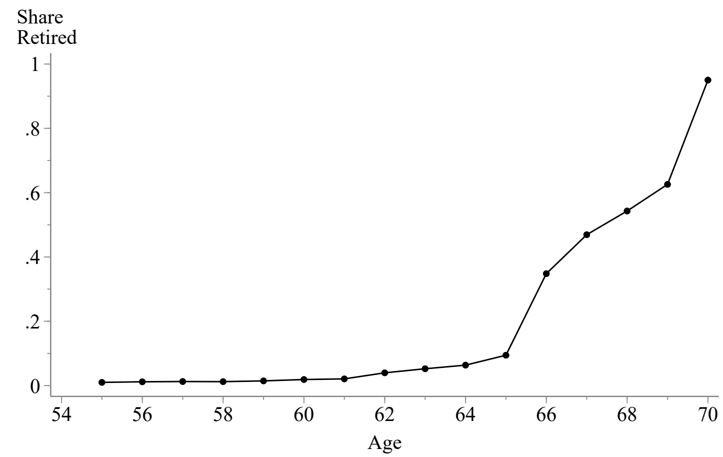
Notes: This figure plots the time evolution of mean individual total income (Panel A), share of physicians in households that are in the top 1% of the national income distribution (Panel B), share of physicians in firms (EIN) with only one physician (Panel C), and share of physicians with no W-2 filing and hence no EIN (Panel D). All panels include our full sample—years 2005 to 2017 and all ages from 20 to 70. Each panel plots the raw time series of means or shares, as well as the regression-adjusted time series. Regression-adjustment equalizes the composition of age, sex, Medicare specialties, and states across time to 2017 levels. We plot the raw means for the same sample as the regression-adjusted sample which requires us to observe age, sex, Medicare specialty, and state. See Appendix B.2 for a more detailed discussion of how we measure total individual income and firm size. Disclosure Review Board approval CBDRB-FY23-0319, CBDRB-FY2023-CES005-024.

Figure E.4: **Physician Labor Supply over the Lifecycle**

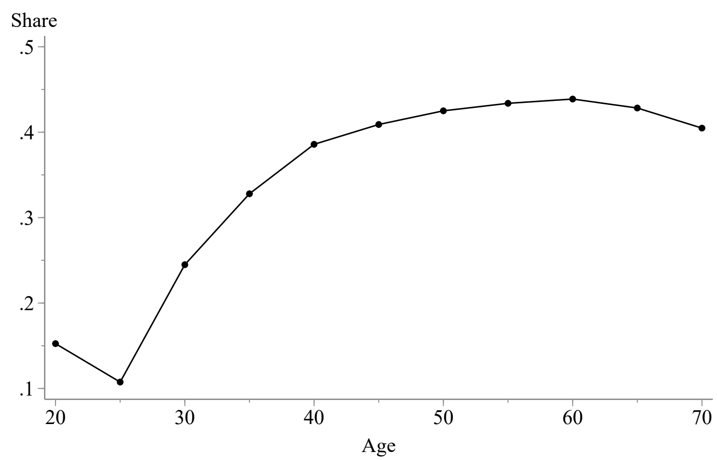
(A) Weekly Work Hours



(B) Retirement

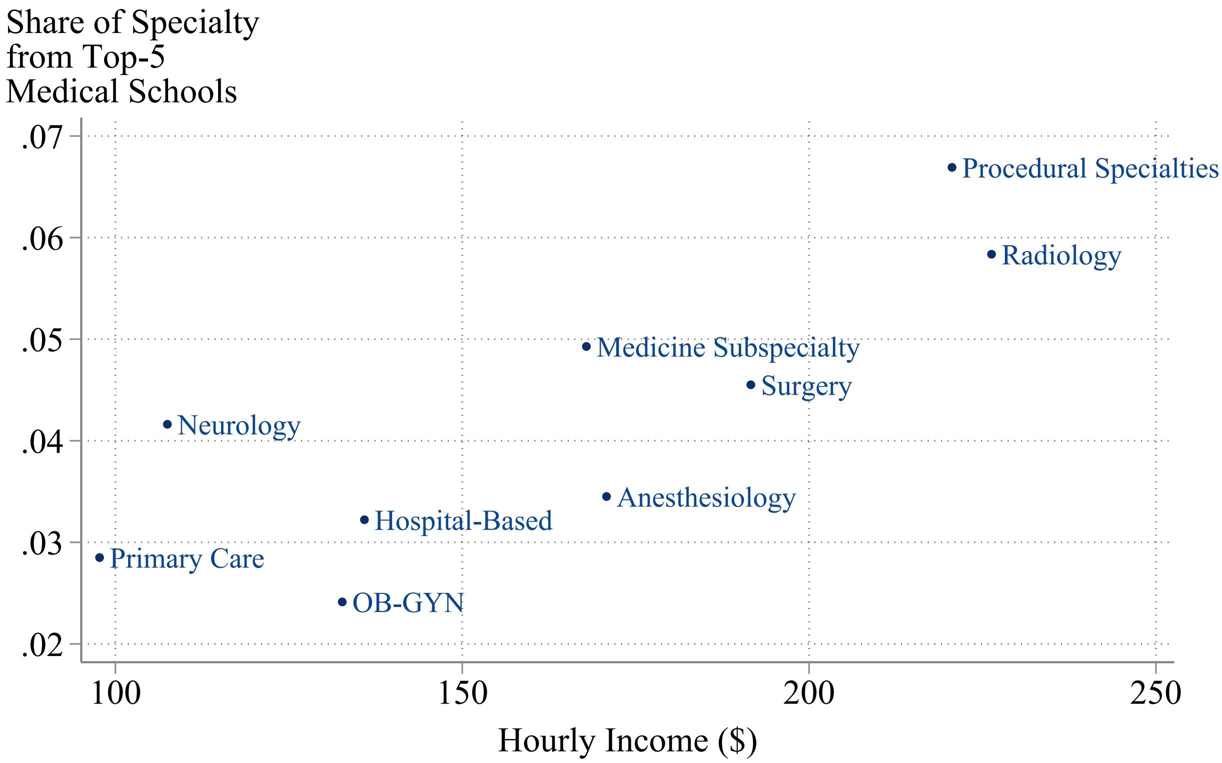


(C) Filed Schedule C



Notes: The figure plots mean weekly hours of work (Panel A), the share of physicians who are retired (Panel B), and the share of physicians filing Schedule C (Panel C) in our 2017 sample of physicians, by 5-year age intervals. Weekly work hours are measured from the subsample of physicians who are observed in ACS data. Retirement is defined as receiving Form 1099-SSA. Filing of Schedule C is directly observed in the tax data. Appendix B.2 provides more measurement details. Disclosure Review Board approval CBDRB-FY23-0319, CBDRB-FY2023-CES005-024.

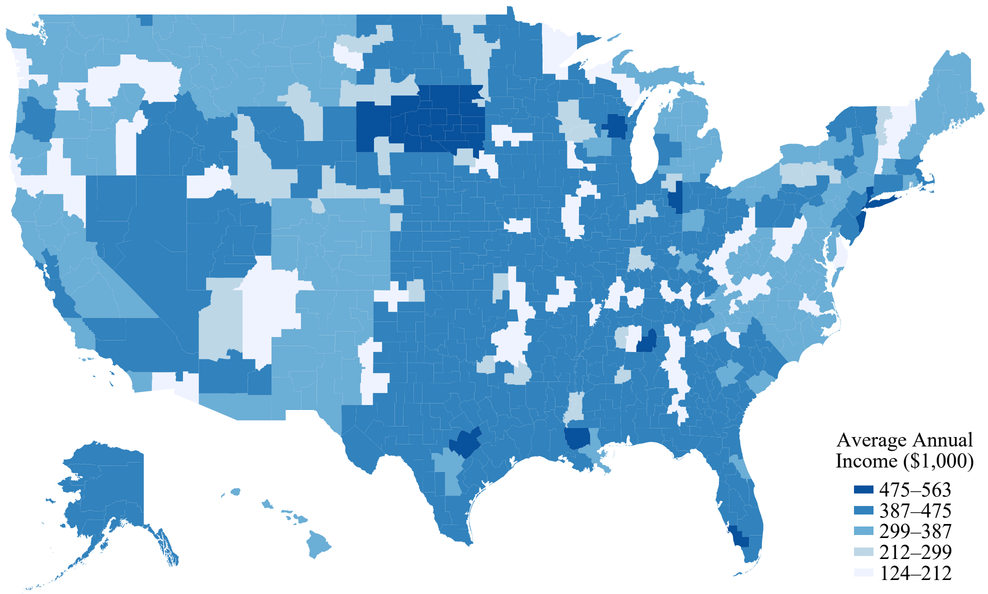
Figure E.5: **Medical School Rank vs. Specialty Income**



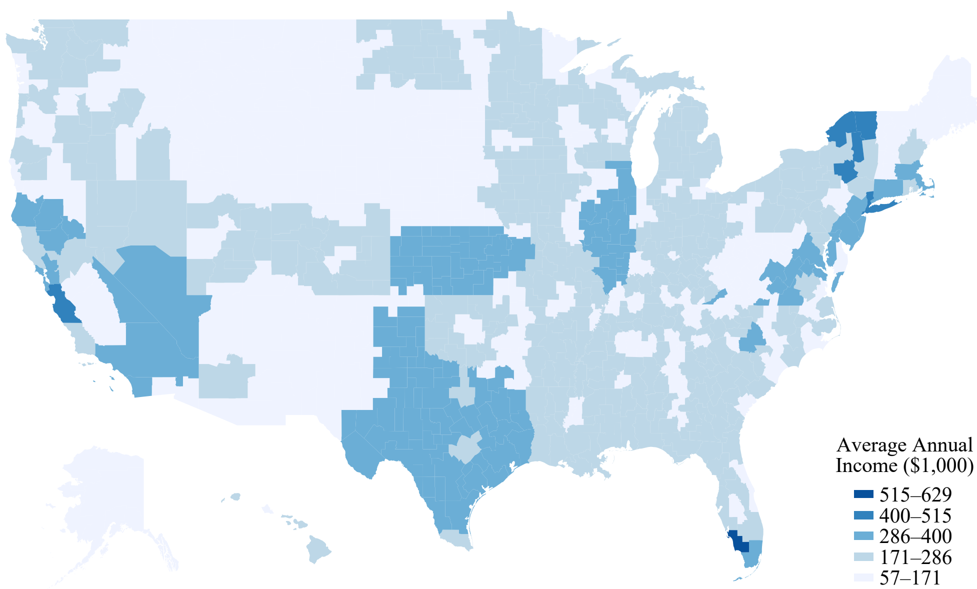
Notes: This figure plots the relationship between mean hourly income in a specialty category and the share of physicians in that specialty that graduated from top-5 MD programs as ranked by the U.S. News and World Report. Mean hourly income is computed as the ratio of mean individual total income among 40–55-year-old physicians in years 2005–2017 in a specialty category to the mean weekly work hours, multiplied by 52 reported, by physicians in the same sample who are also observed in ACS data. The share of top-5 MD graduates is computed on the full sample of physicians for whom we observe the medical school name. "Top-5" is defined as a school that had a rank 1 to 5, inclusive, in one or more year of the U.S. News and World Reports from 2005 to 2018. Disclosure Review Board approval CBDRB-FY23-0319, CBDRB-FY2023-CES005-024.

Figure E.6: **Geographic Variation in Earnings**

(A) Physicians

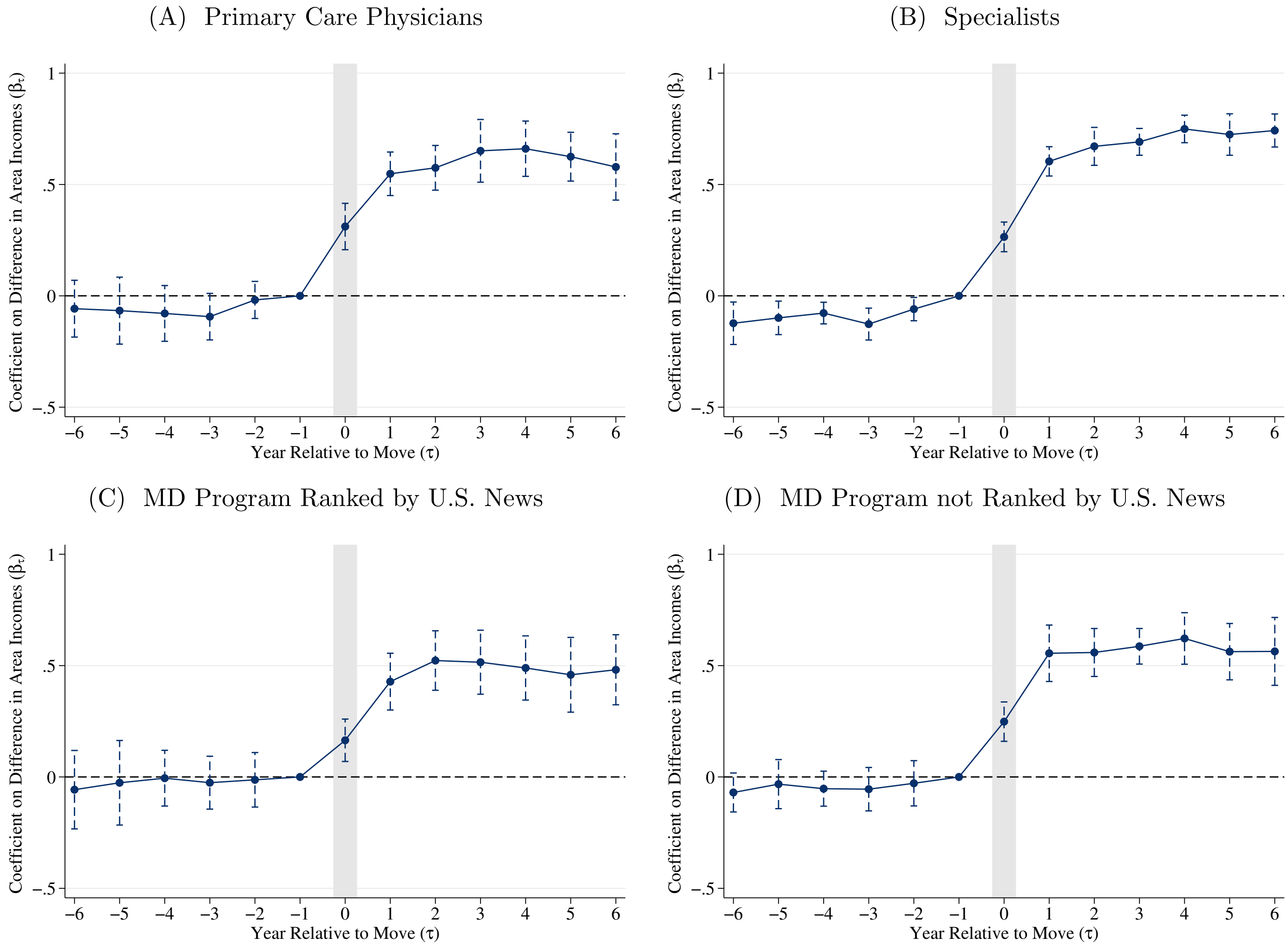


(B) Lawyers



Notes: This figure plots mean individual total income among 40- to 55-year-old physicians (Panel A) and lawyers (Panel B) in year 2017 by Commuting Zone (CZ). Mean income in the 122 largest commuting zones was computed directly. Mean income in remaining commuting zones was computed as an adjusted mean state-level income (state-levels means are shown in Figure 3), weighted by CZ population shares when CZs cross state boundaries. Adjusted mean state-level income excludes 122 CZs that are reported separately using population weights. Disclosure Review Board approval CBDRB-FY23-0319, CBDRB-FY2023-CES005-024.

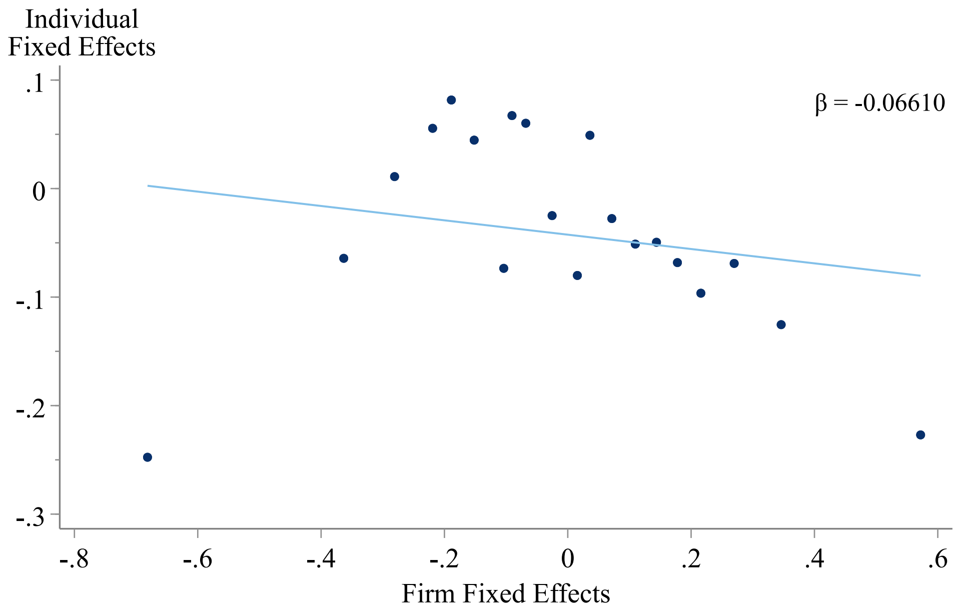
Figure E.7: **Event Study: Subsamples of Physician Movers**



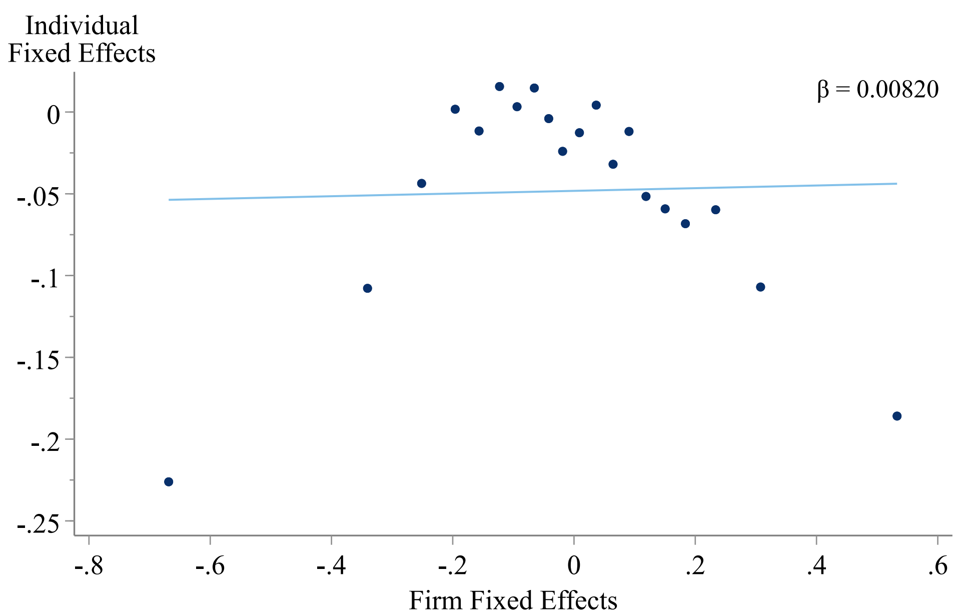
Notes: This figure shows coefficient estimates on the difference between mean physician individual total income in the origin and destination commuting zones ($\Delta\overline{\ln y}_{(j,k)}$) from equation (1) for four subsamples of physician-movers as indicated in panel titles. The coefficient is normalized to 0 in the year prior to the move ($\tau = -1$). The dashed lines mark the 95% confidence intervals. The outcome variable is log individual total income. The independent variables include $\Delta\overline{\ln y}_{(j,k)}$ interacted with physician fixed effects, relative year fixed effects, and age fixed effects. A physician is considered to be a mover if they changed their commuting zone once between years 2005 to 2017, and were age 40 to 55 during that change. Disclosure Review Board approval CBDRB-FY24-0456.

Figure E.8: **Firm and Individual Fixed Effects**

(A) Unconditional

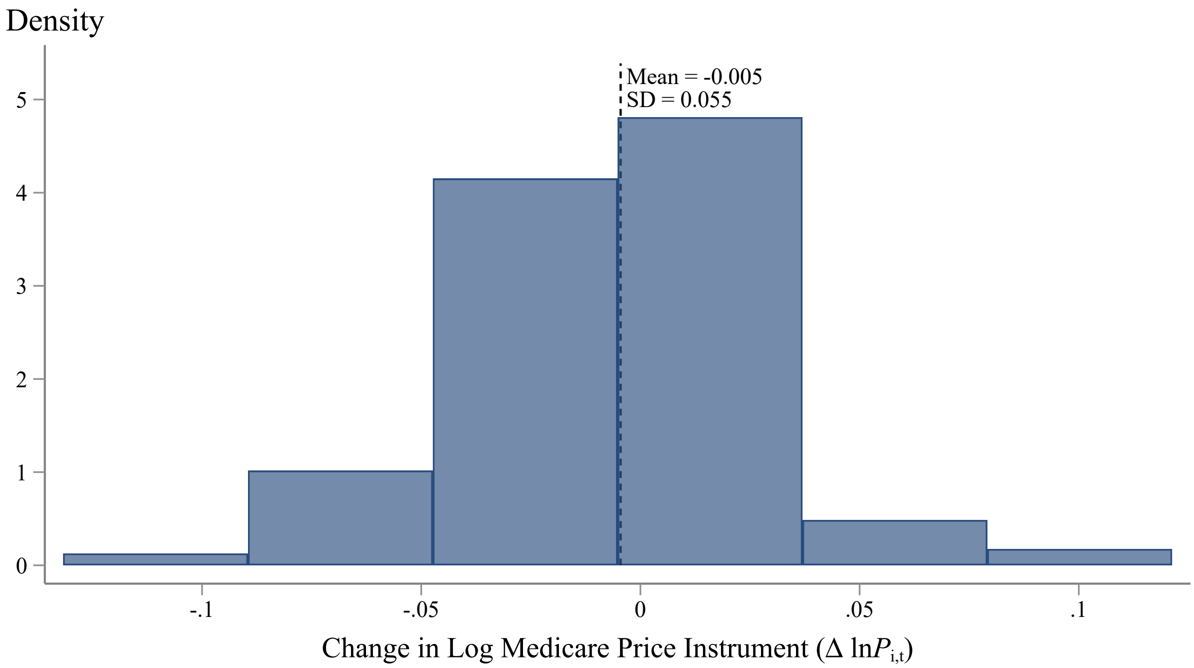


(B) Within Commuting Zone



Notes: This figure plots the relationship between firm effects and person effects based on estimation of the firm analogue of equation (2) in the sample of physicians who switched firms (defined as an EIN) once in the full panel and were age 40 to 55 when they did so. The analysis is restricted to firms with 15 or more physicians. The outcome variable is log individual total income. The independent variables include physician, firm, relative year, and age fixed effects. Panel A is a binned scatterplot that plots the average individual fixed effect within each ventile of the firm fixed effects distribution. In Panel B we residualize the x-axis and the y-axis on commuting zone fixed effects as in Dauth et al. (2022). The line of best fit is a bivariate OLS regression on the underlying data points. Disclosure Review Board approval CBDRB-FY23-0319, CBDRB-FY2023-CES005-024.

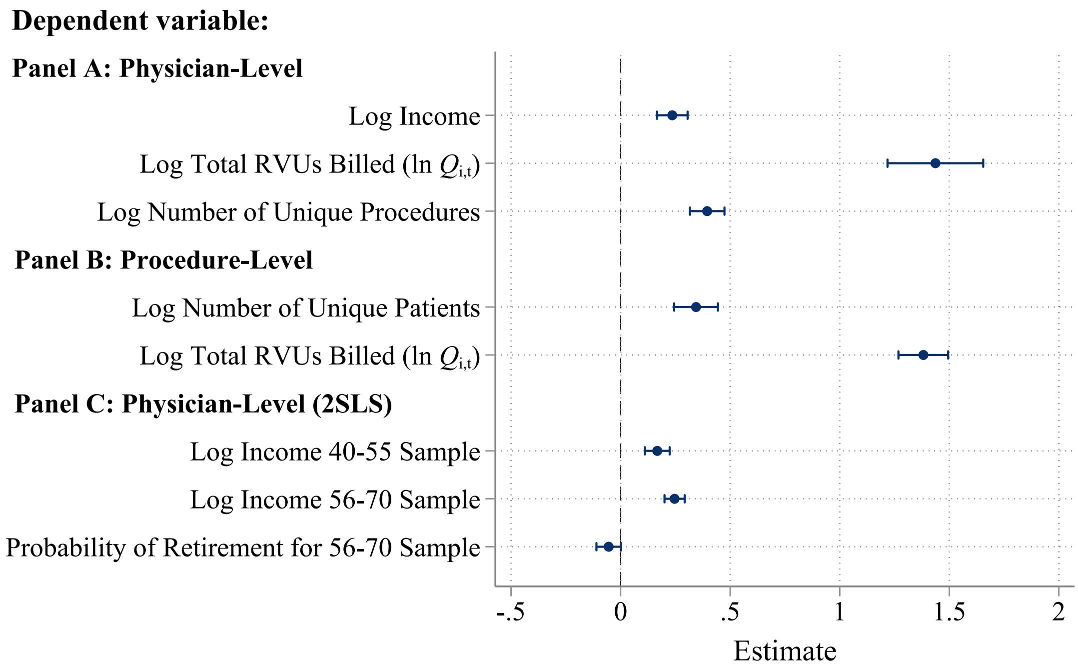
Figure E.9: **Distribution of RVU Changes**



5th Percentile: -0.050; 25th Percentile: -0.010; 50th Percentile: 0.000;
75th Percentile: 0.010; 95th Percentile: 0.030

Notes: This figure reports the distribution of one year changes in $\ln P_{i,t}$—the log of the total number of RVUs for a fixed vector of services by physician i in year t as computed in equation (4). The sample includes all physicians in our baseline sample who were also observed in 2012 to 2017 Physician and Other Supplier Public Use File of the Physician Medicare Provider Utilization and Payment Data (MPUPD). The fixed vector of services is defined as the average number of times each service (defined as a combination of HCPCS procedure code and facility or non- facility place of service designation) was performed by a physician between years 2012 and 2017. Each service in this time-invariant vector is multiplied by the year-specific RVU rate for this service. The resulting total number of RVUs per physician can vary from year to year only if Medicare changes how many RVUs are assigned to a service. Section 3.1 describes further the institutional details of Medicare billing. Disclosure Review Board approval CBDRB-FY23-0319, CBDRB-FY2023-CES005-024.

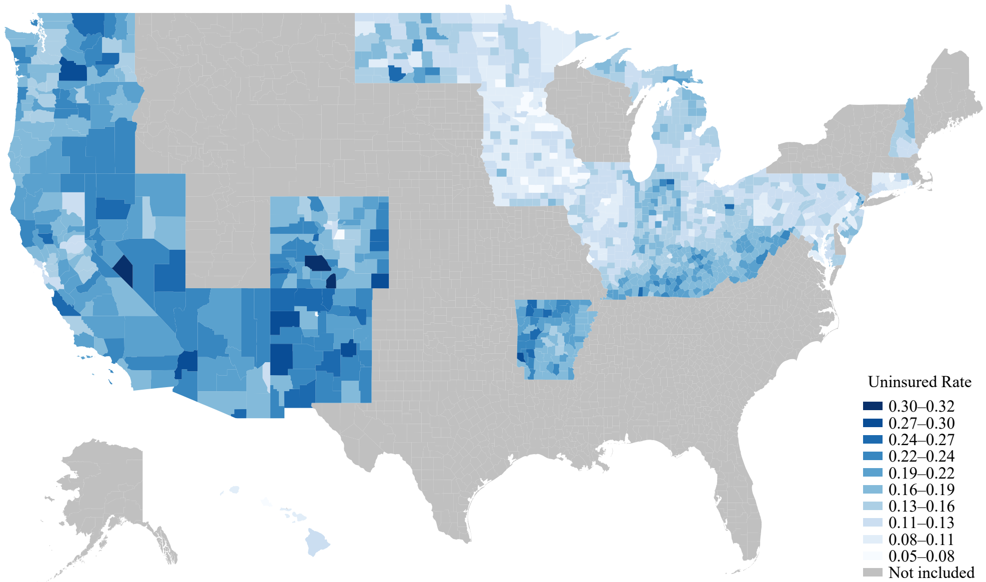
Figure E.10: **Effects of Changes in Medicare RVUs**



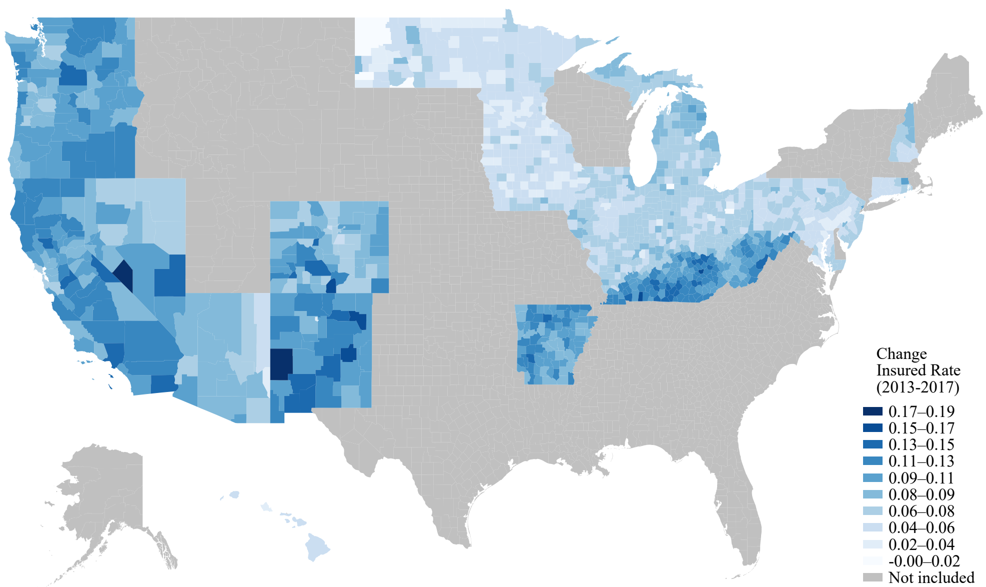
Notes: This figure reports the coefficients and 95% confidence intervals from estimating equation 5 for each outcome variable as indicated on the vertical axis. Each coefficient can be interpreted as an elasticity (or arc-elasticity). For physician-level regressions in Panel A, the main independent variable is $\ln P_{i,t}$, or log Relative Value Units (RVUs) for a fixed vector of services. In Panel B, the main independent variable is the time-varying RVU rate for a serve. Specifications in Panel C regress the outcome variable of interest on the log number of RVUs for performed services instrumented by $\ln P_{i,t}$. Regressions in all panels also include age fixed effects, and Medicare specialty-by-year fixed effects. As described in Section 3.1, the fixed vector of services is defined as the average number of times each service (defined as a combination of HCPCS procedure code and facility or non-facility place of service designation) was performed by a physician between years 2012 and 2017. Each service in this time-invariant vector is multiplied by the year-specific RVU rate for this service as shown in equation (4). The resulting total total number of RVUs per physician can vary from year to year only if Medicare changes how many RVUs are assigned to a service. Disclosure Review Board approval CBDRB-FY23-0319, CBDRB-FY2023-CES005-024.

Figure E.11: **Geographic Variation in Share Uninsured**

(A) Share of Population Under 65 Uninsured in 2013

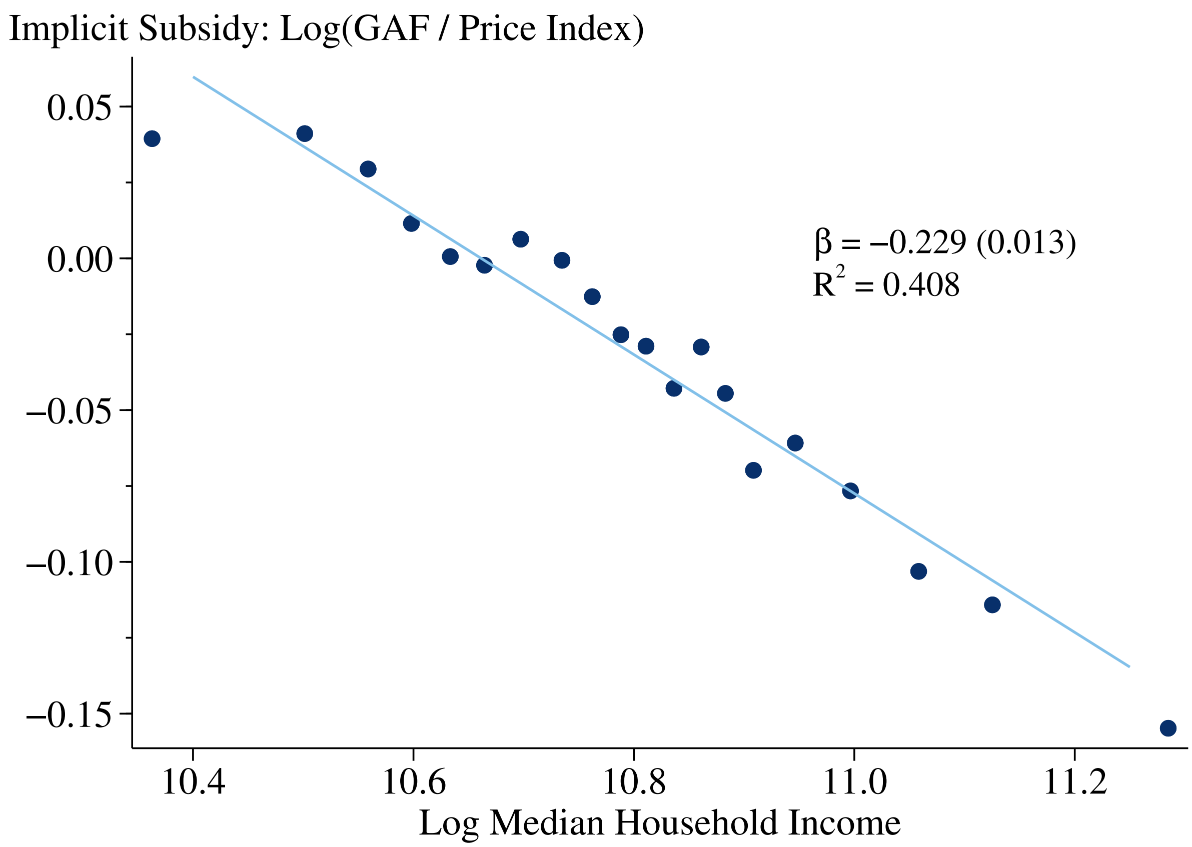


(B) Change in Share of Population Under 65 Insured from 2013-2017



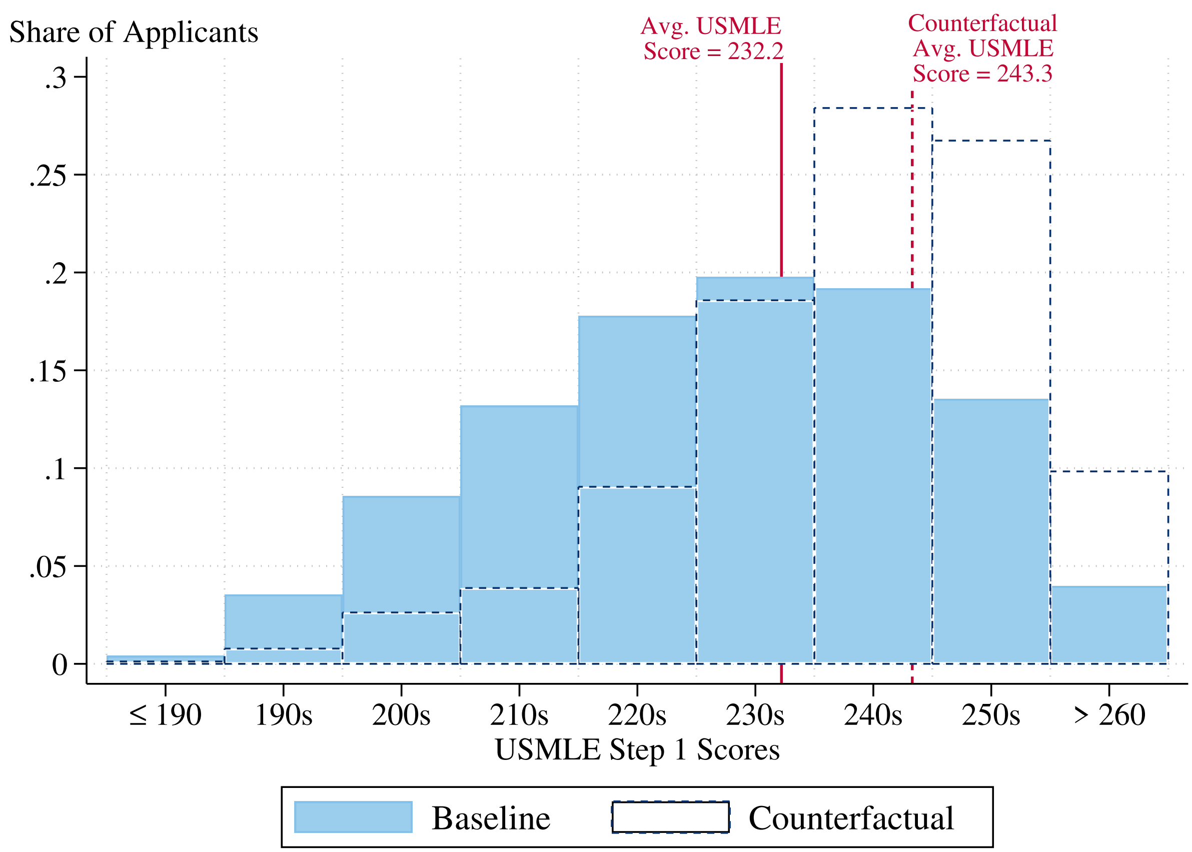
Notes: The figure shows the proportion of the population under 65 years old without health insurance in 2013 (Panel A), and the change in that proportion from 2013 to 2017 (Panel B, shown as change in the rate of insured) for counties that are included in our analyses of the effects of the ACA's expansion in Section 3.2. These counties are located in states that expanded Medicaid in 2014 and 2015, *i.e.* simultaneous with the rollout of ACA Individual Health Insurance Marketplaces. Appendix C.2 provides the list of states and expansion dates. Rate of insurance data is based on U.S. Census Bureau's Small Area Health Insurance Estimates. Disclosure Review Board approval CBDRB-FY23-0319, CBDRB-FY2023-CES005-024.

Figure E.12: **Implicit Subsidy vs. Log Median Household Income**



Notes: This figure plots the relationship between our measure of the implicit geographic subsidy for physician services and CZ level log median household income in 2016. Median household income is as reported in Chetty et al. (2014). The implicit subsidy is calculated as the difference (in logs) between local input costs, measured using a local price index from Diamond and Moretti (2021), and the degree to which Medicare adjusts for those costs, measured using the Medicare Geographic Adjustment Factor (GAF) for physician care. The GAF is a factor that multiplies Medicare reimbursement rates; when this adjustment overestimates local production costs, rural areas are effectively subsidized (GAO, 2022). The figure is a binned scatterplot, where R^2 and the line of best fit are from a bivariate OLS regression on the underlying data points. The regression estimates are reported in Table E.10. Disclosure Review Board approval CBDRB-FY24-0456.

Figure E.13: **Increase Internal Medicine Income to Dermatology Level (2SLS)**



Notes: This figure reports the results of a counterfactual analysis in which we set the mean hourly income in internal medicine to equal the mean hourly income in dermatology. Counterfactual choices are predicted using the 2SLS version of the specialty choice model in equation (9). We first compute predicted choices within each USMLE score group and then re-normalize the data to plot the share of each USMLE score group within one specialty—internal medicine. Disclosure Review Board Approval CBDRB-FY24-0456.

Table E.1: **Definition of Specialty Categories**

Specialty Category	Medicare Specialty Code	Medicare Specialty Description
1	**Primary Care**	
	1	General Practice
	8	Family Practice
	11	Internal Medicine
	17	Hospice and Palliative Care
	23	Sports Medicine
	26	Psychiatry
	37	Pediatric Medicine
	38	Geriatric Medicine
	72	Pain Management
	79	Addiction Medicine
	84	Preventive Medicine
	C0	Sleep Medicine
2	**Medicine Subspecialty**	
	3	Allergy/Immunology
	6	Cardiovascular Disease (Cardiology)
	10	Gastroenterology
	21	Clinical Cardiac Electrophysiology
	29	Pulmonary Disease
	39	Nephrology
	44	Infectious Disease
	46	Endocrinology
	66	Rheumatology
	81	Critical Care (Intensivists)
	82	Hematology
	83	Hematology-Oncology
	90	Medical Oncology
	91	Surgical Oncology
	C3	Interventional Cardiology
	C7	Advanced Heart Failure and Transplant Cardiology
	Undefined	Genetics
	Undefined	Hypertension Specialist
	Undefined	Phlebology
3	**Obstetrics & Gynecology**	
	16	Obstetrics & Gynecology
	98	Gynecological Oncology

(... ... continued on next page...)

Specialty Category	Medicare Specialty Code	Medicare Specialty Description
(...	...	...continued from previous page)
4	**Surgery**	
	2	General Surgery
	14	Neurosurgery
	20	Orthopedic Surgery
	24	Plastic and Reconstructive Surgery
	28	Colorectal Surgery (Proctology)
	33	Thoracic Surgery
	40	Hand Surgery
	76	Peripheral Vascular Disease
	78	Cardiac Surgery
	85	Maxillofacial Surgery
5	**Procedural Specialties**	
	4	Otolaryngology
	7	Dermatology
	18	Ophthalmology
	34	Urology
6	**Hospital-Based**	
	22	Pathology
	25	Physical Medicine and Rehabilitation
	93	Emergency Medicine
	C6	Hospitalist
	Undefined	Pharmacology, Back Office
7	**Anesthesiology**	
	5	Anesthesiology
	9	Interventional Pain Management
8	**Radiology**	
	30	Diagnostic Radiology
	36	Nuclear Medicine
	92	Radiation Oncology
	94	Interventional Radiology
9	**Neurology**	
	12	Osteopathic Manipulative Medicine
	13	Neurology
	86	Neuropsychiatry
	Undefined	Electrodiagnostic Medicine

Notes: Mapping from Medicare Specialty Codes defined by Centers for Medicare and Medicaid Services to nine aggregate specialty categories. The mapping was constructed by the authors.

Table E.2: **Descriptive Variation in Earnings**

	Dependent Variable: Log Individual Total Income										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Female		-0.35								-0.22	-0.22
		(0.002)								(0.002)	(0.002)
Married		0.24								0.16	0.14
		(0.003)								(0.002)	(0.003)
Non-U.S.-Born		-0.05								-0.03	-0.00
		(0.004)								(0.003)	(0.006)
White		0.04								0.03	0.04
		(0.003)								(0.002)	(0.003)
Business Inc. > \$25K						0.43			0.51	0.47	0.38
						(0.002)			(0.002)	(0.002)	(0.002)
Graduated from Top-5 Medical School							0.11	0.02			0.04
							(0.005)	(0.005)			(0.004)
N	829,000	807,000	829,000	829,000	817,000	829,000	441,000	441,000	817,000	795,000	427,000
Age Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Medicare Specialty Fixed Effects	No	No	Yes	No	No	No	No	Yes	Yes	Yes	Yes
Commuting Zone Fixed Effects.	No	No	No	Yes	No	No	No	No	Yes	Yes	Yes
Firm Size Fixed Effects	No	No	No	No	Yes	No	No	No	Yes	Yes	Yes
Birth State Fixed Effects	No	Yes	No	No	No	No	No	No	No	Yes	Yes
R^2	0.14	0.19	0.22	0.14	0.19	0.18	0.07	0.20	0.34	0.37	0.34

Notes: This table reports coefficient estimates and R^2 from cross-sectional OLS regressions of 2017 log individual total income of physicians (age 20 to 70) on their individual-level observables. The sample size differs from that in column (2) of Table 1 because we exclude individuals with zero or negative individual total income. For each regression we report only selected point estimates. All columns include age fixed effects. Column (2) includes all demographic variables: indicators for being female, married, and non-U.S. born (alien history), and White. Column (3) shows the explanatory power of Medicare Specialty fixed effects. Column (4) shows the explanatory power of commuting zone (CZ) fixed effects. Column (5) shows the explanatory power of firm size, which is discretized into size 1, 2, 3, 4, 5, 6 to 25, 26 to 45, 46 to 100, 101 to 400, and greater than 401. Column (6) separately includes an indicator for having more than \$25,000 in business income as defined in Appendix B.2. Column (7) includes an indicator for having graduates from one of top-5 MD programs according to U.S. News and World Report, while column (8) adds Medicare specialty fixed effects to this specification. Column (9) includes all career choice variables jointly: Medicare specialty fixed effects, discretized firm size fixed effects, CZ fixed effects and indicator for having more than \$25,000 in business income. Column (10) includes all variables except top-5 MD indicator that is only available for a subsample as shown in column (11). Section 1 and Appendix B.2 provide details on data sources and measurement of each variable. Disclosure Review Board approval CBDRB-FY23-0319, CBDRB-FY2023-CES005-024, CBDRB-FY24-0456

Table E.3: **Comparison of Tax and ACS Data**

		Mean Individual Total Income	
Sample	N	Tax Data	ACS Data
2017 Tax Sample	848,000	\$350,000	N/A
2017 Tax Sample ∩ 2017 ACS	14,000	\$363,500	\$234,700
2017 Tax Sample ∩ 2017 ACS ∩ report being a physician in 2017 ACS	11,500	\$365,400	\$258,100
2017 Tax Sample ∩ 2017 ACS ∩ do not report being a physician in 2017 ACS	2,500	\$354,500	\$128,600

Notes: The table compares average individual total income computed in tax data to the analogues of this income measure computed from self-reported income variables in ACS. The samples are as defined in the table, starting with our full sample in 2017 (sample in column 2 of Table 1). Individual total income in the tax data is defined as the sum of W-2 wages (including deferred contribution) and the residual of AGI net of household wages and social security income. ACS income is the sum of wages, self-employment income of the index physician, and self-employment income of the spouse as reported in the survey. We discount non-wage incomes of index physicians whose spouse is also a physician by 50%. Appendix B.2 provides more details on the definition of all income measures. Disclosure Review Board approval CBDRB-FY23-0319, CBDRB-FY2023-CES005-024.

Table E.4: **Comparison of Tax and ACS Data by Income Type**

			Business Income			
	Wage | Wage > 0		Unconditional		| Business Inc. > 0	
	(1) Tax	(2) ACS	(3) Tax	(4) ACS	(5) Tax	(6) ACS
Mean Income	\$289,400	\$257,300	\$79,470	\$21,480	\$153,700	\$112,900
N	10,000	10,500	11,500	11,500	6,800	2,200

Notes: The table compares average wage and business income computed in tax data and ACS data among physicians in our baseline sample, who also appear in 2017 ACS and report being a physician in 2017 ACS ($N = 11,500$). Columns (1) and (2) report mean wages among those physicians who had strictly positive wages. Columns (3) and (4) report mean business income. Column (5) and (6) report mean business income, conditional on having strictly positive business income. Appendix B.2 provides more details on the definition of all income measures. Disclosure Review Board approval CBDRB-FY23-0319, CBDRB-FY2023-CES005-024.

Table E.5: **Summary Statistics by Specialty Category**

		Individual Total Income (2017 $)		Wage Income (2017 $)		Adjusted Gross Income (2017 $)		Share in Top 1%	
		(1) 2005	(2) 2017	(3) 2005	(4) 2017	(5) 2005	(6) 2017	(7) 2005	(8) 2017
Anesthesiology	Mean	452,000	463,300	334,900	335,800	517,100	544,100	0.42	0.38
	Median	403,700	407,400	339,200	350,200	442,000	453,700	-	-
Hospital-Based	Mean	315,600	362,200	229,500	252,900	375,200	444,900	0.19	0.24
	Median	267,400	314,100	217,900	254,800	302,900	367,200	-	-
Medicine Subspecialty	Mean	525,600	488,500	355,400	361,000	602,200	593,800	0.45	0.47
	Median	379,400	399,700	273,200	312,000	446,500	491,600	-	-
Neurology	Mean	277,600	310,700	179,600	226,200	351,900	406,200	0.16	0.20
	Median	216,400	262,900	169,200	217,100	266,300	330,600	-	-
OB-GYN	Mean	379,600	412,100	259,400	291,100	458,500	536,700	0.31	0.34
	Median	311,700	333,900	246,200	278,300	366,600	413,800	-	-
Primary Care	Mean	249,200	282,300	156,400	201,200	302,700	381,900	0.11	0.16
	Median	193,600	235,300	155,000	198,000	235,800	298,900	-	-
Procedural Specialties	Mean	562,500	635,700	337,800	378,400	647,900	763,200	0.50	0.56
	Median	422,000	470,100	281,500	327,500	489,300	564,200	-	-
Radiology	Mean	609,400	561,600	451,000	402,300	681,900	657,300	0.64	0.55
	Median	535,000	481,300	438,600	400,500	585,300	545,800	-	-
Surgery	Mean	579,500	658,000	402,800	477,100	631,000	730,400	0.50	0.57
	Median	451,600	522,400	345,400	419,700	493,000	582,400	-	-

Notes: This table reports mean and median of physician individual total income, wage income, AGI, and share in the top 1% of the national income distribution, by specialty category. We include physicians aged 40 to 55 in years 2005 and 2017. Specialty categories are aggregated from Medicare specialties as defined in Table E.1. All dollar-denominated values are inflation-adjusted to 2017 dollars. Section 1 and Appendix B.2 provide more details on data sources and measurement of each variable. Disclosure Review Board approval CBDRB-FY23-0319, CBDRB-FY2023-CES005-024.

Table E.6: **Decomposition of Variation in Earnings**

	No Covariates			Two-Way Fixed Effects With Covariates	
	Two-Way Fixed Effects (1)	Homoskedastic Bias Correction (2)	Heteroskedastic Bias Correction (3)	Individual-Level (4)	CZ-Level / Firm-Level (5)
Panel A: Physicans					
Location Effect: $\mathrm{Var}(\psi_c)$	0.016	0.012	0.011	0.014	0.071
Sorting Effect: $2 \times \mathrm{Cov}(\alpha_i, \psi_c)$	-0.013	-0.008	-0.007	-0.011	-0.086
Panel B: Lawyers					
Location Effect: $\mathrm{Var}(\psi_c)$	0.034	0.013	0.003	0.041	0.325
Sorting Effect: $2 \times \mathrm{Cov}(\alpha_i, \psi_c)$	-0.007	0.024	0.039	-0.015	-0.453
Panel C: Firms					
Location Effect: $\mathrm{Var}(\psi_c)$	0.088	0.073	0.073	0.070	0.184
Sorting Effect: $2 \times \mathrm{Cov}(\alpha_i, \psi_c)$	-0.047	-0.025	-0.025	-0.025	-0.076

Notes: This table reports elements of variance decomposition of individual total income among 40-to-55-year-old physicians (Panels A and C) and lawyers (Panel B) in the sample of movers (see definition in Figure 4.) Estimates are based on equation (2). The outcome variable is log individual total income. The independent variables include physician, commuting zone (Panel A and B) or firm (Panel C), as well as relative year and age fixed effects (in columns 4 and 5 only). The variation in location effects, $\mathrm{Var}(\psi_c)$, is computed as the variance of estimated CZ fixed effects. The effect of sorting of people to locations, $\mathrm{Cov}(\alpha_i, \psi_c)$, is computed as the covariance of individual and CZ fixed effect estimates. Column (1) reports the result of a two-way fixed effect decomposition in equation (2) with no covariates. Columns (2) and (3) report homoskedastic and heteroskedastic corrections of the same specifications based on Andrews et al. (2008) and Kline et al. (2020), respectively, as implemented in Bonhomme et al. (2023). Column (4) reports the results based on estimating equation (2) with a full set of covariates. Column (5) aggregates person-level fixed effects to CZ means before computing the variance decomposition terms, following Card et al. (2021). Disclosure Review Board approval CBDRB-FY23-0319, CBDRB-FY2023-CES005-024.

Table E.7: **Decomposition of Variation in Earnings in Subsamples**

	All Physicians: Without Covariates	All Physicians: With Covariates	Primary Care Physicians	Specialists	Graduates of Ranked MD Program	Graduates of Non-Ranked MD Program	Lawyers
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Person-Level Variance Decomposition							
Location Effect: Var(ψ_c)	0.016	0.014	0.018	0.020	0.017	0.022	0.041
Sorting Effect: $2 \times$ Cov(α_i, ψ_c)	-0.014	-0.011	-0.019	-0.013	-0.017	-0.020	-0.015
Panel B: CZ-Level Variance Decomposition							
Location Effect: Var(ψ_c)	0.067	0.071	0.081	0.157	0.121	0.075	0.325
Sorting Effect: $2 \times$ Cov(α_i, ψ_c)	-0.083	-0.086	-0.092	-0.225	-0.132	-0.095	-0.453

Notes: This table reports elements of variance decomposition of total income among 40-to-55-year-old physicians, overall (in columns 1 and 2) and by subsamples as indicated in column names (columns 3 to 7). Estimates are based on equation (2). The outcome variable is log individual total income. The independent variables include physician, commuting zone, as well as relative year and age fixed effects (except for column 1). The variation in location effects, Var(ψ_c), is computed as the variance of estimated CZ fixed effects. The effect of sorting of people to locations, Cov(α_i, ψ_c), is computed as the covariance of individual and CZ fixed effect estimates. Panel A decomposes variation in individual income. Panel B decomposes variation across CZs—we aggregate person-level fixed effects to CZ means before computing the variance decomposition terms, following Card et al. (2021). Disclosure Review Board approval CBDRB-FY23-0319, CBDRB-FY2023-CES005-024.

Table E.8: **Correlates of Place Effects**

	(1) CZ Log Income	(2) CZ Fixed Effect
Log Population	0.031	-0.060
	(0.013)	(0.014)
Population Density	-0.002	-0.040
	(0.004)	(0.015)
Diamond and Moretti (2021) Price Index	-0.019	-0.065
	(0.008)	(0.009)
Median Household Income in 2016 (vs. Physician Income FE)	0.025	-0.029
	(0.009)	(0.009)
Median Household Income in 2016 (vs. Lawyer Income FE)	0.131	0.024
	(0.026)	(0.022)
Rural Index, 2013	-0.033	0.053
	(0.012)	(0.013)
Share College Graduates	0.005	-0.062
	(0.008)	(0.009)
Job Growth Rate 1990-2010	0.012	-0.048
	(0.010)	(0.011)
Median House Value	0.004	-0.065
	(0.009)	(0.015)
Life Expectancy	-0.018	-0.021
	(0.007)	(0.008)
Finkelstein et al. (2021) Mortality Treatment Effect	0.006	-0.014
	(0.008)	(0.007)
Total Number of Physicans (2005-2017)	-0.006	-0.045
	(0.003)	(0.008)
Number of PCPs per 100,000	-0.005	-0.018
	(0.013)	(0.016)
Number of Non-PCPs per 100,000	0.021	-0.057
	(0.008)	(0.011)
Number of Medicaid Eligible per 100,000	-0.034	0.015
	(0.012)	(0.014)
Number of Medicare Eligible per 100,000	-0.013	0.000
	(0.010)	(0.011)
Share Uninsured	-0.051	-0.012
	(0.014)	(0.016)

Notes: This table reports the results of bivariate OLS regressions of raw average individual total income in a commuting zone (column 1), as well as of place treatment effect on earnings (column 2), on z-scores of the place characteristics indicated in rows. Place treatment effects on earnings are CZ fixed effects from the estimation of equation (2) in the sample of movers as described in Section 2.3.2. Raw mean income is computed in the same sample. CZ-level characteristics are as reported in Chetty et al. (2014); Finkelstein et al. (2021); Diamond and Moretti (2021). Disclosure Review Board approval CBDRB-FY23-0319, CBDRB-FY2023-CES005-024.

Table E.9: **ACA 2SLS Regressions (Excluding 2010–2013)**

Dependent variable:	(1) Log Income	(2) Share with Schedule SE	(3) Share Retired
Share Insured ($I_{c,t}$)	0.412	0.408	-0.099
	(0.111)	(0.087)	(0.032)
Mean of Dependent Variable	12.520	0.429	0.101
Std. Dev. of Dependent Variable	0.896	0.495	0.301
Mean of Independent Variable	0.888	0.887	0.888
Std. Dev. of Independent Variable	0.050	0.050	0.050
Number of Observations	1,221,000	1,193,000	1,820,000
Physician Age Range	40-55	40-55	44-70

Notes: This table displays the results of a 2SLS specification that is described in Section 3.2 and in the notes to Table 4. These are instrumented parametric difference-in-differences estimates of the effects of the ACA insurance expansions on the outcomes indicated in column names, in which we treat the rate of insurance in the under-65 population as the endogenous variable of interest and the rate of uninsured population in 2013 as an instrument. This table replicates columns (5) to (7) of Table 4, except that we drop the post-ACA passage and pre-implementation period (2011-2013). Disclosure Review Board approval CBDRB-FY24-0456.

Table E.10: **Inputs to Analysis in Section 4.1**

	(1) Log $\left(\frac{\text{GAF}}{\text{Price Index}}\right)$	(2) Log GAF	(3) Diamond and Moretti (2021) Price Index	(4) CZ Fixed Effects Physicians
Log Median Household Income	-0.23	0.09	0.33	-0.13
	(0.01)	(0.01)	(0.02)	(0.05)
Constant	2.44	-1.07	-3.57	1.52
	(0.13)	(0.10)	(0.19)	(0.49)
N	500	700	500	700

Notes: Column (1) of this table reports the regression estimate of the bivariate relationship between Medicare's implicit subsidy and the level of CZ earnings graphed in Figure E.12. CZ earnings are measured as 2016 log median household income, reported in Chetty et al. (2014). Columns (2) and (3) show the separate relationships between the numerator and the denominator of the implicit subsidy measure and CZ-level log median household income. In column (4), we show the bivariate relationship between our CZ fixed effects for physician earnings and log median household income. Disclosure Review Board approval CBDRB-FY23-0319, CBDRB-FY2023-CES005-024, CBDRB-FY24-0456.

Table E.11: **Specialty Choice Model**

	Reduced Form		OLS		2SLS	
	(1) Estimate	(2) Standard Error	(3) Estimate	(4) Standard Error	(5) Estimate	(6) Standard Error
Hourly RVUs	-0.229	0.060	-	-	-	-
Hourly Income	-	-	-0.007	0.002	-0.012	0.005
Hourly RVUs/Income × USMLE Score						
× ≤ 190	Reference	-	Reference	-	Reference	-
× 191-200	-0.046	0.050	-0.001	0.001	-0.002	0.002
× 201-210	0.012	0.046	0.003	0.001	0.000	0.002
× 211-220	0.004	0.049	0.004	0.001	0.000	0.002
× 221-230	0.117	0.047	0.009	0.001	0.005	0.002
× 231-240	0.250	0.042	0.014	0.001	0.010	0.001
× 241-250	0.361	0.042	0.018	0.001	0.014	0.001
× 251-260	0.444	0.046	0.021	0.001	0.017	0.002
× > 260	0.516	0.052	0.024	0.001	0.020	0.002
USMLE Score Fixed Effects						
≤ 190	Reference	-	Reference	-	Reference	-
191-200	0.086	0.132	0.122	0.133	0.196	0.186
201-210	0.447	0.116	0.239	0.116	0.419	0.168
211-220	0.801	0.104	0.443	0.110	0.793	0.171
221-230	1.153	0.099	0.497	0.106	0.871	0.160
231-240	1.365	0.101	0.397	0.103	0.762	0.146
241-250	1.757	0.110	0.540	0.107	0.885	0.147
251-260	1.954	0.130	0.565	0.139	0.882	0.178
> 260	2.146	0.145	0.581	0.161	0.899	0.200
Specialty Fixed Effects						
Anesthesiology	Reference	-	Reference	-	Reference	-
Dermatology	-2.374	0.348	-2.767	0.238	-2.293	0.385
Emergency Medicine	0.167	0.072	0.228	0.095	0.025	0.150
Internal Medicine	0.574	0.147	0.656	0.144	0.273	0.266
OBY-GYN	-1.933	0.327	-1.645	0.285	-2.336	0.522
Orthopaedic Surgery	0.626	0.188	0.251	0.242	1.143	0.601
Pathology	-2.350	0.184	-2.218	0.170	-2.587	0.272
Pediatrics	-1.284	0.349	-0.921	0.326	-1.852	0.658
Physical Medicine and Rehabilitation	-2.790	0.218	-2.646	0.197	-3.179	0.367
Plastic Surgery	-1.616	0.160	-1.744	0.148	-1.485	0.214
Psychiatry	-1.892	0.243	-1.634	0.249	-2.384	0.505
Radiation Oncology	-1.955	0.241	-2.368	0.174	-1.756	0.431
Radiology	-0.464	0.132	-0.598	0.125	-0.323	0.212
Surgery	0.601	0.132	0.491	0.095	0.595	0.117
Specialty Characteristics						
Std. Dev. Hourly Income*	0.002	0.006	-0.004	0.006	0.014	0.013
Mean Employer Size*	0.360	0.161	0.350	0.105	0.371	0.107
Share Female	5.838	0.983	5.287	0.733	6.674	1.129
N	750	750	750	750	750	750
					First Stage	
Choice Model Medicare Price Instrument	-	-	-	-	25.880	1.294
N	-	-	-	-	80	80

Notes: The estimates are based on the discrete choice model specified in equation (9). This regression is estimated on group data at the USMLE Step 1 score group by year by specialty level. For each USMLE Step 1 group and year, the outcome variable is the difference in the log probability of choosing an index specialty and log probability of choosing family medicine, which is the reference specialty in the model. For 2SLS estimates in columns (5) and (6) we report the results of an example first stage for one of the interaction terms. For variables indicated by an asterisk (*), the coefficient and standard error have been multiplied by 1,000 to improve readability. Disclosure Review Board approval CBDRB-FY24-0456.

Table E.12: **Own and Cross-Income Elasticities From Specialty Choice Model: Reduced Form**

	USMLE Score > 260		USMLE Score 251-260		USMLE Score 241-250		USMLE Score 231-240		USMLE Score 221-230		USMLE Score 211-220		USMLE Score 201-210		USMLE Score 191-200		USMLE Score $\leq$ 190	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
	$\epsilon_{i,j}^{\text{Inc.}}$ $(i=j)$	$\epsilon_{i,j}^{\text{Inc.}}$ $(i \neq j)$	$\epsilon_{i,j}^{\text{Inc.}}$ $(i=j)$	$\epsilon_{i,j}^{\text{Inc.}}$ $(i \neq j)$	$\epsilon_{i,j}^{\text{Inc.}}$ $(i=j)$	$\epsilon_{i,j}^{\text{Inc.}}$ $(i \neq j)$	$\epsilon_{i,j}^{\text{Inc.}}$ $(i=j)$	$\epsilon_{i,j}^{\text{Inc.}}$ $(i \neq j)$	$\epsilon_{i,j}^{\text{Inc.}}$ $(i=j)$	$\epsilon_{i,j}^{\text{Inc.}}$ $(i \neq j)$	$\epsilon_{i,j}^{\text{Inc.}}$ $(i=j)$	$\epsilon_{i,j}^{\text{Inc.}}$ $(i \neq j)$	$\epsilon_{i,j}^{\text{Inc.}}$ $(i=j)$	$\epsilon_{i,j}^{\text{Inc.}}$ $(i \neq j)$	$\epsilon_{i,j}^{\text{Inc.}}$ $(i=j)$	$\epsilon_{i,j}^{\text{Inc.}}$ $(i \neq j)$	$\epsilon_{i,j}^{\text{Inc.}}$ $(i=j)$	$\epsilon_{i,j}^{\text{Inc.}}$ $(i \neq j)$
Anesthesiology	0.337	-0.010	0.248	-0.011	0.149	-0.010	0.023	-0.002	-0.125	0.011	-0.255	0.019	-0.252	0.013	-0.319	0.014	-0.249	0.029
Dermatology	1.729	-0.141	1.293	-0.104	0.817	-0.040	0.129	-0.003	-0.730	0.005	-1.466	0.007	-1.412	0.009	-1.786	0.008	-1.470	0.026
Emergency Medicine	0.366	-0.020	0.265	-0.024	0.161	-0.016	0.024	-0.003	-0.134	0.018	-0.274	0.030	-0.269	0.025	-0.350	0.021	-0.304	0.005
Family Medicine	0.415	-0.011	0.310	-0.008	0.188	-0.008	0.028	-0.002	-0.152	0.016	-0.293	0.042	-0.270	0.054	-0.303	0.105	-0.263	0.078
Internal Medicine	0.616	-0.182	0.457	-0.139	0.283	-0.083	0.044	-0.013	-0.245	0.069	-0.488	0.141	-0.469	0.138	-0.624	0.142	-0.482	0.157
OB-GYN	0.142	-0.003	0.104	-0.003	0.063	-0.003	0.010	-0.001	-0.052	0.005	-0.104	0.010	-0.101	0.009	-0.127	0.012	-0.111	0.004
Orthopaedic Surgery	0.535	-0.082	0.411	-0.050	0.258	-0.024	0.041	-0.002	-0.237	0.006	-0.480	0.006	-0.465	0.003	-0.587	0.005	-0.485	0.009
Pathology	0.369	-0.010	0.278	-0.005	0.171	-0.002	0.026	-0.000	-0.147	0.002	-0.294	0.004	-0.283	0.005	-0.357	0.006	-0.298	0.005
Pediatrics	0.218	-0.025	0.164	-0.018	0.097	-0.015	0.015	-0.002	-0.081	0.015	-0.162	0.030	-0.153	0.032	-0.200	0.034	-0.167	0.027
Physical Medicine and Rehabilitation	0.717	-0.001	0.534	-0.003	0.326	-0.003	0.050	-0.001	-0.278	0.004	-0.552	0.014	-0.535	0.011	-0.669	0.020	-0.565	0.010
Plastic Surgery	0.482	-0.018	0.363	-0.011	0.225	-0.004	0.035	-0.000	-0.196	0.001	-0.393	0.001	-0.380	0.001	-0.479	0.001	-0.393	0.007
Psychiatry	0.450	-0.008	0.333	-0.009	0.205	-0.005	0.031	-0.001	-0.170	0.011	-0.334	0.027	-0.315	0.034	-0.388	0.052	-0.341	0.026
Radiation Oncology	1.422	-0.049	1.073	-0.026	0.662	-0.013	0.103	-0.001	-0.576	0.003	-1.156	0.002	-1.115	0.003	-1.410	0.002	-1.156	0.021
Radiology	0.554	-0.030	0.406	-0.030	0.252	-0.016	0.039	-0.002	-0.222	0.007	-0.450	0.010	-0.435	0.009	-0.553	0.007	-0.451	0.016
Surgery	0.647	-0.130	0.505	-0.076	0.314	-0.042	0.049	-0.006	-0.278	0.028	-0.563	0.049	-0.561	0.030	-0.718	0.027	-0.611	0.011

Notes: This table presents own- and cross-income elasticities of specialty choice probability computed based on the reduced form version of the discrete choice model specified in equation (9). Table E.11 reports the full set of estimates for this specification. The own-income elasticity (reported in odd-numbered columns) for a specialty i within a score group a is computed as the product of the coefficient on RVUs term for this score group, δ_a, the mean hourly RVUs in specialty i, and 1 minus the share of physicians in score group a who chose specialty i. The cross-income elasticity (reported in even-numbered columns) for a specialty i vis-à-vis RVUs in specialty j is computed as -1 times the product of the coefficient on RVUs term for this score group, δ_a, the mean hourly RVUs in specialty j, and the share of physicians in score group a who chose specialty j. Mean hourly RVUs and observed choice shares are at 2016 levels (the last year of NRMP data). Disclosure Review Board approval CBDRB-FY24-0456.

Table E.13: **Own and Cross-Income Elasticities From Specialty Choice Model: OLS**

	USMLE Score > 260		USMLE Score 251-260		USMLE Score 241-250		USMLE Score 231-240		USMLE Score 221-230		USMLE Score 211-220		USMLE Score 201-210		USMLE Score 191-200		USMLE Score ≤ 190	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
	$\epsilon_{i,j}^{\text{Inc.}}$ $(i=j)$	$\epsilon_{i,j}^{\text{Inc.}}$ $(i\neq j)$	$\epsilon_{i,j}^{\text{Inc.}}$ $(i=j)$	$\epsilon_{i,j}^{\text{Inc.}}$ $(i\neq j)$	$\epsilon_{i,j}^{\text{Inc.}}$ $(i=j)$	$\epsilon_{i,j}^{\text{Inc.}}$ $(i\neq j)$	$\epsilon_{i,j}^{\text{Inc.}}$ $(i=j)$	$\epsilon_{i,j}^{\text{Inc.}}$ $(i\neq j)$	$\epsilon_{i,j}^{\text{Inc.}}$ $(i=j)$	$\epsilon_{i,j}^{\text{Inc.}}$ $(i\neq j)$	$\epsilon_{i,j}^{\text{Inc.}}$ $(i=j)$	$\epsilon_{i,j}^{\text{Inc.}}$ $(i\neq j)$	$\epsilon_{i,j}^{\text{Inc.}}$ $(i=j)$	$\epsilon_{i,j}^{\text{Inc.}}$ $(i\neq j)$	$\epsilon_{i,j}^{\text{Inc.}}$ $(i=j)$	$\epsilon_{i,j}^{\text{Inc.}}$ $(i\neq j)$	$\epsilon_{i,j}^{\text{Inc.}}$ $(i=j)$	$\epsilon_{i,j}^{\text{Inc.}}$ $(i\neq j)$
Anesthesiology	2.686	-0.083	2.188	-0.100	1.681	-0.115	1.016	-0.082	0.216	-0.020	-0.525	0.039	-0.808	0.041	-1.378	0.062	-1.150	0.135
Dermatology	4.182	-0.341	3.458	-0.278	2.796	-0.136	1.759	-0.034	0.382	-0.003	-0.917	0.004	-1.378	0.009	-2.340	0.011	-2.062	0.037
Emergency Medicine	2.561	-0.140	2.046	-0.185	1.591	-0.160	0.948	-0.123	0.202	-0.027	-0.495	0.055	-0.758	0.070	-1.324	0.080	-1.231	0.022
Family Medicine	1.568	-0.040	1.294	-0.035	1.002	-0.041	0.598	-0.040	0.124	-0.013	-0.286	0.041	-0.411	0.082	-0.621	0.215	-0.576	0.170
Internal Medicine	1.787	-0.527	1.466	-0.445	1.161	-0.339	0.710	-0.208	0.154	-0.043	-0.366	0.106	-0.549	0.161	-0.979	0.223	-0.810	0.264
OB-GYN	2.253	-0.042	1.835	-0.061	1.411	-0.077	0.850	-0.060	0.179	-0.016	-0.426	0.041	-0.647	0.057	-1.092	0.101	-1.027	0.037
Orthopaedic Surgery	3.894	-0.594	3.304	-0.403	2.658	-0.252	1.689	-0.091	0.372	-0.009	-0.903	0.011	-1.367	0.010	-2.315	0.018	-2.046	0.037
Pathology	2.311	-0.060	1.927	-0.032	1.518	-0.020	0.927	-0.013	0.199	-0.003	-0.476	0.007	-0.714	0.013	-1.212	0.021	-1.081	0.019
Pediatrics	1.608	-0.186	1.335	-0.148	1.007	-0.156	0.611	-0.101	0.129	-0.023	-0.308	0.057	-0.456	0.094	-0.798	0.134	-0.716	0.117
Physical Medicine and Rehabilitation	2.063	-0.003	1.697	-0.009	1.327	-0.012	0.809	-0.010	0.173	-0.003	-0.410	0.011	-0.620	0.013	-1.043	0.031	-0.942	0.017
Plastic Surgery	2.909	-0.111	2.425	-0.070	1.925	-0.033	1.191	-0.007	0.256	-0.001	-0.613	0.002	-0.925	0.001	-1.567	0.002	-1.377	0.025
Psychiatry	1.844	-0.035	1.511	-0.041	1.187	-0.031	0.714	-0.031	0.150	-0.009	-0.354	0.028	-0.520	0.056	-0.861	0.115	-0.810	0.061
Radiation Oncology	4.055	-0.141	3.384	-0.082	2.669	-0.052	1.652	-0.012	0.355	-0.002	-0.853	0.002	-1.284	0.003	-2.178	0.003	-1.913	0.034
Radiology	2.982	-0.163	2.416	-0.182	1.919	-0.120	1.185	-0.062	0.259	-0.009	-0.627	0.013	-0.945	0.019	-1.615	0.020	-1.408	0.051
Surgery	2.507	-0.504	2.164	-0.324	1.724	-0.229	1.060	-0.134	0.233	-0.023	-0.564	0.049	-0.877	0.046	-1.508	0.058	-1.373	0.025

Notes: This table presents own- and cross-income elasticities of specialty choice probability computed based on the OLS version of the specialty choice model specified in equation (9). Table E.11 reports the full set of estimates for this specification. The own-income elasticity (reported in odd-numbered columns) for a specialty i within a score group a is computed as the product of the coefficient on income term for this score group, δ_a, the mean hourly income in specialty i, and 1 minus the share of physicians in score group a who chose specialty i. The cross-income elasticity (reported in even-numbered columns) for a specialty i vis-à-vis income in specialty j is computed as -1 times the product of the coefficient on income term for this score group, δ_a, the mean hourly income in specialty j, and the share of physicians in score group a who chose specialty j. Mean hourly income and observed choice shares are at 2016 levels (the last year of NRMP data). Disclosure Review Board approval CBDRB-FY24-0456.

Table E.14: **Own and Cross-Income Elasticities From Specialty Choice Model: 2SLS**

	USMLE Score > 260		USMLE Score 251-260		USMLE Score 241-250		USMLE Score 231-240		USMLE Score 221-230		USMLE Score 211-220		USMLE Score 201-210		USMLE Score 191-200		USMLE Score ≤ 190	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
	$\epsilon^{\text{Inc.}}_{i,j}$ $(i = j)$	$\epsilon^{\text{Inc.}}_{i,j}$ $(i \neq j)$	$\epsilon^{\text{Inc.}}_{i,j}$ $(i = j)$	$\epsilon^{\text{Inc.}}_{i,j}$ $(i \neq j)$	$\epsilon^{\text{Inc.}}_{i,j}$ $(i = j)$	$\epsilon^{\text{Inc.}}_{i,j}$ $(i \neq j)$	$\epsilon^{\text{Inc.}}_{i,j}$ $(i = j)$	$\epsilon^{\text{Inc.}}_{i,j}$ $(i \neq j)$	$\epsilon^{\text{Inc.}}_{i,j}$ $(i = j)$	$\epsilon^{\text{Inc.}}_{i,j}$ $(i \neq j)$	$\epsilon^{\text{Inc.}}_{i,j}$ $(i = j)$	$\epsilon^{\text{Inc.}}_{i,j}$ $(i \neq j)$	$\epsilon^{\text{Inc.}}_{i,j}$ $(i = j)$	$\epsilon^{\text{Inc.}}_{i,j}$ $(i \neq j)$	$\epsilon^{\text{Inc.}}_{i,j}$ $(i = j)$	$\epsilon^{\text{Inc.}}_{i,j}$ $(i \neq j)$	$\epsilon^{\text{Inc.}}_{i,j}$ $(i = j)$	$\epsilon^{\text{Inc.}}_{i,j}$ $(i \neq j)$
Anesthesiology	1.351	-0.042	0.873	-0.040	0.341	-0.023	-0.345	0.028	-1.149	0.105	-1.866	0.138	-1.857	0.094	-2.230	0.100	-1.813	0.213
Dermatology	2.104	-0.171	1.379	-0.111	0.567	-0.028	-0.597	0.012	-2.033	0.015	-3.256	0.015	-3.166	0.020	-3.788	0.018	-3.252	0.058
Emergency Medicine	1.289	-0.071	0.816	-0.074	0.323	-0.033	-0.322	0.042	-1.077	0.145	-1.759	0.194	-1.742	0.161	-2.144	0.129	-1.942	0.035
Family Medicine	0.789	-0.020	0.516	-0.014	0.203	-0.008	-0.203	0.014	-0.659	0.069	-1.016	0.147	-0.944	0.189	-1.005	0.349	-0.909	0.269
Internal Medicine	0.899	-0.265	0.585	-0.177	0.236	-0.069	-0.241	0.070	-0.818	0.229	-1.298	0.375	-1.260	0.370	-1.585	0.361	-1.277	0.416
OB-GYN	1.133	-0.021	0.732	-0.024	0.286	-0.016	-0.288	0.020	-0.954	0.085	-1.513	0.147	-1.486	0.130	-1.768	0.163	-1.620	0.059
Orthopaedic Surgery	1.959	-0.299	1.318	-0.161	0.539	-0.051	-0.573	0.031	-1.981	0.051	-3.207	0.039	-3.138	0.022	-3.746	0.029	-3.226	0.058
Pathology	1.163	-0.030	0.769	-0.013	0.308	-0.004	-0.315	0.004	-1.060	0.014	-1.689	0.026	-1.640	0.030	-1.961	0.034	-1.705	0.030
Pediatrics	0.809	-0.094	0.533	-0.059	0.204	-0.032	-0.207	0.034	-0.689	0.124	-1.095	0.203	-1.048	0.216	-1.292	0.218	-1.129	0.184
Physical Medicine and Rehabilitation	1.038	-0.002	0.677	-0.004	0.269	-0.003	-0.274	0.004	-0.922	0.014	-1.456	0.038	-1.425	0.030	-1.688	0.051	-1.485	0.027
Plastic Surgery	1.464	-0.056	0.967	-0.028	0.391	-0.007	-0.404	0.002	-1.362	0.005	-2.179	0.005	-2.124	0.003	-2.537	0.004	-2.171	0.039
Psychiatry	0.928	-0.017	0.603	-0.016	0.241	-0.006	-0.242	0.011	-0.800	0.050	-1.258	0.101	-1.195	0.128	-1.394	0.187	-1.278	0.096
Radiation Oncology	2.041	-0.071	1.350	-0.033	0.542	-0.010	-0.561	0.004	-1.890	0.010	-3.029	0.006	-2.948	0.007	-3.525	0.005	-3.017	0.054
Radiology	1.500	-0.082	0.964	-0.072	0.389	-0.024	-0.402	0.021	-1.378	0.046	-2.227	0.048	-2.171	0.045	-2.614	0.032	-2.221	0.081
Surgery	1.262	-0.254	0.863	-0.129	0.350	-0.047	-0.360	0.046	-1.241	0.123	-2.004	0.175	-2.014	0.107	-2.441	0.093	-2.165	0.039

Notes: This table presents own- and cross-income elasticities of specialty choice probability computed based on the 2SLS version of the specialty choice model specified in equation (9). Table E.11 reports the full set of estimates for this specification. The own-income elasticity (reported in odd-numbered columns) for a specialty i within a score group a is computed as the product of the coefficient on income term for this score group, δ_a, the mean hourly income in specialty i, and 1 minus the share of physicians in score group a who chose specialty i. The cross-income elasticity (reported in even-numbered columns) for a specialty i vis-à-vis income in specialty j is computed as -1 times the product of the coefficient on income term for this score group, δ_a, the mean hourly income in specialty j, and the share of physicians in score group a who chose specialty j. Mean hourly income and observed choice shares are at 2016 levels (the last year of NRMP data). Disclosure Review Board approval CBDRB-FY24-0456.

Table E.15: **Lifetime Earnings of Physicians and Lawyers**

	(1) All Physicians	(2) Primary Care Physicians	(3) Lawyers
Mean PDV Lifetime Income	$10,100,000	$6,500,000	$7,100,000
($\beta = 0.97$, at Age 20)			
Undergrad & Graduate Tuition	$250,688	$250,688	$186,273
PDV Lifetime Income Net of Tuition	$9,849,312	$6,249,312	$6,913,727
Relative to Lawyers	142%	90%	100%
Mean Lifetime Hours Worked	112,900	108,700	105,500
Relative to Lawyers	107%	103%	100%
Higher Weight for Hours >40 / Week	112%	106%	100%

Notes: This table reports our estimates of absolute and relative lifetime earnings between physicians and lawyers. The present discounted value (PDV) of earnings from age 20 to 70 is computed based on simulations described in Appendix B.2. Undergraduate and graduate tuition costs were obtained from the Association of American Medical Colleges and the American Bar Association as also detailed in Appendix B.2. Average annual hours worked are computed by multiplying weekly hours worked by the number of weeks worked reported in ACS. Annual hours worked are averaged within each year of age, and then summed across ages to obtain lifetime hours worked. The final row uses an adjusted work hours measure, which increases the weights for hours worked over 40 per week based on the return to weekly hours worked estimated in Goldin (2014, Table 3, column 5). Disclosure Review Board approval CBDRB-FY23-0319, CBDRB-FY2023-CES005-024.

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