Who Values Human Capitalists' Human Capital? The Earnings and Labor Supply of U.S. Physicians*

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July 22, 2021

Abstract

Is government guiding the invisible hand at the top of the labor market? We combine the administrative registry of U.S. physicians with tax data, Medicare billing records, and survey responses to measure physicians' earnings and estimate the influence of healthcare policies on physicians' incomes and labor supply. Annual earnings average $343,600, with major differences across specialties, and comprise 8.5% of national healthcare spending. The age-earnings profile is steep and business income comprises one-quarter of earnings. Health policy has a major impact on the margin: 30% of incremental Medicare spending on physician care goes to physicians personally, and 60% for Medicaid. Physicians gain 5–10% of public money spent on insurance expansions. Policies that increase reimbursement also increase physicians' supply of care and reduce retirement. We find that government plays a major role in determining the value of physicians' human capital, but that its power is constrained by the market. This limits the scope for policy instruments aiming to reduce U.S. spending on physician services.

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The [healthcare] industry is not very good at promoting health, but it excels at promoting wealth among healthcare providers, including some successful private physicians who operate extremely profitable practices.

(Case and Deaton, 2020)

My hand surgeon should have been paid $4.5 billion for fixing my broken wrist, not $1,000.

(Crawford, 2019)

1 Introduction

Growth in income inequality, concentrated among skilled workers at the top of the income distribution, has led to widespread interest in tax and transfer programs that could affect this distribution (*e.g.* Zidar, 2019). The focus on taxes elides the fact that most government spending is in kind rather than cash or cash-like transfers (CBO, 2020). While an expansive literature in public finance (unified by Hendren and Sprung-Keyser, 2020) studies the value of this spending to the taxpayer and the distributional impact on those who receive its services (*e.g.* Meyer and Mittag, 2019), in-kind transactions have a third participant: the service providers whom the government pays. Due to the difficulty of associating income data with information on who provides government services, the impact of government purchases on the sellers' personal incomes—let alone individuals' behavioral responses—has been difficult to study.[1]

[1]In contrast, the incidence of government payments on *firms* has been explored across a variety of procurement contracts, including in healthcare and health insurance, (*e.g.* Cabral et al., 2018; Duggan et al., 2016; Garthwaite et al., 2018; Decarolis et al., 2020), defense (Carril and Duggan, 2018), and infrastructure (Krasnokutskaya and Seim, 2011). In recent work, Kroft et al. (2020) study firms' imperfect competition for workers in construction contracting.

We examine personal incomes and labor supply of skilled workers at the top of the largest public procurement enterprise: physicians. Physicians are quintessential "human capitalists" (Smith et al., 2019a) and are the single most common occupation in the top percentile of income earners (Gottlieb et al., 2018). To determine the government's influence on their labor market outcomes requires knowing (1) what physicians earn, (2) how much government policy influences these earnings, and (3) how physicians respond to these policies. We estimate these three empirical moments using new linkages of tax data, Medicare billing records, American Community Survey responses, and the administrative registry of U.S. physicians.

We start by providing novel descriptive facts essential to understanding physicians' labor markets, such as the level and composition of their earnings, how earnings evolve over time, and differences across geography and specialty. While this market is of longstanding academic interest (Friedman and Kuznets, 1945), the modern literature has been hamstrung by measurement challenges that obscure even these basic facts. Next, we ask how several types of policy changes affect physicians' incomes. We find that healthcare policies substantially influence physicians' personal earnings. Further, we use tax and billing data to estimate labor supply responses to these same policies. We generally find positive short-run supply responses. Finally, we conduct a more speculative analysis of cross-sectional labor market patterns. We examine additional dimensions along which long-run supply can respond to government policies, such as specialty choice and the choice to practice medicine altogether. We conclude that the government's influence is not merely redistributive, but affects real outcomes in physicians' labor markets. Labor market fundamentals thus constrain policy choices.

Despite the abundance of research on health policy—and reimbursement in particular—physicians' earnings have previously been difficult to study, as even measuring them is challenging. Existing evidence (*e.g.* Baker, 1996; Nicholson and Souleles, 2001; Bhattacharya, 2005; Vaughn et al., 2010; Nicholson and Propper, 2011; Esteves-Sorenson and Snyder, 2012;

Chen and Chevalier, 2012; Jagsi et al., 2012; Seabury et al., 2013; Altonji and Zhong, 2019; LoSasso et al., 2020) has relied on survey data and faced measurement challenges, such as top-coding and complicated income structures. The broader public is also ill-informed about physicians' incomes, as we determined through a nationally-representative survey. Our data overcome many (though not all) of these issues and allow us to newly establish basic facts about physicians' earnings.

We find mean physician professional earnings in 2017 of $343,600, with a median of $255,200. This implies that physicians' own incomes account for 8.5% of the United States' $3.5 trillion in medical spending, even though billing for physician and clinical services accounts for about 20% of national health spending (CMS, 2019). One quarter of physician households are in the top percentile of the overall income distribution, and half are in the top two percentiles. Business income plays a crucial, and previously underappreciated—as it tends to be underreported in survey data—role in physician incomes, accounting for about a quarter of professional earnings at the peak of physicians' careers.

There is substantial heterogeneity by specialty, with the average primary care physician earning $243,400 and the average surgeon earning more than $500,000. Physicians' age-earnings profile is steep, with average incomes doubling from age 30 to age 40 and then flattening. This pattern is especially pronounced among top-earning specialties, for whom business income generates substantial growth during the most productive years. We have made data on physician mean incomes at the commuting zone level, and by physician specialty, publicly available for other researchers to use.[2]

Having established these facts, we ask how much government influences physician earnings and labor supply at the margin. Of course, there are many margins and many relevant policies: reimbursement rates from public insurers, direct bonuses for practicing in

[2]Data are available at https://www.census.gov/programs-surveys/ehealth/information/examining-earnings.html.

"shortage areas", entry restrictions, insurance subsidies, taxation, and others. We focus on government payments in health insurance systems—reimbursement rates and insurance coverage—as they seem likely to have the most direct relationship to physicians' earnings.

Even so, it is not theoretically obvious what pass-through to expect, if any. On the one hand, labor economists tend to find limited sharing of firms' marginal rents with most workers (Card et al., 2018). Contemporary physicians are rarely the sole practitioners of yore, but now work in firms with multiple physicians and other employees. So risk and reward could be absorbed by insurers, employers, changing cost structures, or distributed across the group. On the other hand, Kline et al. (2019) find more rent-sharing with high-income workers.

We use three quasi-experimental strategies to study how changes in public spending affect physician earnings and labor supply. Our identification relies on the fact that changes in government payments and insurance subsidies typically only affect physicians in some specialties, in some geographic areas, at some point in time. We examine idiosyncratic changes in Medicare's reimbursements for different medical services (comparing across physicians within a specialty); an increase in Medicaid payments for primary care services (comparing physicians within and across specialties based on their exposure to primary care); and the expansion of insurance coverage due to the Affordable Care Act (ACA) (comparing physicians across counties with different baseline insurance coverage).

The government's influence is dramatic. On the margin, 30% (in Medicare) to 60% (in Medicaid) of reimbursement dollars in social insurance programs, as well as 5% to 10% of public spending on private and public insurance expansions under the ACA, flows into physicians' incomes. These changes in public spending are powerful enough to shape the distribution of top incomes. Changes in Medicaid's payments alone increased by 10 percent the share of physicians with high exposure to primary care in the top percentile of the national income distribution. To gauge the magnitudes, we compute the income tax changes

that would be necessary to influence average incomes as much as the reimbursement changes do for physicians. We find that they would be historically large.

Since we find that government can indeed influence earnings at the margin, one might consider using policy to reduce physicians' average earnings (Baker, 2017; Pollin et al., 2018; Case and Deaton, 2020). Physician offices produce over $700 billion of output per year (CMS, 2019), and additional physicians are employed in hospitals and other industries. This might suggest a large scope for reimbursement cuts to address two public concerns simultaneously: high health spending and top income inequality.

But such changes could affect labor supply, to which we turn next. We use linked Medicare billing data to directly measure supply of care, and tax return data to capture formal retirement. Doctors who are past the lifetime earnings peak appear to increase the care they provide and delay retirement when exposed to positive earnings shocks. These estimates are noisier than the earnings results, but tend to show positive short-run labor supply elasticities.

Long-term labor supply responses are naturally harder to estimate. While we can't overcome the inherent challenge of identifying causal effects of slow-moving decisions, we use the richness of our data to uncover key facts relevant for long-run labor supply decisions—specifically, career and specialty choices. We first consider the choice of specialty. We use our data to estimate work hours and training length by specialty. We find that they both move strongly with average specialty earnings, although there are some exceptions. For example, ophthalmologists and hematologist-oncologists have similar earnings even though ophthalmologists work an average of 7 fewer hours per week and have slightly shorter training. Such deviations from the income prediction based on hours and training length do not appear to be a compensating differential for some unmeasured aspect of the specialty: if they were, we would not expect a relationship between these deviations and applicants' desire to enter the specialty. But we do see a strong positive relationship: 89% of ophthalmologists attended U.S. medical schools, compared with 59% of hematologist-oncologists. Given hospitals' pref-

erence for domestic applicants, those with larger choice sets prefer ophthalmology. This is consistent with labor supply responding positively to income net of disamenities.

We briefly consider the choice to enter medicine altogether. For this we compare lifetime earnings of physicians to another high human capital occupation—lawyers. Lawyers have a reasonably comparable labor market structure but less restrictive entry, so are a plausible outside option for physicians. Accounting for the fact that physicians work 19% more hours than lawyers, the former earn an average of 25% more over their working lives. Primary care physicians have longer work hours and lower income than an average lawyer, however, suggesting that outside options in the labor market are likely driving the left tail of the physician income distribution.

We conclude that government payment rules play a key role in valuing one of society's most expensive assets: physicians' human capital. At the same time, physicians work long hours, endure extensive training, and face attractive outside options in the labor market. So even if government payments drive high earnings at the margin, this does not imply that economic rents are widespread or that physician incomes could be inconsequentially altered to reduce healthcare spending. While government reimbursements are powerful tools, their potential for reducing spending is constrained by the other attractive opportunities open to skilled workers in the 21st century.

2 Institutional Background, Data, and Measurement

This section presents basic institutional features and introduces our data. Institutionally, the key fact is that physicians receive both wages and business income (section 2.1). We link tax data with physician records (section 2.2) to construct a more comprehensive measure of physician earnings (section 2.3). Section 2.4 briefly presents survey evidence on the public's understanding before we report actual earnings in section 3.

2.1 How are Physicians Paid in the United States?

Since physicians' personal earnings have been hard to observe, their institutional features have received little attention in the literature. The earnings structure can be classified into three broad models. One extreme is physicians who only earn wage or salary income reported on Form W-2. This is common in larger organizations such as academic medical centers. The second model is a sole proprietorship, generating income that only appears on the physician's personal tax return.[3] While the easiest form of business to set up, this structure offers no particular tax advantage or liability protection.

The third model involves a pass-through entity, usually an S-corporation or a partnership. A medical practice organized as an S-corporation pays physicians a market wage, reported on Form W-2, plus a share of profits that remain after all practice expenses.[4] The S-corporation structure may be more complex for larger group practices. A large practice might have a joint S-corporation that hires non-physician staff in addition to individual S-corporations for each physician in the practice. The exact legal structure affects the tax liability and the profit-sharing incentives within the practice.

The upshot is that physicians' earnings can be complex. Section 2.3 describes how we go beyond W-2s to measure total professional earnings throughout this paper.

2.2 Data Sources

Our primary source is the universe of individual federal income tax returns from 2005 to 2017 merged with an administrative registry of all healthcare providers in the U.S. We augment these with additional administrative and survey datasets.

[3]Specifically, Schedule C ("Profit or Loss from Business, Sole Proprietorship") of IRS Form 1040.

[4]This would be reported on Schedule K-1 ("Partner's Share of Income, Deductions, Credits, etc.") and then on Schedule E ("Supplemental Income and Loss") of Form 1040.

Tax Data The federal income tax extract available to us from the IRS includes the universe of individual tax returns for tax years 2005 through 2017, but only a limited number of variables. From Form 1040, we observe the tax unit's filing status, adjusted gross income (AGI), wage income, taxable dividend and interest amounts, and social security income.[5] We inflation-adjust all dollar amounts to 2017 dollars using BLS CPI deflators.

We augment the individual returns with third-party information returns, notably W-2 and 1099-SSA forms. W-2s report wage earnings for each filer in the tax unit. We aggregate W-2s across multiple employers when applicable. Observing W-2s at the individual-employer level means that we can observe wage income separately for the index physician and the spouse when married and filing jointly. We measure retirement as occurring in the year when an individual first receives form 1099-SSA ("Social Security Benefit Statement"), indicating receipt of social security benefits.[6]

Physician Registry We merge federal income tax returns with the physician registry maintained by the Centers for Medicare and Medicaid Services (CMS). Individuals and organizations that provide healthcare services in the U.S. must use their unique 10-digit National Provider Identifiers (NPIs) to identify themselves throughout the healthcare system. These NPIs are recorded in the National Plan and Provider Enumeration System (NPPES) file, along with information on physicians' specialties.[7] We map sixty Medicare specialties into nine specialty categories, allowing us to simplify the exposition of specialty-level information (see Appendix A.2 and Table A.4. The merge uses the Census Bureau's Protected Identification Key (PIK)-based data linkage infrastructure, which Wagner and Layne (2014) describe in detail.

[5] We follow the Chetty et al. (2014) approach for harmonizing raw Form 1040, 1099-SSA, and W-2 data.
[6] 1099-SSA data is available from 2003 through 2017.
[7] Physicians are all providers with a primary specialty taxonomy code that starts with "20". We keep physician-year observations for which there are no tax records, setting all income measures for these individuals to zero. Additional details are in Appendix A.2, which also explains how we compute the length of training in each specialty and the cost of getting a medical degree. Our NPPES file is from April 2018.

Demographic Data We merge individuals' date of birth from the Census Bureau's version of the Social Security Administration's Numerical Identification (Numident) database (described in, *e.g.*, Bailey et al., 2020; Polyakova et al., 2021). We add the state and county of residence reported on the tax return.[8] Our baseline sample is a panel of physician-year observations for years 2005 to 2017 for all physicians listed in the April 2018 NPPES with a Census PIK. We exclude physician-year observations for years in which the individual is younger than 20, older than 70, or is deceased.[9]

American Community Survey We merge the tax records and NPPES data with responses to the American Community Survey (ACS). ACS samples repeated cross sections of approximately 1% of the U.S. population each year since 2001.[10] We add the following ACS variables to the tax data for any physician whose ACS responses are successfully linked by a PIK: wages, self-employment income, spousal income; the number of hours an individual reports working per week; whether the individual is self-employed; and whether the individual works for the government.

We construct a sample of lawyers to use in section 5.2 when considering earnings potential along alternative career paths. This sample includes 2005–2017 tax returns of ACS respondents who report a legal occupation.[11]

Medicare Data Finally, we add detailed data on treatments physicians provide to Medicare patients. For each provider who treated fee-for-service Medicare patients, CMS releases a dataset with the NPI of the provider (which allows us to merge it with NPPES and tax data), the list of services performed by the provider, the number of times each procedure

[8] If no address is available on Form 1040, we use information returns or other survey and administrative sources.

[9] Date of death, when applicable, is from Numident.

[10] ACS full implementation happened in 2005. Prior to 2005, sample sizes were much smaller.

[11] Occupational codes for a legal profession include lawyers, judges, magistrates, judicial law clerks, and other judicial workers.

was performed, the place of service, and total payments the physician's practice received for each procedure.[12] These data are available starting in 2012. The procedure codes and place of service allow us to determine Medicare's reimbursement rules for the service in question. As section 4.1 describes, this pricing scheme is based on service-specific Relative Value Units (RVUs), which we obtain from CMS and merge by service code.[13]

2.3 Defining Income

Physician incomes come through a diverse and changing array of mechanisms. This mish-mash of sources makes it particularly challenging to study physician earnings and highlights the advantage of using tax rather than survey data to measure income.

We are interested in capturing income from the contemporaneous professional labor of a physician, and excluding passive financial income. Our preferred measure of professional earnings is the sum of wage income and business income, which we compute separately, and then add up. For ease of exposition, we refer to this sum simply as "income" throughout.

We directly observe individual wage income reported on W-2 forms.[14] Measuring business income is more challenging. First, our data do not directly record the amount of business or self-employment income on Schedules E and C. Second, non-wage income on Form 1040 is reported at the tax unit rather than individual level. We therefore use the following procedure to infer business income. We start with Adjusted Gross Income (AGI). We then subtract W-2 wages of all members of the tax unit. This leaves us with a combination of business and

[12] By "service" or "procedure" we mean the code billed using the Healthcare Common Procedure Coding System (HCPCS). The file from CMS is called the Physician and Other Supplier Public Use File of the Physician Medicare Provider Utilization and Payment Data (MPUPD). The data are publicly available at https://www.cms.gov/Research-Statistics-Data-and-Systems/Statistics-Trends-and-Reports/Medicare-Provider-Charge-Data/Physician-and-Other-Supplier. They exclude procedure codes that a physician provides to Medicare patients ten or fewer times in a given year.

[13] https://www.cms.gov/Medicare/Medicare-Fee-for-Service-Payment/PhysicianFeeSched/PFS-Relative-Value-Files

[14] Specifically, we sum the amounts reported in box 1 on all of an individual's W-2 forms. This includes all wages, tips, and other compensation before payroll deductions.

financial income at the tax unit level. We subtract financial income—the taxable portion of social security payments, taxable dividends, and taxable interest—and treat the remainder as business income. For those physicians who file joint returns with a spouse, this object technically captures business income of both spouses. It may also include capital gains and other forms of income that are not necessarily professional income. That said, it is not clear capital gains should be excluded—a physician's income from selling her practice is clearly part of her return to practicing medicine. We use various approaches to approximate 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. Appendix A.3 describes the details of these calculations. Following the literature on income inequality, we use the tax unit's AGI to characterize physicians' position in the national income distribution. We otherwise focus on the physician's professional earnings.

2.4 Survey Evidence: Public Perceptions of Physician Incomes

We conducted a nationally-representative survey to determine public knowledge and perceptions of physicians' incomes. Among 1,071 respondents conducted via both internet and telephone in June 2021,[15] 36% considered physicians overpaid, while 50% said they were paid "the right amount" and 11% chose underpaid. But when forming these opinions, respondents had widely dispersed views about the underlying facts: only 19% believed that the average physician earned above $300,000 and another 33% believed the number was $200,000 to $300,000.

Knowledge and perceptions of nurse earnings were very different. 59% thought nurses were underpaid, 32% said nurses were paid "the right amount," and only 6% chose overpaid.

[15]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. Additional details are in Appendix A.1.

Respondents had a broadly accurate impression of nurse pay—40% thought average nurses were paid between $50,000 and $75,000 annually, and another 31% chose $75,000 to $125,000.

3 How Much Do U.S. Physicians Earn?

Basic Facts

In 2017, the most recent year of our tax data, our baseline physician sample has 863,000 physicians.[16] Table 1 summarizes the data. The average physician is 49 years old, works 50.5 hours per week, earns $343,600 per year, and has completed 4.8 years of residency and fellowship training. The median physician earns $255,200. 26% of physicians' tax units are in the top percentile of the national income distribution.

These basic facts about earnings, training, and labor supply vary substantially across specialty categories.[17] The lowest-earning category is the most common—primary care physicians (PCPs), whose earnings average $243,000 ($200,600 at median), comprise 44% of our sample. The highest earners are procedural specialists and surgeons, whose average earnings are more than double PCPs'—$535,100 and $521,100, respectively—and together comprise 15% of physicians. While procedural specialists and surgeons have similar average incomes, surgeons spend almost a year longer in residency, and work nearly ten hours more per week on average. Given the relative attractiveness of the procedural specialties, it is not surprising that a larger share of proceduralists attended U.S. medical schools.

These statistics imply that physicians together earn $297 billion, or 8.5% of total U.S. healthcare spending (CMS, 2019). Put differently, out of $10,682 that an average American spent on healthcare in 2017, physicians earned $915. While one-fifth of the national health expenditure is attributable to billing for physicians' clinical services, less than half of this amount

[16] Recall that we exclude physicians above age 70 from this sample. All numbers in the manuscript are rounded according to U.S. Census Bureau disclosure protocols.

[17] See Appendix Table A.6 for the same summary statistics at the more granular Medicare specialty level.

is physicians' actual take-home pay.[18] One third of the $297 billion in take-home pay goes to PCPs. The two highest-paid categories—procedural specialists and surgeons—together account for 23% of total physician earnings, or 1.9% of national healthcare spending.

Age Profile of Earnings

Figure 1A plots physicians' average annual income by five-year age groups in 2017. The solid line plots raw means, and the dashed line reflects a regression adjustment for sex, state, and specialty category. The regression-adjusted and raw means are broadly similar, though the regression adjustment tends to increase earnings at younger ages and reduce them at older ages, reflecting the different sex and specialty compositions of older cohorts. The earnings profile is very steep. Physicians earn $50,000 to $60,000 on average in their twenties, while they are still in training. This escalates rapidly to an average of nearly $200,000 in the early thirties, and peaks at around $400,000 at age 50. Physicians start scaling back their work hours at age 60, but continue earning close to $200,000 into their mid-70s.

Figure 1B shows relative income—the share whose household income is in the top percentile of the national earnings distribution. At the earnings' peak between ages 40 and 50, over one-third of physicians live in households with earnings in the top percentile.

Administrative vs. Survey Data

Figure 1C uses the sub-sample present in both the 2017 tax data and 2017 ACS to highlight the advantage of administrative data. The comparison of professional earnings measured in tax data versus the ACS—for the same individuals—highlights that income from these sources is underreported in the ACS. The difference is especially large at the career peak. During physicians' most productive years, the ACS underestimates annual income by about $150,000, or nearly one third of the average at that point. Early-career differences are

[18] This distinction is a major limitation of previous studies that use health record or claims data to infer something about physicians' own earnings, such as the gender pay gap (*e.g.* Ganguli et al., 2020).

smaller, but reach $50,000 by age 35. Tax earnings grow much more rapidly during the highest-growth ages. The difference between the two measures is driven by the extensive margin underreporting of business income in the survey data (Appendix A.4)—a crucial part of physicians' earnings, as we discuss next.

Role of Business Income

As Figure 1D illustrates, business income accounts for a substantial share of physician earnings. This is especially true from age 40 onward, presumably after physicians have completed training and established or joined practices. At the age-50 earnings peak, less than three-quarters of average earnings come from W-2 wages. Business earnings are less prevalent for younger physicians, many of whom may still be in training. This pattern is consistent with survey evidence from the American Medical Association, which reports practice ownership rates among physicians age 55 and older nearly twice those among physicians under 40 (54.9% vs. 27.9% in 2016; Kane, 2017). Business income drives the growth in income during the highest-earning years—ages 40 to 60. Average wages are nearly flat at around $280,000 throughout these ages, while business income grows steadily.

Top Earners among Physicians

Figure 2 examines the variation in physicians' average earnings. Panel 2A illustrates the full distribution of professional earnings in 2017. More than 25% of physicians earn above $400,000. Around 10,000 physicians have earnings exceeding $1.5 million. Panel 2B illustrates the distribution of physicians' household income relative to the national distribution. Over one quarter of physician households are in the top percentile of the national income distribution and 53% are in the top two percentiles. The location of physician households in the national income distribution varies substantially by specialty. While nearly half of surgeons and proceduralists are in the top percentile of the national income distribution,

only 14% of PCPs are (Table 1 and Appendix Figure A.1).

The top physician earners present a particularly interesting case study for understanding the right tail of the national income distribution. Physicians are a textbook example of the highly skilled "human capitalists", who dominate the top of the income distribution (Smith et al., 2019a). Table 2 examines how top earners differ from average physicians. First, as with the general population, the income gradient is steep at the top. The top 1% of physicians average $3.9 million in annual earnings, 12 times the average annual earnings in the sample and more than twice the average earnings in the top five percent.[19]

Second, business income is crucial for the top earners. 91% of physicians in the top 1% report meaningful business income,[20] compared to 45% for the top half of physicians and 32% overall. The share of earnings coming from business sources is substantially higher among top earners: 78% for physicians in the top percentile, but 36% for above-median, and 32% for average physicians.

Third, top earners disproportionately work in specialties other than primary care—44% of physicians are in the primary care specialty category, but they comprise only 18% of top earners—are twice as likely to live in New York or Florida than an average physician, and are slightly more likely to work in a metropolitan area. Though they are almost four years older on average, the top 1% of physicians work four hours more per week than an average physician.

Overall, the evidence on top physician earners is consistent with those in the general population (Smith et al., 2019a). The very top incomes are observed among highly trained physicians, whose earnings come from skill-intensive firms during the prime of their careers.

[19]For each cutoff in the table, mean incomes among physicians above the cutoff are very nearly double the cutoff point itself. This suggests the physician income distribution is close to Pareto with a shape parameter of 2 throughout the top half of the physician distribution, as Gottlieb et al. (2018) assumed previously.

[20]We require business income of at least $25,000 to count business income as "meaningful."

Variation in Earnings over Time

The remainder of Figure 2 shows additional moments of the physician earnings distribution. Panel 2C estimates how incomes have changed over time. Since physicians in our sample are all identified from the 2018 NPPES, this is a constant sample of individuals (with the exception of deaths). Thus, each year's raw mean (the green line marked as "unadjusted") comes from observing incomes of the same physicians at different points in their careers. The black line ("regression adjusted") uses a flexible regression to adjust (log) earnings for changes in age, sex, state, and specialty category over time. So this time series can be interpreted as showing the mean (real) income for a comparable physician over time. It grew from around $280,000 in 2005 to nearly $360,000 in 2017, or at a rate of 2% annually.[21]

Geographic Variation in Earnings

Geographic variation in physician incomes appears unique relative to other high-human-capital workers. The map in Panel 2D displays average professional earnings in 2017, adjusted for differences in physicians' ages, sex, and specialty category composition across states. The highest average physician earnings are not in states with the highest incomes for other workers, the highest costs of living, or productivity.[22] Instead, average physician earnings are significantly higher in rural states, with notably higher earnings in the Great Plains and Indiana. Physician earnings are at or even below the national average in many high-productivity, high cost-of-living places, such as New York, Massachusetts, Maryland, and California. But these averages mask important heterogeneity across the income distribution. As Table 2 shows, the very top earners among physicians are nearly twice as likely

[21] For comparability between the series, the unadjusted line restricts the baseline sample to observations with positive professional earnings, observed age, sex, state, and specialty category.

[22] The geographic variation in the earnings of lawyers found in Appendix Figure A.2 provides a useful benchmark. The pattern for lawyers follows general regional income differences: average lawyer earnings are highest on the coasts, plus Illinois and Texas. In contrast, nine of the ten states with physician earnings in the highest quintile have lawyer earnings in the bottom three quintiles. In other words, with the exception of Texas, the geographic variation in earnings of physicians is largely flipped relative to lawyers.

to be practicing in New York and Florida than average physicians.

4 Government Influence on Physician Earnings

We use three sources of policy variation to estimate how much government payments affect physician incomes and labor supply. We examine changes in reimbursement rates in the two large public insurance programs, Medicare and Medicaid, plus expansion of health insurance coverage under the Affordable Care Act (ACA). By design, we estimate short-run elasticities of income and labor supply to government policies. In section 5 we argue that responses along additional margins could amplify these short-run estimates, and discuss the implications of our findings for health policy.

4.1 Price Changes in Medicare

Research Design

One of the U.S. government's most influential health policy instruments is the design of Medicare, a program comprising one-fifth of the total federal budget and a similar share of national health expenditures. Medicare reimburses physicians' professional services in both outpatient and inpatient settings based on a fee-for-service schedule that specifies a payment rate for each medical service. We rely on two facts about this system. First, each service is assigned a value, called Relative Value Units (RVUs), reflecting the time and effort it requires. In 2017, a standard office visit was worth 2.06 RVUs, while inserting a cardiac stent was worth 17.24 RVUs.[23] Crucially, Medicare payment for a service may vary across time and geography, but not across individual physicians.

[23] CMS (2017) establishes these valuations. 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).

Second, Medicare's RVU Update Committee (RUC) regularly reviews how many RVUs are assigned to each service. The reviews can be triggered by changes in the service, by Medicare's request, or based on a five-year review cycle; the timing of when a particular code is reviewed is uncertain (Chan and Dickstein, 2019). We use the changes in the RVUs assigned to each service to estimate how much Medicare payments influence physician incomes.

While service-level updates have constant effects everywhere, different physicians perform different bundles of services. So they have different exposures to each year's set of RVU changes. We exploit these differences. Each year t, Medicare can update the RVUs assigned to service k.[24] For a physician i, who performs a set of services K, we compute the effective composite change in the RVUs of physician i's services as:

$$\Delta\overline{RVU}_{i,t} = \sum_{k \in K} w_{i,k} \frac{RVU_{k,t} - RVU_{k,t-1}}{RVU_{k,t-1}}, \tag{1}$$

where $w_{i,k}$ is a time-invariant weight that captures the importance of each service k in physician i's portfolio. We compute $w_{i,k}$ as the aggregate share of physician i's Medicare revenue from service k in Medicare billing data from 2012–2017. Appendix Figure A.3 shows the distributions of these shocks. Panel A shows the distribution of service-level RVU changes and Panel B shows the distribution of physician-year-level changes, $\Delta\overline{RVU}_{i,t}$. The 5th percentile physician-level change is below -4% and the 95th percentile is above 8%.

We then estimate the following empirical relationship to determine how physician i's earnings in 2013 through 2017,[25] denoted by $y_{i,t}$, respond to changes in RVUs:

$$\Delta \ln(y_{i,t}) = \sum_{\tau=-2}^{2} \beta_\tau \Delta\overline{RVU}_{i,t+\tau} + \theta_{a(i,t)} + \eta_{t,s(i)} + \varepsilon_{i,t}. \tag{2}$$

[24] 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 includes around 13,000 unique codes) and place of service (facility or non-facility).

[25] This is because the aggregate Medicare billing data are only available beginning in 2012.

$\Delta \ln(y_{i,t})$ is the change in log earnings from year $t-1$ to t. $\theta_{a(i,t)}$ captures fixed effects for physician i's age in year t, accounting for the unbalanced age composition of our panel. We restrict our estimation sample to physicians during their prime working ages—30 to 65—to remove trainees with fixed incomes and minimize the mechanical decline in income due to retirements. $\eta_{t,s(i)}$ are Medicare-specialty-by-year fixed effects, so we identify exclusively off within-specialty variation in physicians' procedure shares, combined with the national RVU changes. By estimating the impact of RVU changes within a specialty, we remove the concern that changes in RVUs may be predictable at the specialty-year level (for example, if Medicare announces that it wants to reduce RVUs for ophthalmology services in advance of the actual changes).[26] Our identifying assumption is that, conditional on age-year and specialty-year, the physician's exposure to RVU changes must be orthogonal to other factors affecting her income, or $\mathbb{E}\left[\Delta\overline{RVU}_{i,t+\tau}\varepsilon_{i,t}\right] = 0$ for each $\tau \in \{-2, 2\}$. We cluster standard errors by specialty.

Equation (2) includes the contemporaneous percent change in RVUs and two leads and two lags, indexed by τ. The leads allow us to test if physicians' incomes respond to future changes in RVUs, which would challenge our identifying assumption. The lags allow us to measure earnings responses that take time to appear. To account for the large variability in Medicare billing volumes across providers, we use the average number of RVUs each physician billed in the 2012-2017 data as regression weights.

Our coefficient of interest, β_0, measures the reduced form effect of changes in the Medicare fee schedule on physician incomes.[27] We also estimate analogous regressions with other dependent variables. First, to ensure our measure accurately captures the RVU changes as physicians perceive them, we estimate the relationship between changes in RVUs and changes

[26] In practice, even at the specialty level, code review timing is uncertain. Chan and Dickstein (2019) explain the uncertainty in which specialties will be able to propose code reviews at any given RUC meeting.

[27] To the extent that changes in Medicare fee schedule can trigger changes in private insurers' reimbursement rates, as in Clemens and Gottlieb (2017), our reduced form estimate will capture both the direct and indirect effects of Medicare's reimbursement on physician earnings.

in physicians' total Medicare revenue. We also use a dependent variable that indicates whether physician i's household is in the top percentile of the national AGI distribution.

Changes in physician earnings triggered by Medicare may also affect labor supply. We investigate whether physicians change the total care they provide in response to RVU changes. We use the Medicare billing data to estimate a regression analogous to equation (2). We ask whether physicians change the total number of RVUs they supply.[28] If there is no behavioral response to changes in RVUs and the physician continues performing exactly the same collection of services, then this regression estimate would be zero. We estimate this relationship on our main sample and on near-retirement physicians (ages 56–70).

We next consider the extensive margin elasticity of labor supply. In general, we expect this elasticity to be small in the very short run that we are considering—physicians during their prime working age are unlikely to change their occupation or exit the labor force in response to short-run changes in income. But changes in earnings could affect the probability of retirement at older ages. We test for this possibility in a specification analogous to equation (2) among physicians aged 56 to 70, using the retirement measure we construct from tax data—receiving Form 1099-SSA—as the outcome.

Results

Figure 3 shows coefficients $\hat{\beta}_\tau$ for the contemporaneous effect ($\tau = 0$), two leads ($\tau > 0$), and two lags ($\tau < 0$) when estimating (2) for our various outcomes.[29] Panel 3A shows that a 1% change in RVUs leads to a 0.98% change in physicians' Medicare revenue, suggesting we accurately capture the RVU changes as implemented. Panel 3B reports the estimates for log earnings. A 10% increase in average RVUs leads to a 3% increase in physicians' professional

[28] We define total RVUs provided as a product of the year-specific number of times the service is performed ("line items") and the service's average RVU weight of that service across years 2012-2017; this weighting is time-invariant and so avoids introducing mechanical changes in total RVUs. This measure of total RVUs incorporates both changes in how many times a procedure is performed and which procedure is performed.

[29] Appendix Table A.7 reports the numerical values of the contemporaneous ($\tau = 0$) estimates.

earnings, which is 50% higher than the average annual earnings growth we observe in the time series data (2%). The earnings response is concentrated in the year when the RVU change becomes effective. We do not observe earnings responding to expected changes in RVUs—which supports our identification argument.

The point estimate for revenue suggests limited behavioral response to changes in RVUs for an average physician. Consistent with this result, we find only very noisy change in the quantity of total billed RVUs and are not able to reject a zero labor supply response in our main sample. Among physicians closer to retirement age, however, we find a more elastic response. Panel 3C shows that a 1% increase in RVUs leads to 0.4% more total RVUs supplied.[30] This response is not driven by the extensive margin of labor supply—we do not find any effect on these physicians' retirement (Panel 3D). Instead, it appears that RVU increases causes near-retirement physicians to delay their intensive-margin reduction in work effort.

In sum, changes in Medicare prices affect average physicians' earnings and the labor supply of those near retirement. To understand the magnitude, we convert our earnings estimates into a pass-through—how much would physicians' take-home earnings increase if the government paid them one dollar more? Our estimates imply that physicians earn $84 of each $100 in additional *Medicare* spending.[31] But private insurers copy these types of Medicare reimbursement changes (Clemens and Gottlieb, 2017; Clemens et al., 2017). Accounting for the fact that each Medicare dollar induces additional private insurance spending, we find that each $100 of *any insurance spending* increases the physician's earnings by $35.[32] Under

[30] Recall that this excludes the mechanical effect of change in RVUs, as described in footnote 28. So the effects Panel 3C shows come from increases in the number of services provided or a change in composition towards more intensive services. Note that the weighting described in footnote 28 means the effect of RVU policy changes on Medicare revenue (Panel 3A) is not exactly one plus the effect in Panel 3C; our fixed-weight estimate of RVUs is not exactly the RVUs applicable in a given year. Even so, the confidence interval on the revenue effect includes one plus the estimated RVU response.

[31] Appendix A.5 explains the pass-through calculations for all three of our empirical analyses.

[32] 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

either interpretation, pass-through is quite large. We conclude that Medicare significantly moves earnings of these highly skilled professionals on the margin.

4.2 Price Changes in Medicaid

Research Design

We next examine a second policy that directly changed government payments to physicians—a one-time bump in Medicaid payments for primary care. One provision of the ACA mandated states to increase their Medicaid reimbursement rates for primary care services to equal or exceed Medicare rates. Compared with the Medicare changes, this strategy has two advantages: private insurers don't copy Medicaid rates, removing the conceptual challenge with computing pass-through, and it is a one-time large change for affected physicians, as opposed to the frequent but smaller RVU changes. The disadvantage is that, as discussed below, we don't know precisely which physicians are treated.

States started implementing the policy in 2013, and the peak of federal government expenditures was in 2014. Although the policy was only meant to be present in 2013 and 2014, payments were delayed into 2015 and some states kept the fee bump even after the federal program expired. Alexander and Schnell (2019) and Polsky et al. (2015) examined the effect of this policy change on physicians' propensity to see new Medicaid patients. They found that increased Medicaid payments decreased the reports of being turned away by physicians and improved self-reported health, which suggests that practices likely collected some additional revenue as a result of this policy change.

To estimate how much this reimbursement increase affected physicians' take-home income, we again rely on variation in exposure to the program. To be eligible for this "fee

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 $4,468. The total increase in Medicare-attributable earnings is $7,676, implying a pass-through of 35%.

bump," physicians had to attest to being a primary care provider. This required either board certification in one of designated specialties ("categorically eligible"), or attestation that at least 60% of their Medicaid billing volume for the prior year was for primary care services. These rules suggest two comparisons. Among categorically eligible physicians, we compare incomes among those providing different shares of primary care services. Among providers not categorically eligible, we compare income between those who were and were not likely to exceed the required primary care threshold. We don't directly observe this group's eligibility, but use Medicare billing data to construct a proxy.

These comparisons motivate two event study specifications. Among physicians *in categorically eligible specialties*, we estimate:

$$\ln(y_{i,t}) = \left[\sum_{t\neq 2012} \beta_t \times \mathbb{1}_t \times PCshare_i\right] + \gamma PCshare_i + \theta_{a(i,t)} + \eta_{t,s(i)} + \lambda_{g(i,t)} + \epsilon_{i,t}. \quad (3)$$

Separately, among physicians *in other specialties*—who could only qualify based on their billing history—we estimate:

$$\ln(y_{i,t}) = \left[\sum_{t\neq 2012} \gamma_t \times \mathbb{1}_t \times Qualify_i\right] + \mu\, Qualify_i + \theta_{a(i,t)}^{Qualify_i=1} + \theta_{a(i,t)}^{Qualify_i=0} + \eta_{t,s(i)} + \lambda_{g(i,t)} + \epsilon_{i,t}. \quad (4)$$

where $y_{i,t}$ denotes physician i's earnings in year t, $\theta_{a(i,t)}$ are fixed effects for physician i's age in year t—we allow these to differ between qualifying and non-qualifying physicians in equation (4)—$\eta_{t,s(i)}$ are specialty-by-year fixed effects, and $\lambda_{g(i,t)}$ are state fixed effects. The coefficients of interest are β_t on the interaction of year indicators $\mathbb{1}_t$ with the share of primary care services provided ($PCshare_i$) among categorically eligible physicians, and γ_t on the interaction with $Qualify_i$ among non-categorically eligible physicians.[33] Both equa-

[33]Since we don't observe Medicaid billing, we use Medicare billing data to compute the share of primary

tions limit the sample to prime-working-age physicians (ages 30 to 65) and cluster standard errors at the state-year level. We exclude nine states that either didn't change the reimbursement or had reimbursement changes prior to 2013 from our analysis.[34] Our identifying assumption is that, conditional on state, age-year, and specialty-year, the physician's exposure to the fee bump must be orthogonal to other factors affecting her income. That is, for all t, $\mathbb{E}\left[\mathbb{1}_t \times PCshare_i \times \epsilon_{i,t}\right] = 0$ for categorically-eligible physicians and $\mathbb{E}\left[\mathbb{1}_t \times Qualify_i \times \epsilon_{i,t}\right] = 0$ for the non-categorically-eligible.

We estimate analogous regressions for the relative measure of earnings—being in the top percentile of households—and for labor supply. We measure labor supply using retirement among 56- to 70-year old physicians. Retirement is especially interesting in this context, as the concerns about impending shortages of primary care providers in the U.S. are often driven by primary care physicians' anticipated retirement (Dall et al., 2020; Petterson et al., 2016). The effect of primary care payment generosity on PCPs' decisions to stay in the labor force is thus itself of immediate policy interest.

Results

Figures 4 and 5 plot our estimated coefficients $\hat{\beta}_t$ and $\hat{\gamma}_t$, respectively.[35] For the continuous measure of treatment exposure among categorically eligible physicians (Figure 4), $\hat{\beta}_t$ measure whether physicians more exposed to the fee bump had faster earnings growth than those less exposed. For the binary measure of likely treatment among non-categorically-eligible physicians (Figure 5), the coefficients measure whether earnings grew differently for physicians

care services. This assumes that any given physician performs a roughly similar composition of services across patients with different types of insurance. The indicator $Qualify_i$ is one if at least two-thirds of physician i's line items performed in 2012 MPUPD are primary care services—defined as Evaluation and Management procedure codes 99201-99499, or vaccination codes 90460, 90461, 90465, 90466, 90467, 90468, 90471, 90472, 90473, and 90474—and zero below one-third. This estimation excludes physicians between these two cutoffs to minimize the measurement error from using MPUPD to proxy for Medicaid billing patterns.

[34] We exclude Arkansas, Delaware, D.C., Minnesota, Mississippi, Montana, North Dakota, Oklahoma, and South Dakota. States' Medicaid reimbursement histories are from Alexander and Schnell (2019, Figure A.2).

[35] Appendix Tables A.8 and A.9 report the estimates from a pooled difference-in-differences regression that collapses the time dimension into pre- and post-2012.

who likely qualified for the fee bump compared with those who didn't. Our estimates of pre-trends are noisy, but generally support the identifying assumption that, absent the fee bump, the incomes and labor supply of more-exposed or likely-eligible physicians would have continued on a similar trend as less-exposed or ineligible physicians.

Among categorically-eligible PCPs, a one standard deviation (30 percentage point) increase in exposure implies 2.6% higher earnings, or $6,570, and a 0.6 percentage point (or 2.4%) increased likelihood of being in the top percentile of income. The labor supply estimates are noisier, but suggest that primary care physicians more exposed to the reform slightly were less likely to retire.

We find qualitatively similar results among physicians who were not categorically eligible for the fee bump based on their speciality, but could still qualify for the program based on their pre-program billing patterns. We find that earnings among physicians who qualified for the program grew by 9.2% (or $32,664), which increased the probability of their households being in top 1% by 4.7 percentage points (or 10%).[36] Physicians qualifying for the fee bump were also about 1 percentage point less likely to retire, although these estimates are noisy.

To get a better sense of these magnitudes, we again consider what share of the total government spending on this program accrued to physicians personally. We scale the earnings bump implied by our estimates by aggregate national expenditure on the fee bump, and find that 63% accrued to physicians personally. 36% went to categorically eligible specialties—those normally considered "primary care"—and 27% to non-PCPs who were eligible due to their billing records. Again, this sizable pass-through implies that government payment policy has a major influence on different specialties' compensation.

[36] As with the RVU exercise, this calculation is subject to even more caveats than the usual ones, as we are not taking into account how percentiles of the underlying national distribution may shift when incomes of one group change.

4.3 ACA Insurance Expansion

Research Design

We now consider a different kind of policy: increasing demand for physician services through public financing of increased insurance coverage. If insurance increases the use of healthcare (Einav and Finkelstein, 2018), this should in turn increase demand for physician services. We estimate whether these policies affect physicians' take-home pay.

We use variation from the expansion of health insurance coverage following the ACA's implementation. The ACA increased the insured share of the non-elderly population through two main mechanisms. First, 37 states expanded Medicaid eligibility. Second, individuals in all states were offered means-tested subsidies for individual health insurance on newly created health insurance Marketplaces. Most of these expansions were rolled out in 2014 and 2015. We restrict our analysis to states where the package of key ACA reforms was relatively uniform and took place roughly on the same timeline. This leads us to analyze physician incomes in 24 states that expanded Medicaid in 2014 or early in 2015, coinciding with the rollout of Marketplaces in 2014.[37] As all states we include experienced ACA insurance reforms at the same time, our identification relies on differences in the scale of coverage expansion depending on the pre-existing uninsurance rate.[38] This rate varied from under 10% of the population in Minnesota to over 30% in some counties of Nevada (Appendix

[37]Based on Medicaid expansion dates (listed below in parenthesis) obtained from the Kaiser Family Foundation at https://www.kff.org/health-reform/state-indicator/state-activity-around-expanding-medicaid-under-the-affordable-care-act/, we include the following states into 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., 2019; 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.

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

Figure A.4). It is reasonable to assume that ACA expansions had less effect on the rate of insurance coverage in areas that had a higher rate of coverage prior to 2014. We directly test this in the data by estimating a first-stage relationship between the rate of insurance $I_{c,t}$ in year t and the share of the under-65 population uninsured in 2013, $U_{c,2013}$:

$$I_{c,t} = \left[\sum_{t=2010, t \neq 2013}^{2017} \pi_t \times \mathbb{1}_t \times U_{c,2013} \right] + \kappa_t + \psi_c + \epsilon_{c,t} \tag{5}$$

where κ_t denotes calendar year fixed effects and ψ_c are county fixed effects. The coefficients of interest π_t measure whether the insurance coverage rate grew faster after the ACA rollout in counties with higher baseline uninsurance.

We then estimate the reduced form impact on physician earnings. We allow the impact of the ACA rollout to vary with the same baseline uninsurance rate and estimate:

$$\ln(y_{i,t}) = \left[\sum_{t=2010, t \neq 2013}^{2017} \beta_t \times \mathbb{1}_t \times U_{c(i,t),2013} \right] + \delta_t + \mu_c + \theta_{a(i,t)} + \epsilon_{i,t}. \tag{6}$$

$\hat{\beta}_t$ are the coefficients of interest on year fixed effects interacted with the baseline rate of uninsurance among the non-elderly in 2013. These coefficients measure whether physicians in counties with higher baseline uninsurance rates—so more affected by the ACA expansion—experienced faster income growth than those in counties with lower baseline uninsurance rates. We include physicians in their prime earning ages of 30 to 65 during the four-year window around the reform rollout. δ_t capture calendar year fixed effects, μ_c are county fixed effects, and $\theta_{a(i,t)}$ are age fixed effects for physician i in year t. To interpret $\hat{\beta}_t$ as a measure of how much increasing insurance affects physician earnings, we need the identifying assumption that, absent ACA insurance expansion, physician incomes across counties with different rates of uninsurance among the non-elderly population in 2013 would have followed parallel trends, or $\mathbb{E}\left[\mathbb{1}_t \cdot U_{c(i,t)} \cdot \epsilon_{i,t}\right] = 0$ conditional on the fixed effects. While this assumption is

not directly testable, the event study specification in (6) allows us to test whether counties with differential rates of uninsurance in 2013 followed a parallel trend in physician earnings prior to 2013. We cluster standard errors at the county level.

We estimate analogous specifications for the relative measure of earnings—being in the top percentile of households—and labor supply. As in our analysis of Medicaid reimbursement changes, we measure labor supply using retirement during "at risk" ages 56 to 70.

Results

Figure 6 plots coefficients $\hat{\pi}_t$ and $\hat{\beta}_t$.[39] Panel 6A—the first stage—shows that counties with a ten percentage point higher baseline uninsurance rate saw a 4.9 percentage point higher rate of insurance coverage post-expansion. Expanding insurance coverage tended to moderate pre-existing geographic differences in coverage, as in Finkelstein (2007). Panels 6B and 6C show that physicians' earnings grew faster in these more affected areas. We estimate that a ten percentage point higher baseline uninsurance rate leads to 1.9% higher physician income on average, and increases the share of physicians in the top percentile by 0.6 percentage points. We find suggestive evidence of a decline in the retirement probability. Scaling the income effect by the coverage effect, 10 percentage points higher growth in insurance coverage (which is an 11% increase over the average sample insurance rate of 88% in 2013) increases physician income by 3.9 percent. The elasticity of physicians' earnings to the non-elderly insurance coverage is thus 0.35.

We conclude this section by computing the pass-through of public funds. This exercise asks what share of insurance spending on marginally insured patients goes to physicians—a key issue for the political economy of health insurance. The analogous question among hospitals is well-studied (Garthwaite et al., 2018), but not among physicians. Based on our pooled estimate, 5.6% of the $110 billion annual spending on the ACA insurance expansion

[39] Appendix Table A.10 reports the estimates from a pooled difference in differences regression that collapses the time dimension into pre- and post-2013.

(CBO, 2016) accrued to physicians. Using the peak estimate from the event study, this pass-through increases to 10%. Since physicians' baseline share of medical spending is 8.5%, their gain from expansions was thus approximately proportional to their baseline expenditure share.

4.4 Heterogeneity in the Government's Influence

Our findings across all three sources of quasi-experimental variation in government payments to physicians differ from the modest level of rent sharing with workers found in response to many other shocks (Card et al., 2018). This could be because the institutional setting of physician care is different from other industries. Our setting features payments for specific professional services, often provided by self-employed physicians or small partnerships whose output is not very diversified. Physicians are also high earners, perhaps more similar to those who benefit from patent rents (Kline et al., 2019).

To understand what drives the high incidence of government payments on physicians' take-home pay, we examine which physicians' earnings are most responsive to government payment changes across our three empirical strategies. We consider three categories of potential heterogeneity. First, we compare physicians who are self-employed versus not.[40] Second, we compare physicians working for small versus large (more than 5 physicians) firms, and with high versus low diversification across specialties.[41] For each physician-year we compute the proportion of physicians in his or her EIN who have the same specialty. We consider physician-year observations to be in a diversified firm if they are at above the median of the distribution of specialty shares within their specialty-year. And finally, we compare physicians directly employed by the government (e.g. the Veterans Health Administration)

[40] We classify a physician-year to be self-employed if a Schedule C or E was filed and wages were less than 25% of that year's income.

[41] The firm is defined as the EIN listed on a physician's W-2.

to those working in the private sector.[42]

Appendix Tables A.7 to A.10 report the estimates. In most cases, our estimates are noisy, as the splits reduce sample size substantially. We find suggestive evidence that the effect of direct and indirect government payments is larger for self-employed physicians. This would imply that self-employed physicians bear more of the incidence of a marginal dollar of healthcare payments, but this incidence falls elsewhere under other organizational forms. For the Medicare reimbursement changes and ACA insurance expansions, we also observe the highest incidence of government dollars on take-home earnings among physicians in small, less diversified practices. While being in larger and more diversified firms means that less is passed-through to physicians' incomes when government procurement rates increase, it also implies less pass-through when rates decrease. As more policy proposals suggest cuts in public reimbursement rates, one reason for the observed trend towards bigger and more diversified physician practices (Welch et al., 2013) could be the desire to reduce income risk from payment changes.

Finally, in the Medicaid fee bump and ACA expansion estimates, we observe government policy affecting incomes of physicians who are not directly working for the government (89% of our sample are not). The government doesn't appear to adjust income of its own comparable employees—at least in the short run—even when their privately-employed counterparts experience changes.

In short, the pass-through effects are not driven by physicians with direct government employment, but tend to be concentrated among those working privately. They are stronger among the self-employed, among those in smaller firms, and among those in firms with less diversification across specialties. These factors point to physicians' unique employment

[42] As the tax data do not themselves classify firms as government or non-governmental, we use our ACS records of being a government employee for this analysis. Since ACS is a cross-section, the classification into the sub-sample of government employee versus not, is time-invariant. Our Medicare reimbursement strategy requires panel observations, so we cannot estimate heterogeneity along this dimension for that strategy.

structures as an important explanation for the higher rent-sharing we find.

4.5 Magnitude: Is Health Policy More Powerful than Tax Changes?

One way to interpret the magnitude of our estimates is to compare the power of health care policy to affect top incomes with that of tax policy—the domain that commands most policy attention in discussions of income inequality.

While tax rate changes can affect the full income distribution (Scheuer and Slemrod, 2019) most estimates of the elasticity of taxable income rely on partial equilibrium approaches. This is appropriate for our setting, since we obtain partial equilibrium estimates, as we compare across physicians, specialties, or locations. Using an income tax elasticity ϵ from the literature, and a starting tax rate τ_0, we can find the tax rate τ_1 that would generate an increase of Δy in log physician earnings using the formula:[43]

$$\tau_1 = 1 - \exp\left(\frac{\Delta y}{\epsilon} + \ln(1-\tau_0)\right). \tag{7}$$

Table 3 shows the tax changes that would be needed to generate effects comparable in magnitude to those that we find in our three empirical strategies. The changes needed would be dramatic. To move top incomes by as much as the Medicaid fee bump or ACA expansion changed physicians' earnings would require tax changes larger than those generated by the Tax Cut and Jobs Act of 2017, which lowered the top federal income tax rate from 39.6 to 37 percent; by the ACA, which increased the Medicare payroll tax on high earners by 0.9 percentage points; by the American Taxpayer Relief Act of 2012, which increased the top rate for high earning households from 35 to 39.6 percent; and by the Economic Growth and Tax Relief Reconciliation Act of 2001, which lowered the top rate from 39.6 to 35 percent. While the ranges of tax rates in most of the table are well beyond the available empirical evidence,

[43] Equation (7) follows immediately from the definition of the elasticity of taxable income by solving equation (7) for Δy.

this only strengthens our point: payment policy has a dramatic effect on physicians' top earnings relative to marginal tax rates.

5 Implications for Health Policy

We have seen that three different government healthcare policies have significant power over physicians' earnings. We have also seen that these changes engender short-run labor supply responses, for which policymakers must account when considering policies that change these incomes. But longer-run responses may differ in both magnitude and kind; measuring the effect of income only on retirement timing could miss other consequential changes. Over longer time horizons, physicians could change their investments, specialty, and even career choice (Clemens and Gottlieb, 2014; Clemens et al., 2020; Nicholson and Souleles, 2001).

These longer-horizon effects are naturally difficult to estimate, and of course depend on the particular policy in question. In this section we use descriptive patterns to understand the static equilibrium in physician labor markets. We then draw suggestive implications about the long-run consequences of policies that affect physician earnings.

5.1 Physician Earnings and Career Options within Medicine

We first consider specialty choice. We ask how earnings differences across specialties relate to job characteristics—training length and working hours—and try to tease out whether higher incomes make specialties attractive or compensate for unattractive features.

Figure 7 shows how average specialty earnings relate to characteristics of each job. Panel A looks at the relationship with weekly working hours. The horizontal axis shows the average self-reported hours worked among physicians of each specialty who responded to the ACS. Specialties in which physicians report longer work weeks have higher incomes, with ten extra hours a week adding about $160,000 in annual income (Appendix Table A.11

reports the linear fit). Two notable outliers well above the regression line are dermatology and ophthalmology. Family practice, internal medicine, and pediatrics are all below the regression line. In Panel B we observe a very strong relationship between each specialty's income and physicians' average length of training.[44] Each extra year of training between four and seven corresponds to about $100,000 in extra annual income.

Hours worked and training length are themselves equilibrium outcomes: they may reflect other factors that drive differences in specialties' productivity. They could also be screening mechanisms for allocating individuals with different ability to different specialties; variation in earnings may reflects returns to ability rather than labor market fundamentals. So clearly neither panel portrays a causal relationship. But they do show a sensible labor market equilibrium: more training and longer hours generally go along with higher earnings. Cardiac surgeons have the longest training duration at nearly 7.5 years—they train for three and a half years more than family practitioners, and subsequently earn an additional $391,100 annually, while working 17 hours more per week. Returning to Panel A, we see that cardiac surgeons also work an average of 13 hours per week more than anesthesiologists, and earn about $227,000 more annually. This amounts to $336 in hourly earnings for 676 extra hours per year. This premium hourly rate is twice that of the $144 per hour anesthesiologists earn for their 52-hour work weeks and nearly four times what family practice physicians earn per hour for their 48-hour weeks.

Panels A and B both show clear relationships, but also a fair amount of variation around the regression lines (R^2=0.34 in Panel A and 0.52 in Panel B). Any specialty we observe above the regression lines must either have compensating differentials for unobserved characteristics

[44] Although training is largely standardized within a specialty, there is variation across programs and across individuals. To systematically determine each specialty's *actual* average training length, we develop a method to estimate it empirically using the tax data. We look at the sample of physicians who we see during the ages of residency and fellowship. We then examine their income patterns during that time to identify the years in which they start and finish residency and any fellowship. This allows us to determine each specialty's average length of training. See Appendix A.2 for more details.

of their job (such as better flexibility, time on call, lower liability risk, etc.) or be more attractive to potential entrants.

One way to gauge whether earnings above the regression line are likely to be compensating differentials is to examine labor supply given the bundle of earnings, training, and hours that each specialty offers. The centralized way that medicine allocates residency and fellowship slots generates a natural measure of this labor supply: the share of domestic medical students who match to each specialty. Residency and fellowship programs generally prefer domestic applicants to foreign graduates. So each specialty's share of domestic students is a metric of how attractive the specialty is to incoming physicians.

Panel C shows how this share relates to the unexplained part of specialty earnings. We residualize both the share of U.S.-trained physicians and specialty mean income with respect to training duration and work hours. We then plot the residualized U.S.-trained share against residualized income (with sample means of each variable added to the residuals). We observe a clear upward slope, with an elasticity of 0.38. Conditional on hours and training, a specialty with 10% higher income has a 3.8% higher share of domestically-trained physicians. This suggests that income above the regression lines in Panels A and B is largely an attractive feature of a specialty, rather than a compensating differential.

While this is only a cross-sectional pattern, it suggests that longer-run effects echo—or even compound—the short-run labor supply responses we found in section 4. When government policy reshapes physician earnings, it likely has meaningful consequences for the quantity and the composition of physicians in the market.

5.2 Physician Earnings and Career Options outside of Medicine

An even more consequential margin is the choice to practice medicine. While we lack the data to study this choice directly, we instead compute one important input into this choice: the distribution of lifetime earnings. We do this for physicians and for a plausible alternative

career, being a lawyer. Comparing the lifetime distributions of earnings for these two career paths 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. Law schools require professional society accreditation and graduates have to pass state bar exams. At the same time, lawyers face lower barriers to entry than physicians. Limits to medical school accreditation and the restricted number of Medicare-funded residency slots are frequently cited as entry barriers that boost physicians' incomes. In some states such as California, in contrast, individuals aren't even required to attend a law school to take the bar exam. Anecdotally, there is no shortage of law school spots, and there is no analogue to limited residency slots. So it seems plausible that most people who become a physician could have become a lawyer.

Physicians and lawyers have very different lifecycle earnings patterns, so simple comparisons of mean earnings between working physicians and working lawyers would be misleading. To paint a richer picture of the financial return to practicing medicine and law, we use the panel dimension of our data to estimate the distribution of total career earnings.[45] Panel 7D reports the simulated distributions of present discounted value (PDV) of income for future physicians and lawyers at age 20. With 3% annual discounting, we estimate that physicians' average PDV of earnings is $9.6 million. The analogous estimate for lawyers is $6.7 million (medians of $8.6 million and $5 million, respectively). Physicians' mean of $9.6 million is equivalent to an annuity payment of $360,000 for 51 years at a 3% interest rate.

Three facts are apparent from this figure. First, we estimate significant dispersion in earnings among both physicians and lawyers. The dispersion is slightly higher among lawyers; the coefficient of variation of their distribution is 0.7, compared to 0.5 among physicians. Second, physicians have limited downside risk, with the 25th percentile of the earnings

[45] Appendix A.6 describes our methods.

distribution at $6 million and the 75th percentile at $12 million. The bottom 5% of simulated physicians still earn nearly $4 million over their careers. Only about 6% of physicians in our data have expected income under $4 million, while more than one-third of physicians exceed $10 million. Third, the distribution of earnings for both occupations has a long right tail. The top 1–2% of physicians earn substantially more than the median physician—around $24 million at the top versus $8.6 million at the median.

Against these discounted earnings we must count the cost of training. Table 4 shows data that we have assembled on the cost of undergraduate and professional education for physicians and lawyers: $207,000 for physicians and $165,000 for lawyers.[46] The difference between the occupations is primarily because law school is one year shorter than medical school. Once we account for this $42,000 tuition difference, an average physician earns 44% more over their lifetime than an average lawyer.[47]

Table 4 presents a similar calculation for primary care physicians, who have some of the lowest earnings among physicians. We estimate that they earn $6.1 million in present discounted value over the course of their careers. So medical school tuition, and any associated debt, naturally presents a bigger burden for them. Accounting for the same (rather extreme) potential debt we compute in footnote 47, the total cost is 3.3% of lifetime earnings. This implies that an average PCP earns slightly less than an average lawyer—about half a million

[46]Physician data come from the Association of American Medical Colleges and lawyer data from the American Bar Association. These numbers correspond to 2% of average lifetime earnings for physicians and 2.5% for lawyers. Even if we inflate them to account for borrowing costs (see footnote 47), it is clear that medical school tuition is not comparable in magnitude to the lifetime earnings that it enables.

[47]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 and their pure rate of time preference is zero. Medical students might borrow an extra $100,000 relative to lawyers to cover the additional year of schooling (tuition of $42,000 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 $136,920 over 10 years. Assuming a 40% marginal tax rate, but ignoring any beneficial tax treatment of student loans, physicians would need to earn $228,200 in undiscounted income to repay this extra loan. Under this extremely conservative calculation, the extra debt constitutes 8% of the extra $2.8 million in discounted income that an average physician earns relative to an average lawyer.

dollars less over their careers—and pays about a percentage point more for their training. Nevertheless, 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) even for an average PCP.

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). We estimate that if physicians and lawyers had the same base hourly income, physicians would earn 19% more based purely on the difference in hours. This leaves a 25% difference in earnings attributable to forces beyond time in training and hours worked.[48] Primary care physicians—the largest and lowest-paid group of physicians—have lower income and longer work hours than average lawyers.

This evidence along with our estimates of meaningful labor supply responses suggest that policies aiming to cut physician earnings across the board could encounter serious problems. We have seen that the government has the power to make these sorts of changes. But income cuts may push lower-paid physicians, such as primary care physicians, further below realistic outside options. In contrast, we have seen that many non-primary care specialties appear especially attractive after accounting for length of training and long work weeks.

6 Conclusion

This paper uses a novel administrative data linkage to describe earnings among the universe of U.S. physicians. Physicians' care commands one-fifth of healthcare resources, and their personal incomes comprise 8.5% of U.S. healthcare spending. Beyond their central role in healthcare decisions, physicians are the most common occupation in the top percentile of the

[48] A higher discount rate may better reflect the decision-making of undergraduates or recent college graduates choosing a career. With 5% discounting, we estimate that discounted earnings average $5.9 million for physicians' and $4.2 million for lawyers. This scenario suggests that physicians earn $141 for every $100 earned by lawyers, and 22% of these extra earnings are not explained by simple labor market fundamentals.

U.S. income distribution. Over half of physicians' households are in the top two percentiles of the national income distribution.

We find that government decisions of how to value physicians' care play a central role in defining incomes for these textbook "human capitalists". We estimate that one-third to two-thirds of insurance spending specifically on physician care passes through to physicians' earnings. Overall insurance expansions accrue to physicians approximately in proportion to their baseline share of medical spending. We conclude that the government possesses a unique mechanism—more direct than taxes—for altering the top of the income distribution.

But attractive outside options and elastic labor supply mean that the market constrains this power. Cutting physicians' earnings would likely distort their labor market choices. Average physicians earn $9.6 million over their careers, equivalent to a $360,000 annuity. This is $2.9 million more than an average lawyer, but it varies dramatically by specialty. Higher-earning specialties generally have longer work hours and training length. Primary care comprises nearly half of physicians and is the lowest-paid specialty, with earnings similar to average lawyers. This suggests the government has limited scope for reducing earnings among the largest group of physicians.

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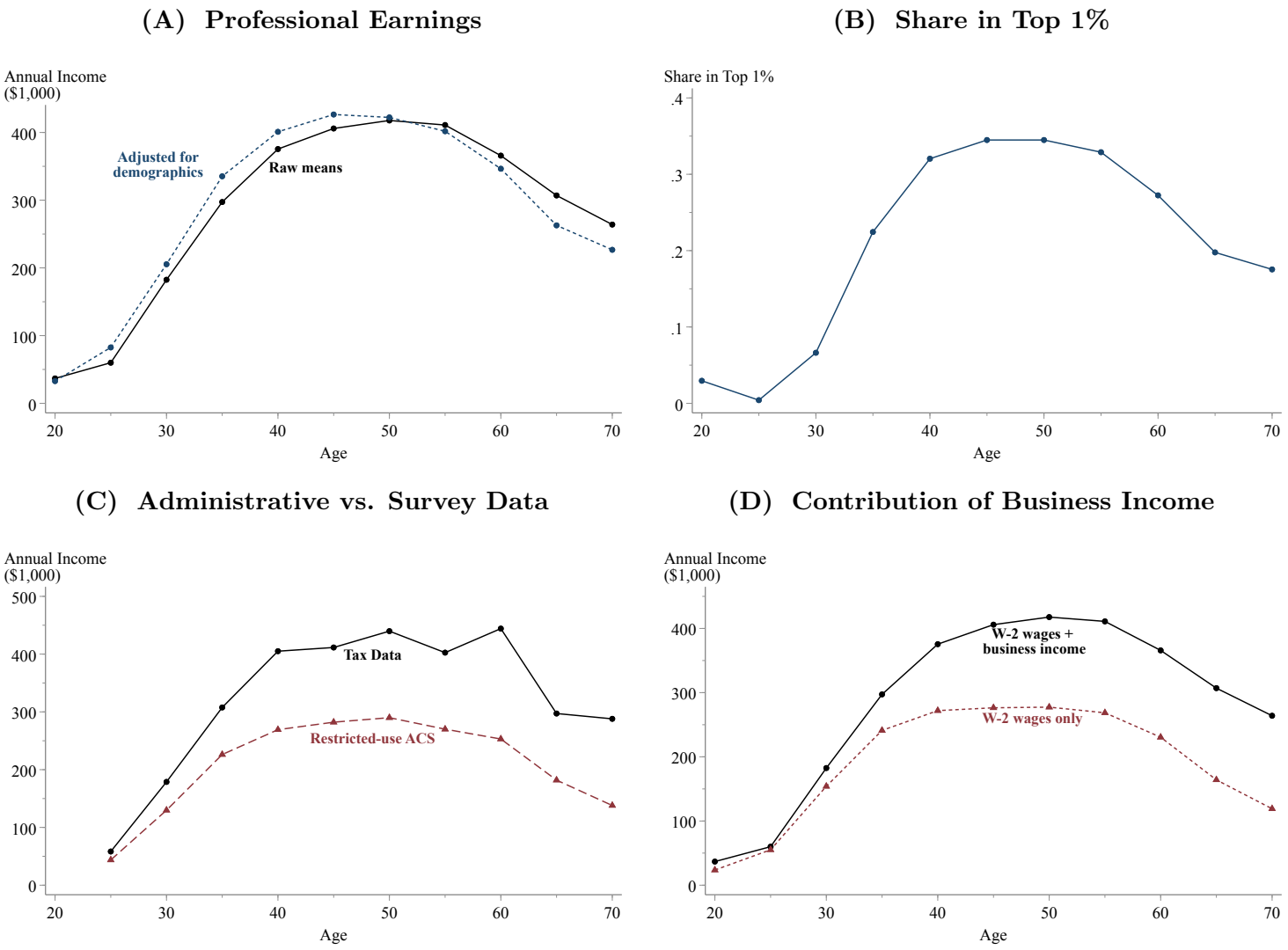
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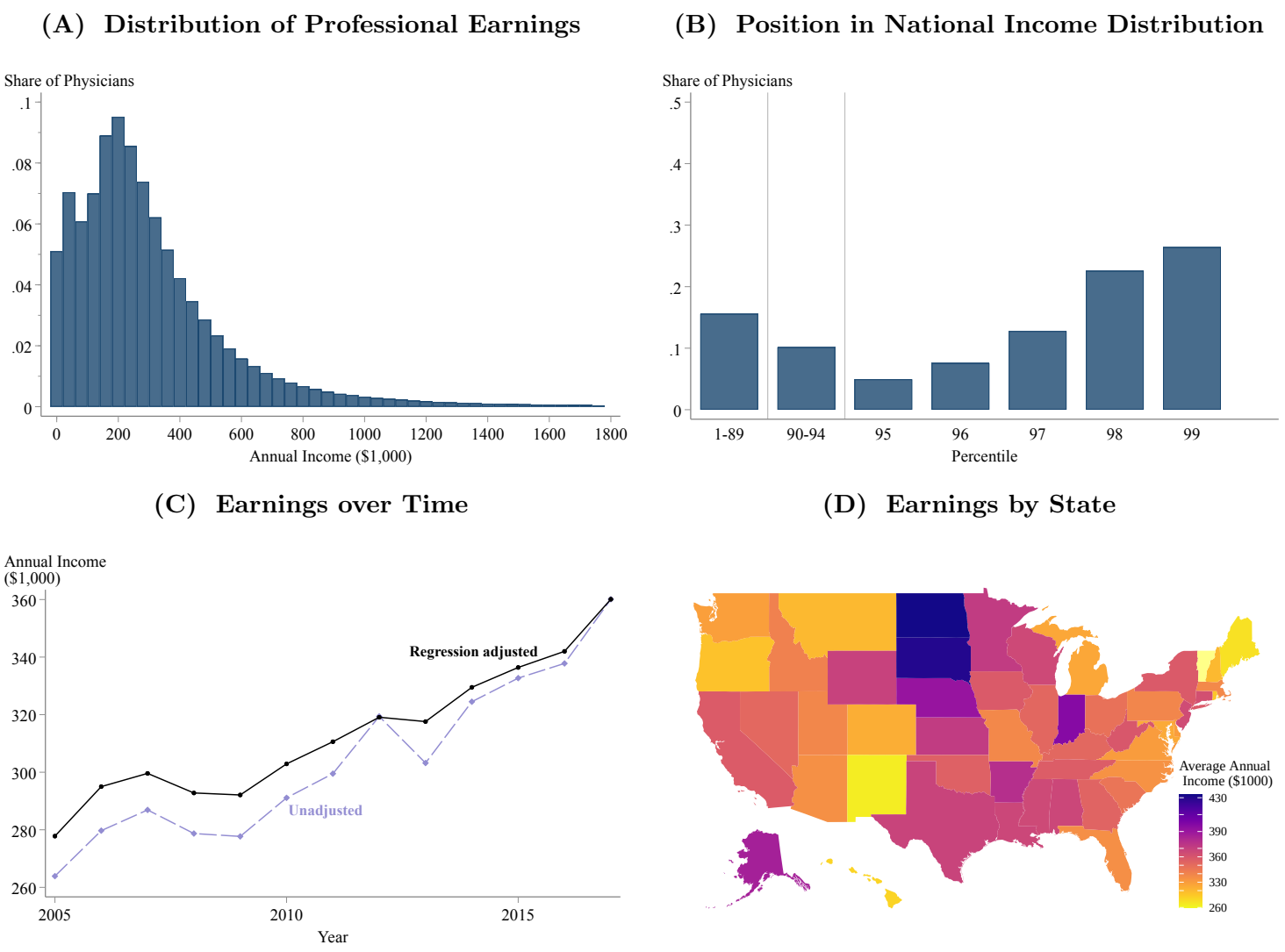
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Figure 1: Physician Earnings over the Lifecycle



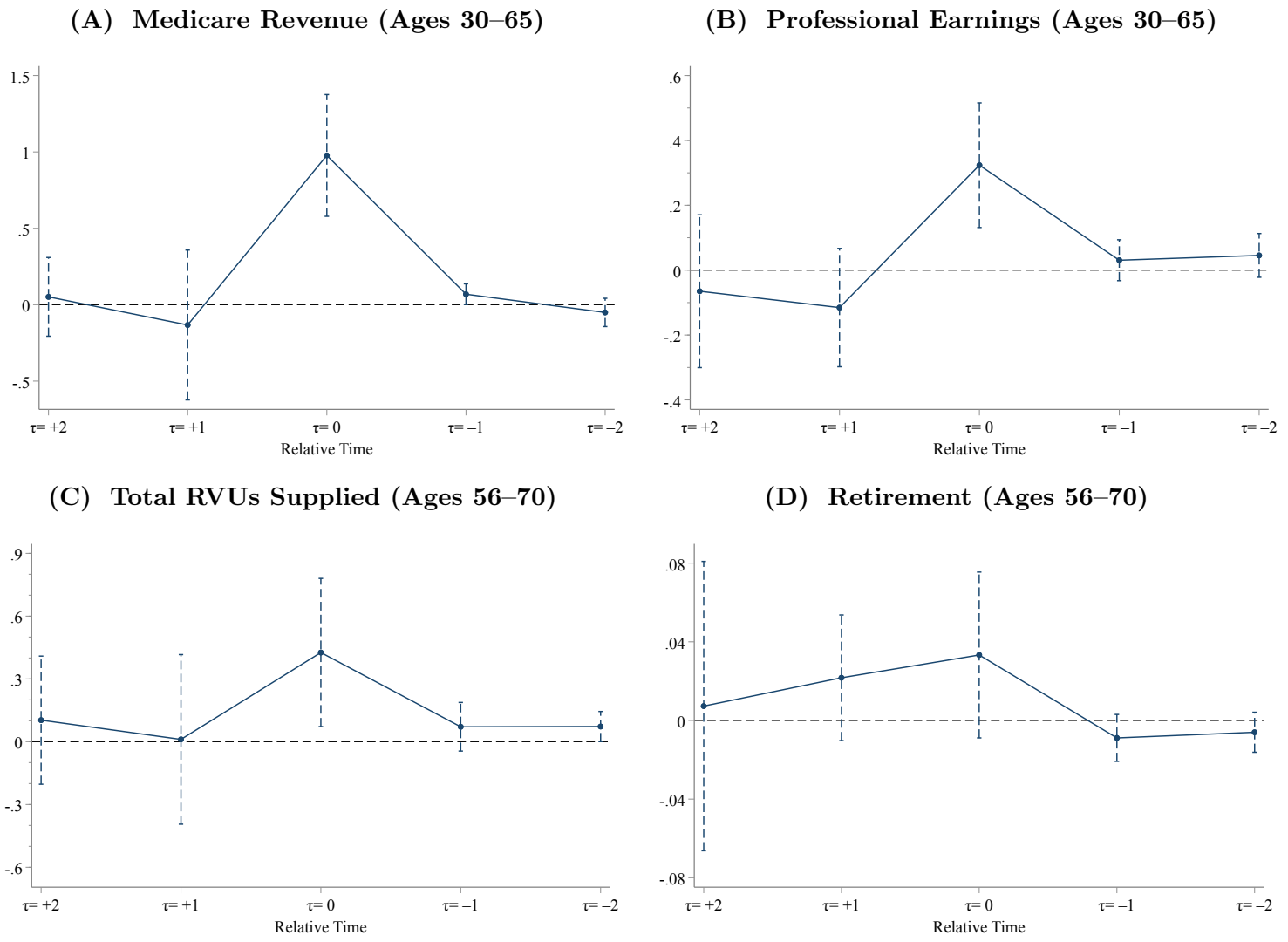
Notes: The figure illustrates 2017 professional earnings (Panels A, C, D) and the share of physician tax units with adjusted gross income in the top percentile of the national income distribution (Panel B) by 5-year age intervals among 863,000 physicians in our baseline sample. Professional earnings are defined as the sum of W-2 wages and imputed business income. Business income (removed from the dashed line in Panel D) is a residual of AGI net of household wages, social security income, interests, and dividends. The dashed line in Panel A regression-adjusts income to account for compositional differences by sex and state across cohorts. Panel C reports survey-based and tax-based income measures for the same subsample of individuals, observed both in ACS and tax data. ACS income is the sum of wages, self-employment income of the index physician, and self-employment income of the spouse. Sources for this and all subsequent tables and figures are authors' calculations based on NPPES (2018), ACS (2001–2017), tax returns (2005–2017), Census Numident (2018), Medicare payment data (2012–2018) and additional external sources in the text.

Figure 2: Variation in Physician Earnings



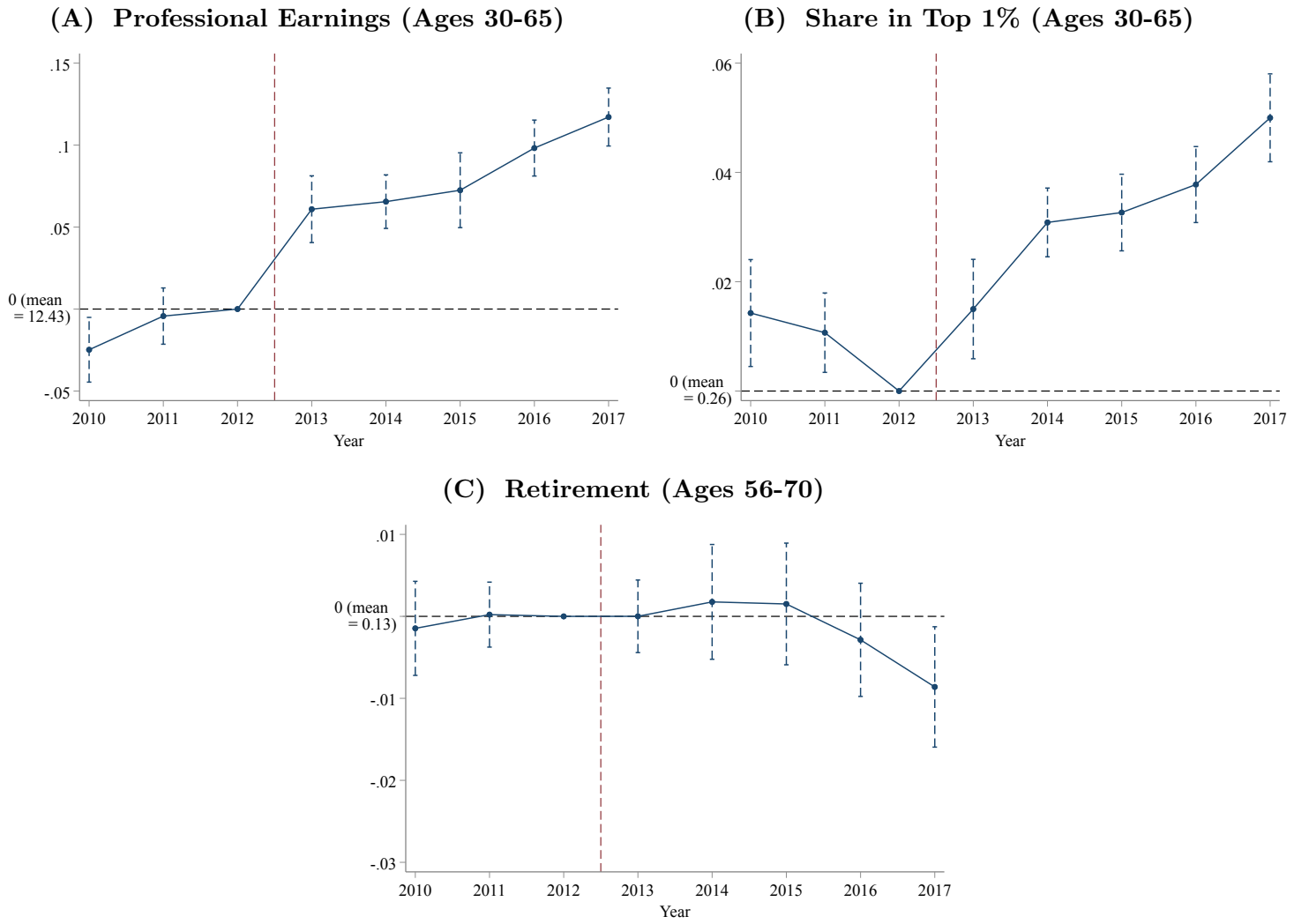
Notes: Panel A shows the distribution of 2017 professional earnings among 863,000 physician in our baseline sample. Professional earnings are defined as the sum of W-2 wages and imputed business income (see note to Figure 1). Panel B plots the share of physicians with 2017 AGI in different percentiles of the national income distribution, as marked on the x-axis. Panel C shows average inflation-adjusted professional earnings over time, from 2005–2017. The solid line regression-adjusts for compositional differences in age, sex, state, and specialty over time. The unadjusted time series restricts the sample to observations with non-missing age, sex, geography, and specialty. Panel D plots average regression-adjusted (for age, sex, and specialty) professional earnings of physicians in each state, from 2017.

Figure 3: Effects of Medicare Reimbursement Changes



Notes: This figure illustrates the effects of changes in Medicare reimbursement rates, obtained by estimating equation (2). For each index year included in the estimation (2013–2017), the outcome variables are first differences in: log Medicare revenue that physicians received according to Medicare MPUPD billing records (Panel A), log professional earnings (Panel B), log total RVUs provided (computed using time-invariant average RVUs per service over the whole period of MPUPD data) (Panel C), and an indicator for having currently or previously received Form 1099-SSA, which is our measure of retirement (Panel D). The independent variables are the percent changes in Relative Value Units (RVUs) calculated according to (1) for the index year, two years before ($\tau < 0$), and two years after ($\tau > 0$) the index year. The sample includes physicians in NPPES aged 30–65 (Panels A and B) or 56–70 (Panels C and D) who billed services to Medicare between 2012 and 2018. Error bars represent 95% confidence intervals, with standard errors clustered by Medicare specialty.

Figure 4: Effects of ACA Medicaid Primary Care Fee Bump (Categorical Eligibility)



Notes: This figure shows event study estimates of the effect of physicians' exposure to the Medicaid payment increase for primary care services to match Medicare rates ("fee bump"), implemented in January 2013. The dependent variables are log professional earnings (Panel A), having AGI in the top percentile of tax units (Panel B), and an indicator for currently or previously receiving Form 1099-SSA, which is our measure of retirement (Panel C). The independent variables are the interaction of year fixed effects with our measure of exposure to the fee bump, as defined in section 4.2. Regression equation (3) also includes age fixed effects, Medicare-specialty-by-year fixed effects, and state fixed effects. The sample is physicians in specialties "categorically eligible" for the fee bump as defined in section 4.2, who appear in the MPUPD in 2012, and who billed at least 50 line items to Medicare. Physicians in nine states where the fee bump was not binding, or where rates changed substantially before 2013, are excluded. Average values of the dependent variables are reported on the y-axis in parentheses. Error bars represent 95% confidence intervals, with standard errors clustered by Medicare specialty.

Figure 5: Effects of ACA Medicaid Primary Care Fee Bump (Billing-Based Eligibility)



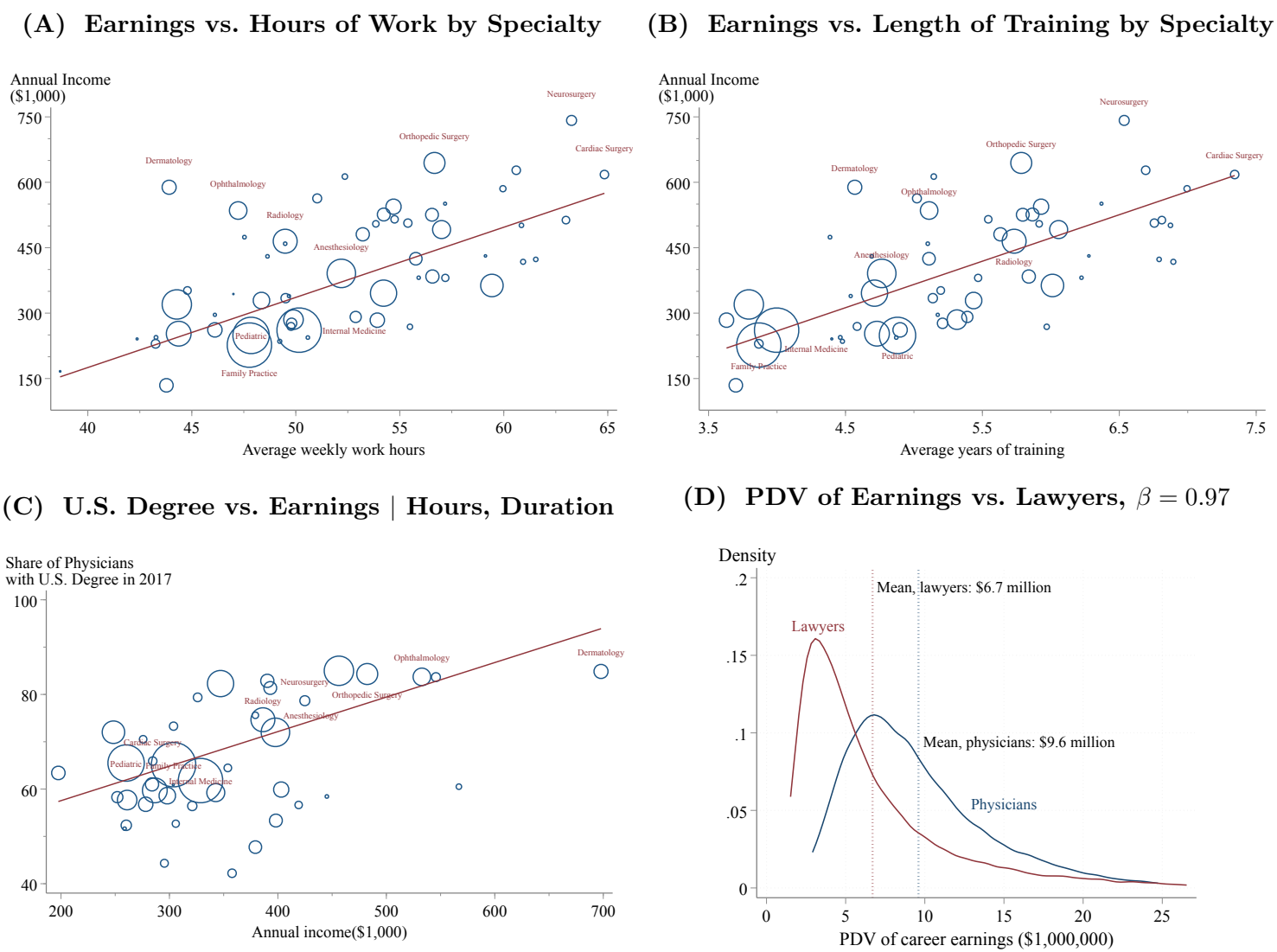
Notes: This figure shows event study estimates of the effect of physicians' likely eligibility for increased Medicaid payment for primary care services to match Medicare rates ("fee bump"), implemented in January 2013. The dependent variables are log professional earnings (Panel A), having AGI in the top percentile of tax units (Panel B), and an indicator for currently or previously receiving Form 1099-SSA, which is our measure of retirement (Panel C). The independent variables are the interaction of year fixed effects with an indicator for billing-based eligibility for the fee bump, as defined in section 4.2. Regression equation (3) also includes age fixed effects, specialty by year fixed effects, and state fixed effects. The sample is physicians who were not "categorically eligible" for the fee bump, but who could qualify based on their billing history, who appear in the MPUPD in 2012, and who billed at least 50 line items to Medicare. Physicians in nine states where the fee bump was not binding, or where rates changed substantially before 2013, are excluded. Average values of the dependent variables are reported on the y-axis in parentheses. Error bars represent 95% confidence intervals, with standard errors clustered by Medicare specialty.

Figure 6: Effects of ACA Insurance Expansions



Notes: This figure shows event study estimates of the ACA insurance expansions beginning in 2014 obtained by estimating (5) (Panel A) at the county level and (6) (Panels B–D) at the individual physician level. The dependent variables are the county-level insured share (Panel A), log professional earnings (Panel B), having AGI in the top percentile of tax units (Panel C), and an indicator for currently or previously receiving Form 1099-SSA, our measure of retirement (Panel D). The sample is physicians in the NPPES aged 30-65 (Panels B-C) or 56-70 (Panel D) in states that expanded Medicaid in 2014 or 2015 (see section 4.3). Counties in Panel A are weighted by the number of physicians in our baseline sample in that county that year. Average values of the dependent variables are reported on the y-axis in parentheses. Error bars represent 95% confidence intervals, clustered at the state (Panel A) or county level (Panels B-D).

Figure 7: Long-run Labor Supply



Notes: Panels A and B plot, for each Medicare specialty, average professional earnings (see note to Figure 1) against the average number of hours worked per week as reported in 2005-2017 ACS (Panel A) and average imputed years of training (Panel B). Panel C plots the specialty's share of physicians with a U.S. degree (Appendix A.2 describes the data source and variable construction) against average earnings, conditional on the number of work hours and years of training. Years of training is imputed from tax data as described in Appendix A.2. Work hours are computed on the subsample of physicians who are observed in 2005-2017 ACS. Circle sizes in the graphs are proportional to the number of individuals in each Medicare specialty in our baseline sample in 2017. The point estimates for the corresponding regression lines are reported in Appendix Table A.11. Panel D displays the PDV of professional earnings from age 20 to 70 for physicians and lawyers, computed using the simulations described in Appendix A.6 at 3% discounting rate.

Table 1: Summary Statistics (2017)

Specialty category	(1) N	(2) Mean Age	(3) Mean Income ($)	(4) Median Income ($)	(5) Share in Top 1%	(6) Hours per Week	(7) Years of Training	(8) Share US-Degree
Physicians	863,000	49.3	343,600	255,200	26%	50.5	4.8	67.7%
By Specialty Category:								
Procedural Specialties	50,500	49.8	535,100	378,600	46%	49.5	5.2	87.9%
Surgery	77,500	49.1	521,100	406,900	46%	58.9	6.1	80.8%
Radiology	42,500	49.9	477,700	405,900	47%	49.9	5.7	83.8%
Medicine Subspecialty	102,000	51.0	444,900	348,700	42%	54.8	5.8	60.6%
Anesthesiology	51,000	49.9	398,900	360,500	34%	52.2	4.8	69.9%
Ob/Gyn	43,000	49.7	350,100	277,500	28%	54.4	4.8	78.3%
Hospital-Based	93,500	47.3	308,800	271,100	20%	46.5	4.0	75.3%
Neurology	25,500	49.9	282,700	232,800	19%	50.0	5.4	62.7%
Primary Care	377,000	49.0	243,300	200,600	14%	48.1	4.2	60.2%

Notes: This table summarizes data for individuals who had a physician National Provider Identifier in the April 2018 version of the National Plan and Provider Enumeration System, had a Census Protected Identification Key, were age 20 to 70 (inclusive) in 2017, and were alive in 2017. Age is measured based on the year of birth observed in the Numident file. Income is our measure of professional earnings (W-2 wages plus imputed business income) as defined in section 2; see note to Figure 1. Mean incomes have been rounded to four significant digits. For non-filers with a W-2 return, we use W-2 earnings as a measure of income. For non-filers with no third party reports, income is set to zero. Share in top 1% reflects the proportion of physician tax units with adjusted gross income in the top 1% of all tax units in 2017. Specialty categories are aggregations of Medicare specialty codes as defined by the authors in Appendix Table A.4. Hours of work per week are based on self-reported work hours in the American Community Survey. Only physicians observed in ACS in years 2005–2017 are included in computing average hours. We first compute average hours across all years 2005–2017 at the Medicare specialty level. Then we take a weighted average of these to aggregate to the specialty category level. The weights are equal to the count of physicians in each Medicare specialty in 2017. We compute years of training based on income growth patterns, as described in Appendix A.2. Average years of training is computed within each Medicare specialty first and then re-weighted as with work hours. Share of physicians with a U.S. degree uses external data; the variable construction is detailed in Appendix A.2.

Table 2: Characteristics of Top Earning Physicians (2017)

	Top X% of Physicians by Income					
	1%	5%	10%	25%	50%	All
Professional Earnings:						
Mean Income ($1000s)	3897	1702	1222	793	559	344
Income Cutoff Values ($1000s)	1799	885	648	412	255	0
Share Reporting Business Income	0.91	0.78	0.70	0.56	0.45	0.32
Share of Income from Business	0.78	0.61	0.52	0.42	0.36	0.32
Share of Income from Labor	0.22	0.39	0.48	0.58	0.64	0.68
Share in Selected Specialties:						
Cardiology	0.030	0.046	0.052	0.047	0.034	0.023
Neurosurgery	0.042	0.042	0.033	0.018	0.010	0.007
General Surgery	0.026	0.034	0.042	0.049	0.042	0.035
Family Practice	0.037	0.030	0.034	0.047	0.085	0.140
Primary Care (specialty category)	0.180	0.140	0.150	0.180	0.290	0.440
Share by Other Characteristics:						
Share in New York	0.120	0.088	0.077	0.068	0.067	0.066
Share in California	0.110	0.098	0.099	0.110	0.120	0.110
Share in Florida	0.110	0.086	0.077	0.069	0.064	0.064
Share in MSA	0.980	0.970	0.960	0.950	0.950	0.940
Mean Age	53.0	52.4	52.1	51.3	50.4	49.3
Mean Weekly Hours Worked	54.8	56.2	56.2	55.4	53.8	50.8
Number of physicians (1000's)	8.63	43.2	86.3	216	432	863

Notes: This table shows the characteristics of physicians in different parts of the distribution of physician earnings. Each column shows, for selected cutoff values, the characteristics of physicians in the top X percent of the distribution. Data are based on the baseline sample of 863,000 physicians described in Table 1. Professional earnings ("income") are the sum of W-2 income ("labor income") and imputed business income based on administrative tax records as defined in section 2; also see note to Figure 1. The share reporting business income requires business income of at least $25,000 to be included. Weekly hours worked is reported for the subsample of individuals for whom American Community Survey responses were available. Shares in selected specialties use Medicare specialty definitions, except for Primary Care specialty category as defined in Table A.4. MSA stands for Metropolitan Statistical Area.

Table 3: Tax Changes Needed for Comparable Income Changes

Elasticity of Taxable Income ϵ	Income Growth Δy	Original Tax Rate τ_0	New Tax Rate τ_1
A. Medicare Reimbursement: RVU Changes			
0.19	0.030	37%	26%
0.19	-0.030	37%	46%
0.57	0.030	37%	34%
0.57	-0.030	37%	40%
B. Medicaid Reimbursement: Billing-Based Eligibility			
0.19	0.092	37%	-2%
0.19	-0.092	37%	61%
0.57	0.092	37%	26%
0.57	-0.092	37%	46%
C. ACA Insurance Expansion			
0.19	0.057	37%	15%
0.19	-0.057	37%	53%
0.57	0.057	37%	30%
0.57	-0.057	37%	43%

Notes: The table uses equation (7) to compute the top income tax rates needed to move top earnings by the same amount as the various policy changes we examine actually did move physician earnings. The estimated income changes come from Tables A.7 to A.10. Panel A considers the impact of a 10 percent RVU change estimated from Table A.7, Panel B the impact of a physician likely being eligible vs. ineligible for the fee bump from Table A.9, and Panel C the impact of a 30 percent baseline uninsurance rate (approximately the maximum) from Table A.10. The elasticities of taxable income come from Kopczuk (2005) and Gruber and Saez (2002).

Table 4: Outside Options: Earnings of Physicians versus Lawyers

	Physicians	PCPs	Lawyers
Mean PDV lifetime income ($\beta = 0.97$, at age 20)	\$9,600,000	\$6,100,000	\$6,700,000
Undergrad & grad tuition	\$207,000	\$207,000	\$165,000
PDV lifetime income net of tuition	\$9,393,000	\$5,893,000	\$6,535,000
PDV lifetime income net of tuition, relative to lawyers	144%	90%	100%
Mean lifetime hrs. worked	113,400	108,100	104,300
Mean lifetime hrs. relative to lawyers	109%	104%	100%
Mean lifetime hrs. w/premium for >40/wk.	119%	111%	100%

Notes: Mean lifetime professional earnings ("PDV lifetime income") is based on simulations described in Appendix A.6. PDV net of tuition subtracts undergraduate and graduate tuition costs obtained from the Association of American Medical Colleges and the American Bar Association. Primary care physicians ("PCPs") include physicians in the Medicare specialty codes listed in Appendix Table A.4. Mean lifetime hours worked are calculated by multiplying usual weekly hours worked by the number of weeks worked in the year for respondents in the 2017 ACS to obtain annual hours worked. Annual hours worked are averaged within each year of age, and then summed for ages 20–70 to obtain lifetime hours worked. The final row is 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 Goldin (2014, Table 3, column 5).

A Appendix

A.1 Survey

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.
  - 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[49] 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.

A.2 Additional Details of Data Sources

Physician registry April 2018 version of NPPES is a cumulative list of all providers with an NPI who are either active on April 2018 or have been delisted since 2005. Thus our sample only captures physicians who had an active NPI in 2018 or had an NPI at some point between 2005 and 2018. We do not observe individuals whose NPIs were discontinued prior to 2005 (for example, because they retired or died). This implies that our sample includes relatively younger physicians in the older years of data. To address the age censoring concern for the earlier years of tax data, we non-parametrically control for age in all our regression analyses.

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

NPPES NPI registry reports providers' medical specialty that we use in our analysis. NPPES uses detailed Health Care Provider Taxonomy Code ASC X12 to categorize specialties.[50] We use two crosswalks to aggregate provider specialties into larger categories. The first crosswalk, obtained from CMS, maps NPPES provider taxonomy into 60 Medicare specialty codes.[51] The second crosswalk, which we constructed ourselves, maps sixty Medicare specialties into nine specialty categories, allowing us to simplify the exposition of specialty-level information. Specialty categories that we use throughout our descriptive analysis are primary care, medicine subspecialty, obstetrics and gynecology, surgery, procedural specialties, hospital-based providers, anesthesiology, radiology, and neurology. Appendix Table A.4 presents the mapping between Medicare specialties and these nine specialty categories.

Measuring tuition costs We calculate the average tuition cost for a medical education—which we define as the cost of pursuing 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, as well as the proportion of students in each category. We aggregate them up, taking appropriately weighted averages, to compute average tuition. The underlying sources are:

- American Association of Medical Colleges, Medical School Graduation Questionnaire (https://www.aamc.org/data/gq/)
- American Association of Medical Colleges, Tuition and Student Fees Report (https://www.aamc.org/data/tuitionandstudentfees/)
- National Center for Education Statistics, 2017 Digest of Education Statistics, Table 330.10 (https://nces.ed.gov/programs/digest/d17/tables/dt17_330.10.asp). This reports average undergraduate tuition and fees and room and board rates charged for full-time students in degree-granting postsecondary institutions.

Measuring location and length of training We obtain statistics on physicians' residency training from two sources. First, the AAMC provides administrative estimates of how many physicians in each specialty attended medical school in the United States (as opposed to training abroad).[52] AAMC data is reported at a specialty level that does not correspond to either Medicare specialty level, or NPPES taxonomy level. We crosswalk the AAMC reporting level to NPPES taxonomy level, assuming that all NPPES taxonomies that fit

[50] The full taxonomy system is maintained by the Washington Publishing Company and incorporates information about the type of provider and provider's area of specialization. Provider Taxonomy codes and their description can be found on the Washington Publishing Company (http://www.wpc-edi.com/reference/codelists/healthcare/health-care-provider-taxonomy-code-set/).

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

[52] https://www.aamc.org/data-reports/workforce/interactive-data/active-physicians-us-doctor-medicine-us-md-degree-specialty-2017

under the AAMC categories have the same share of U.S. trained physicians. Then, to aggregate to the specialty category level in Table 1, we take the weighted average of the share of U.S. trained physicians across NPPES taxonomies that fall under each specialty category. we only include NPPEs taxonomies that we matched to AAMC categories. The weights are the counts of physicians in our baseline sample in each matched NPPES taxonomy in 2017. To aggregate to Medicare specialty level as reported in Figure 7B and Table A.6, we take the analogous weighted average across all crosswalked NPPES taxonomies that fall under each Medicare specialty level.

Second, 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 real 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 income information available every year from 2005 through 2017. Given that residencies begin halfway through the year, we can identify new residents as those who earn about half the typical resident's income in year t (assuming they do not have meaningful income while in their last semester of medical school) and then see their 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 income between \$15,000 and \$35,000 (roughly half the 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 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, as well as the possibility that residents might have income from other sources. We identify a person as completing their training in the first year that they experience another 30% increase in their income from the prior year, and that year's income is at least \$80,000. Variations on these parameters produce similar results. We were able to identify both starting and ending years of training for 85,000 people and use these to estimate the duration of training. We perform these calculations for each Medicare specialty and for each (of nine) specialty category.

A.3 Details of Income Measurement

This section describes the tax variables we use to construct physicians' professional earnings. Table A.5 shows the means and medians of these variables and how they aggregate using 2017 tax data. The first row shows the mean and median adjusted gross income (AGI) among all tax units with a physician aged 20–70, identified from the NPPES, who filed Form 1040 for tax year 2017. We see a mean of \$436,000 and median of \$330,700. The right-hand side of the table limits the sample to those who report positive professional earnings, as defined below. This is intended to remove those out of the labor force, to the extent possible. This

reduces the sample size from 824,000 to 808,000, and increases mean AGI slightly to $445,200 and the median to $335,600.

All subsequent rows in the table add non-filers to the sample. To do this, we add individuals who received a Form W-2, but did not file Form 1040 in tax year 2017.[53] This expanded sample has 863,000 physicians. Mean AGI in this expanded sample is $422,600, or $14,000 lower than among 1040 filers only, as we set AGI for non-filers to W-2 values, or to zero, if no wage information is available.

The subsequent rows show the components of AGI. Wage and salary (W-2) income from the tax unit overall accounts for 70% of the total, or $293,800 on average. Of this amount, 80% or $234,300 is the physician's own wage and salary. The remainder comes from the spouse, but note that we are not conditioning on the presence of a spouse or on having a spouse in the labor force. So the difference between these numbers is not informative about spousal earnings among married physicians.

Professional earnings include W-2 wage income and business income (Section 2.3). Business income is not provided directly in our data, so we back it out from AGI and the other components we do observe. These are reported on the table's subsequent rows. Taxable dividends average $12,990, taxable interest averages $3,515, and we estimate taxable social security earnings of $2,863.[54] Our estimate of the physician's professional earnings is AGI minus spousal W-2 earnings, taxable dividends, interest, and social security. This variable averages $343,600, with a median of $255,200 in the full sample.[55] The conditioning on the right-hand side of the table is specifically requiring our computed professional earnings to be positive. For this sample, mean earnings are $359,900 and the median is $264,100. This professional earnings measure includes everything in AGI that we have not removed—that is, the physician's wage and salary, business earnings, and potentially some other types of capital income.[56] Subtracting the physician's own wage and salary income (mean of $243,000) from professional earnings gives us an estimate of business earnings of $109,300 on average and $10,220 at the median.

[53] We also include few individuals who did not have any record in the tax data, but were observed in NPPES, had a PIK, had a record in the Numident file, and were not deceased in 2017. We set their income to zero.

[54] The tax data provide the full amount of social security received. Only a portion of this is taxable, and the non-taxable portion does not show up in AGI. We estimate taxable social security following the worksheet in IRS Publication 915 as closely as possible, given the income measures available in our data. The rules governing taxability of social security benefits do not change during the period we consider.

[55] The components reported in the table do not exactly add up to this total due to rounding.

[56] For instance, we do not separately observe capital gains, private retirement income, or property rental income, so have no way to precisely eliminate them from professional earnings. Note that some capital gains could indeed be professional earnings, such as if the physician or spouse sells shares of a practice they own. We have conducted an empirical exercise that attempts to back out likely capital gains income based on each year's national trends. In this exercise, we estimate a tax unit's capital gains income by multiplying its dividend income by the ratio of aggregate capital gains to dividend income that year, using estimates from Smith et al. (2019b) through 2014 and IRS Statistics of Income from 2015 on. Results based on this capital gains-adjusted income measure are qualitatively similar to those reported in this paper.

A.4 Comparison of Tax and Survey Data

We use 2017 American Community Survey (ACS) to directly compare physicians' self-reported income and occupation to similar information from the administrative tax and NPPES data. We start with our baseline sample of 863,000 physicians and restrict it to 14,000 individuals who are also observed in 2017 ACS. Among these individuals, 11,500 also report being a physician in ACS, while 2,500 report other occupations. We observe a large difference in the average level of our measure of professional income between the tax data and ACS for both subsamples. For ACS, we define professional income as the sum of individual wage and self-employment income of the index individual plus business income of the spouse—this gives us a measure that is analogous to the measure of professional income in the tax data as outlined in Section 2.3.[57] In the sample of 11,500 individuals who are physicians according to our administrative records and report being physicians in the survey data, average professional income in the tax data is $363,400, while ACS income is $260,500—a more than $100,000 (28%) difference in annual income between the tax and survey data. We summarize the sample sizes and average income levels in Table A.1:

Table A.1

Sample	N	Average Professional Income in Tax Data	Average Professional Income in ACS
(1) Baseline sample	836,000	$343,600	N/A
(2) Baseline sample ∩ 2017 ACS	14,000	$361,500	$237,000
(3) Baseline sample ∩ 2017 ACS ∩ report being a physician in 2017 ACS	11,500	$363,400	$260,500
(4) Baseline sample ∩ 2017 ACS ∩ do not report being a physician in 2017 ACS	2,500	$352,800	$130,000

Notes: The table compares average income computed based on the tax data to self-reported ACS income for three subsamples of our baseline sample of 863,000 physicians. Tax-based income is defined as the sum of W-2 wages and imputed business income. Business income is a residual of AGI net of household wages, social security income, interests, and dividends. 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 focus on the sample in row (3) of Table A.1 to examine the large discrepancy in average tax-based and average survey-based professional income among physicians. Among

[57] 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 account for in the tax data, including one's own business, professional enterprise, or partnership income.

individuals with positive tax or positive ACS income, we observe average tax-based income of $370,800 and survey-based income of $270,200, respectively, suggesting that the $100,000 difference in income in Table A.1 is not driven either by the labor force participation margin or the possibility of having negative income in the tax data. Table A.2 reports average income for the sample of earners with positive total income, by income type, while Table A.3 reports average and self-employment income conditional on each type of of income being non-zero.

Table A.2

	Wage		Self-employment income of self + spouse	
	Tax Income	ACS Income	Tax Income	ACS Income
Average Income	$253,100	$245,400	$117,700	$24,800
N	11,000	11,000	11,000	11,000

Notes: The table compares average wage and self-employment income computed based on tax data to self-reported ACS income among physicians in our baseline sample, who also appear in 2017 ACS and report being a physician in 2017 ACS, and report positive total tax income (in the "tax income" column) or positive total ACS income (in the "ACS income" column).

Table A.3

	Individual wage is greater than zero		Self-employment income of self + spouse is greater than zero	
	Tax Income	ACS Income	Tax Income	ACS Income
Average Income	$282,700	$257,300	$159,100	$125,600
N	10,000	10,500	8,400	2,200

Notes: The table compares average wage and self-employment income computed based on tax data to self-reported ACS income among physicians in our baseline sample, who also appear in 2017 ACS, report being a physician in 2017 ACS, and report positive wage or self-employment income in either tax data or ACS.

Average wages are similar between tax and survey data. Self-employment income, however, is substantially lower in ACS. Most of the difference stems from the extensive margin of self-employment income reporting in ACS. While the difference in unconditional average self-employment income is nearly $90,000 between tax and ACS data, the difference shrinks

by nearly a third when we condition on positive self-employment income. Only 20% of individuals report positive self-employment income in ACS, while we estimate that 76% have some form of business income in the tax data.

The difference in professional income between survey and tax data thus primarily stems from fewer individuals reporting any business income source in the survey data. Yet, as we saw in Section 3, for physicians this type of income accounts for a substantial share of overall professional earnings.

A.5 Pass-Through Calculation

RVU Changes An extra $1 per RVU raises Medicare's payments to providers by 2.6% relative to the current rate of $37.89 per RVU. Applying our estimate of the elasticity of earnings to RVUs, a 2.6% in RVUs would increase physician earnings by 0.78%, or $2,680 (0.78% of $343.600). In our sample, the average physician provides 3,208 RVUs, which means that $3,208 in extra government spending generates $2,680 in extra income.

Medicaid Fee Bump To estimate the pass-through of the primary care fee bump to physicians' personal earnings, we calculate the excess earnings implied by the regressions for both categorically eligible and potentially eligible physicians. We then sum these amounts and scale them by the total national spending on the fee bump. According to the Medicaid Budget and Expenditure System expenditure reports for 2013 to 2017, the federal government spent $6.25 billion on the fee bump program in 2014.[58]

For categorically eligible physicians, $\hat{\beta}_{2014}$ from equation (3) gives the average proportional change in income from 2012 to 2014 attributable to the fee bump for a categorically eligible physician who provided 100% primary care services. We then calculate the dollar value of this change for a physician with the average income in 2012, who provided the mean share of primary care services in 2012 as:

$$\begin{aligned}\hat{y}_{bump} &= \exp\left(\bar{y}_{2012} + \hat{\beta}_{2014} \times \overline{PCshare}\right) - \exp\left(\bar{y}_{2012}\right) \\ &= \exp\left(12.43 + .0655 \times 0.657\right) - \exp\left(12.43\right) = \$11,002. \end{aligned} \tag{8}$$

This gives us an estimate of $11,002 in extra earnings per categorically eligible physician in 2014. With 205,000 categorically eligible physicians aged 30 to 65 in 2012, this yields total excess earnings for categorically eligible physicians of $2.26 billion.

We perform a similar calculation for specialties potentially eligible based on their billing history. Since the treatment variable here is categorical rather than continuous, we multiply the earnings increase implied by the coefficient by the number of physicians deemed eligible

[58] We focus on 2014 since it is the only full year of federal spending; the policy was also in effect in calendar year 2013, but payments were often delayed. So 2014 offers the cleanest full-year spending estimate with comparable earning response. Data are from https://www.medicaid.gov/medicaid/financial-management/state-expenditure-reporting-for-medicaid-chip/expenditure-reports-mbescbes/index.html.

in 2012, and use their mean income in 2012 rather than that for the entire sample:

$$\begin{aligned}\tilde{y}_{bump} &= \exp\left(\bar{y}_{2012}^{qualify} + \hat{\gamma}_{2014}\right) - \exp\left(\bar{y}_{2012}^{qualify}\right) \\ &= \exp\left(12.59 + 0.078\right) - \exp\left(12.59\right) = \$23,818. \end{aligned} \tag{9}$$

While we estimate a considerably larger increase in earnings for these physicians, this is not surprising, since they are required to provide more than 60% primary care services to qualify. So their average treatment intensity is actually higher than in the categorically eligible group. These treated physicians from non-primary care specialties also had somewhat higher baseline earnings, even though they provide a large share of primary care services.

Although the extra earnings per physician are higher for this group, they are a smaller population, numbering only 71,000. As a result their aggregate earnings from the fee bump are smaller than the categorically eligible group, at $1.69 billion.

Since all physicians are either categorically eligible or potentially eligible based on their billing history, the sum of these two quantities gives an estimate of the total excess earnings attributable to the fee bump that accrued to working age physicians in 2014 of $3.95 billion. This corresponds to 63.2% of the $6.25 billion spent by the federal government on the fee bump in fiscal year 2014.

ACA Insurance Expansion Policy reports suggest that ACA expansion resulted in approximately 5.9 percentage points more people insured among non-elderly in total (Tolbert et al., 2020); the uninsurance rate went down from 16.8% in 2013 to 10.9% in 2015. Applying our elasticity estimate, this expansion led to a 2.1% increase in physician incomes, or $7,215 per physician. In aggregate, this means $6.2 billion of extra spending, or 5.6% of the $110 billion in annual spending. Using peak estimates from the event studies, we get an elasticity of 0.54, and a pass-through of 10%.

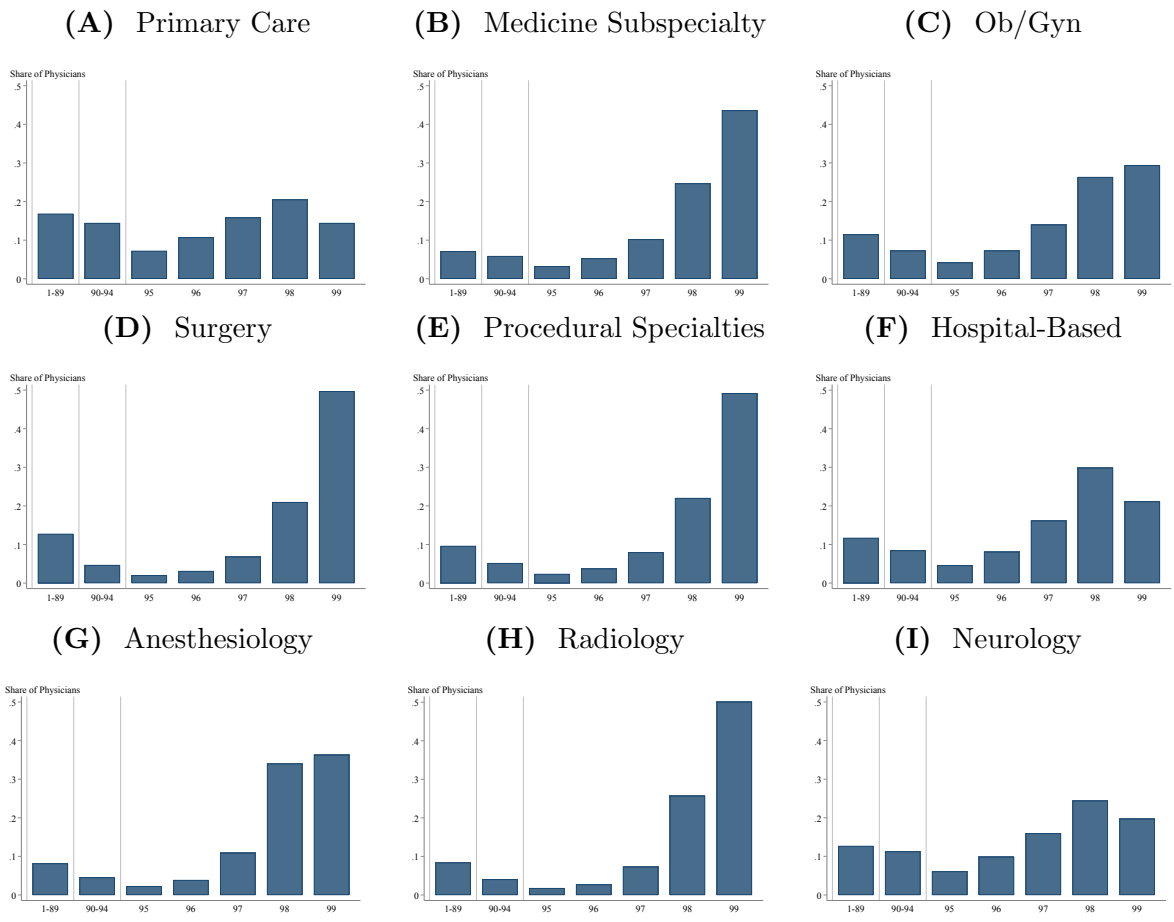
A.6 Present Discounted Value of Earnings

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. 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.

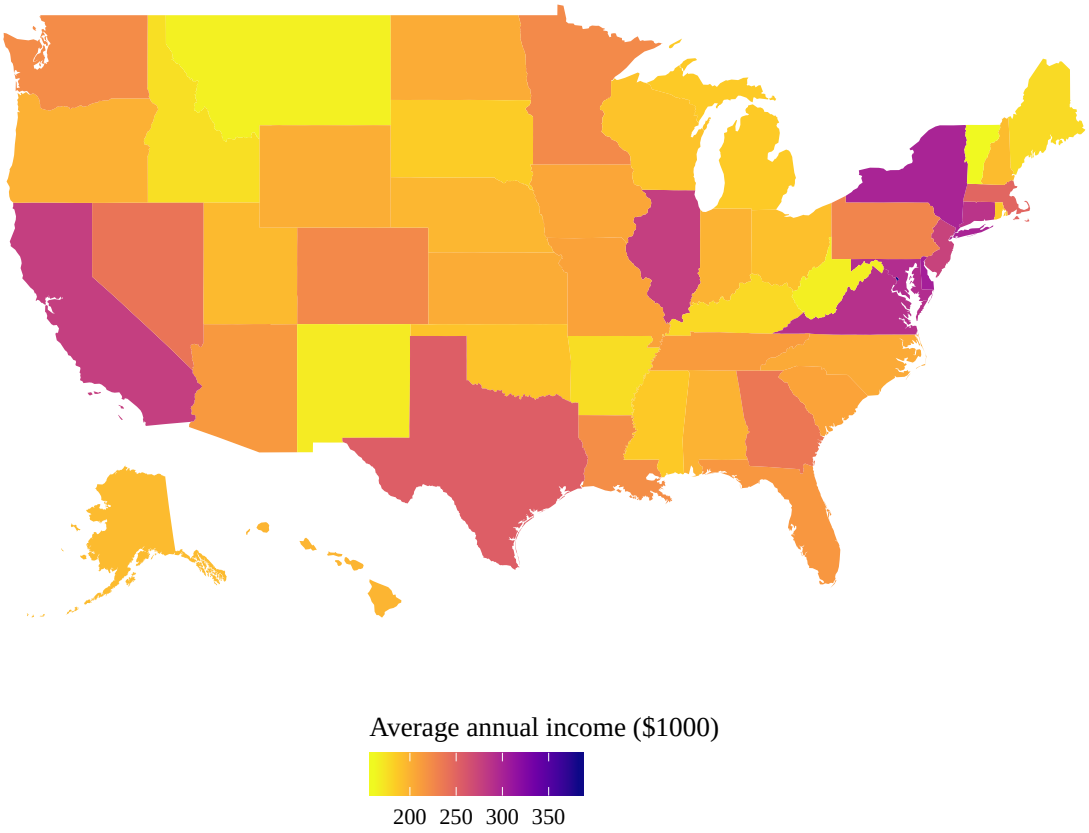
We estimate one-year transition probabilities across income bins for each year of age beginning at age 20 and ending at age 70. We use the empirical distribution of income levels at the starting age and age-specific transition probabilities to simulate 50,000 careers for physicians and lawyers, which 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.

Figure A.1: Position in the National Income Distribution



Notes: The figure replicates Figure 2B by specialty category. Specialty categories are defined by the authors based on Medicare specialty code as described in Table A.4. Each panel plots the share of physician tax units of the specialty category as specified in the panel title with 2017 AGI in different percentiles of the national income distribution, as marked on the x-axis.

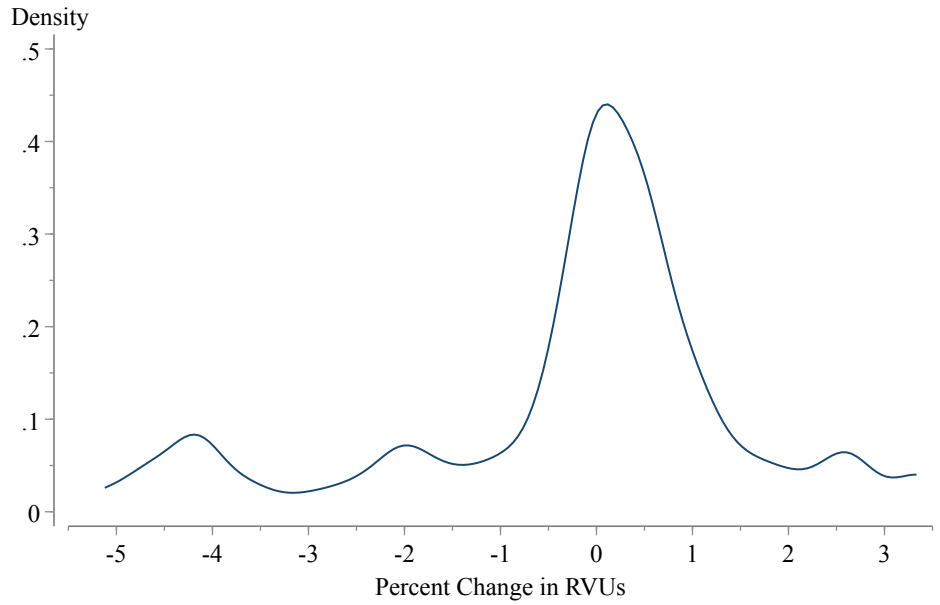
Figure A.2: Lawyers' Earnings by State



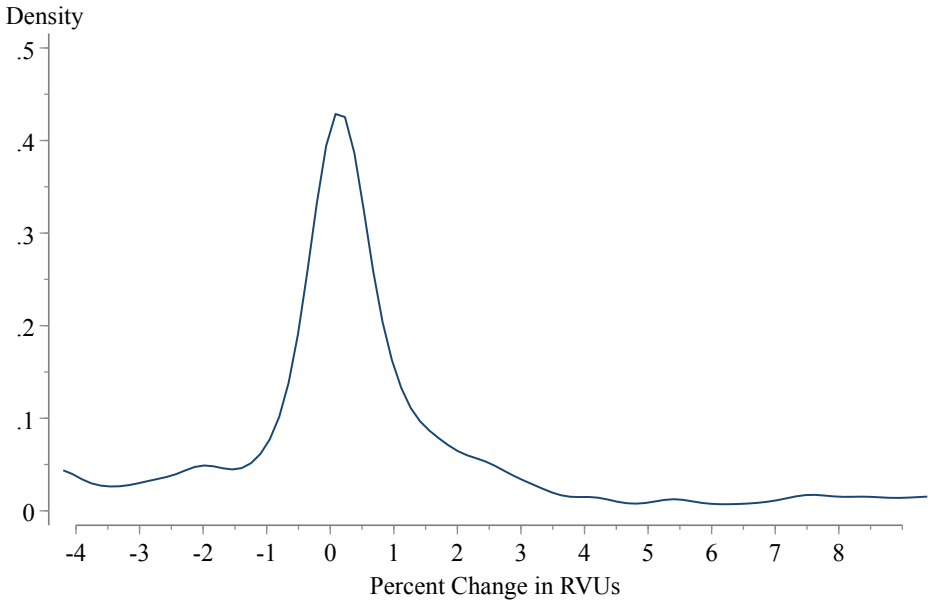
Notes: The figure plots average professional earnings in 2017 among lawyers, by state, adjusted for differences in age and sex composition across states. The sample consists of all tax filers who were present in any ACS sample from 2001–2017 and reported occupational codes related to law. Occupational codes related to law include lawyers, judges, magistrates, judicial law clerks, and other judicial workers. Professional earnings for lawyers are constructed analogously as for physicians using tax data. Professional earnings are defined as the sum of W-2 wages and imputed business income. Business income is a residual of AGI net of household wages, social security income, interests, and dividends.

Figure A.3: RVU Change Variation

(A) Distribution of RVU Changes Across Services



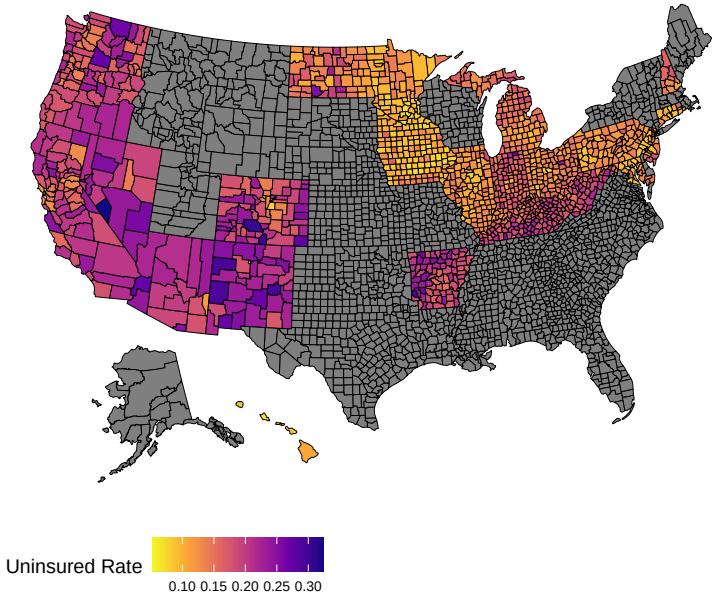
(B) Distribution of Physicians' Exposure to RVU Changes



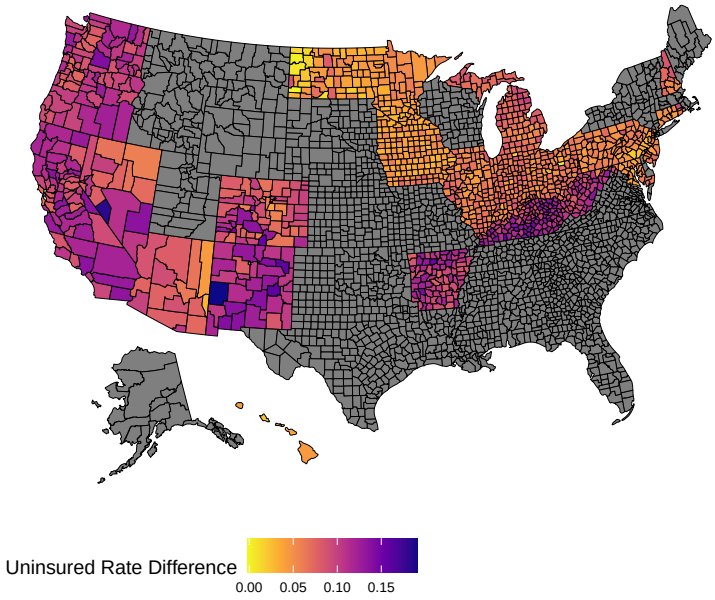
Notes: Panel A illustrates the distribution of year-over-year changes to the RVUs assigned by Medicare to procedure codes over the period from 2012 through 2018. The level of data is procedure-year. Panel B shows the distribution of the aggregate RVU changes faced by individual physicians over that time period, generated by applying the changes in RVUs for each procedure to that physician's average basket of services as specified in equation (1). The graphs show kernel densities, restricted to percentiles 5 to 95 of the distributions.

Figure A.4: Geographic Variation in Share Uninsured

(A) Share Uninsured Population by County, 2013



(B) Difference in Share Uninsured Population by County, 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). We only plot the data for counties which are included in our analyses of the effects of the ACA's expansion of health insurance coverage (see Section 4.3). These counties are located in states that expanded Medicaid in 2014 and 2015, i.e. simultaneous with the rollout of ACA Marketplaces. The data is based on U.S. Census Bureau's Small Area Health Insurance Estimates.

Table A.4: Definition of Specialty Categories

Specialty category	Medicare code	Medicare 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
	U1	Genetics
	U3	Hypertension Specialist
	U4	Phlebology
3	**Obstetrics & Gynecology**	
	16	Obstetrics & Gynecology
	98	Gynecological Oncology
...	...	Continued on next page...

Specialty category	Medicare code	Medicare description
...	...	...continued from previous page
4	**Surgery**	
	2	General Surgery
	14	Neurosurgery
	20	Orthopedic Surgery
	24	Plastic and Reconstructive Surgery
	28	Colorectal Surgery (Proctology)
	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
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
	U5	Electrodiagnostic Medicine

Notes: The table gives the mapping from physicians' Medicare specialty codes to the broader specialty categories used throughout the paper. The mapping was constructed by the authors.

Table A.5: Components of Income Measurement (2017)

Income Measure	All Earnings ($)		Positive Earnings ($)	
	Mean	Median	Mean	Median
AGI (1040 filing sample)	436,000	330,700	445,200	335,600
Wage and Salary: Physician and Spouse (if present)	293,800	247,700	303,000	255,900
Wage and Salary: Physician	234,300	198,200	243,000	205,400
Taxable Dividends	8,820	119	8,861	157
Taxable Interest	2,387	66	2,250	74
Taxable Social Security	1,944	0	1,985	0
Professional Earnings	343,600	255,200	359,900	264,100
Business Income	109,300	10,220	116,900	12,590
Number of Physicians (1040 filing sample)	824,000		808,000	
Number of Physicians (baseline sample)	863,000		831,000	

Notes: The table reports summary statistics for different components of physician earnings as observed in the tax data. Unless specified otherwise, the sample are individuals who had a physician National Provider Identifier in the April 2018 version of the National Plan and Provider Enumeration System, had a Census Protected Identification Key, were age 20 to 70 (inclusive) in 2017, and were alive in 2017. The "1040 filing sample" excludes individuals who did not file Form 1040 with IRS, for whom AGI is not observed. Non-filers are included in the baseline sample. For non-filers with a W-2 return, we use W-2 earnings as a measure of income and all other income types are set to zero. For non-filers with no third party reports, all types of income are set to zero. Wage and Salary report the sum of all W-2 income. Professional earnings are defined as the sum of W-2 wages and imputed business income. Business income is a residual of AGI net of household wages, social security income, interests, and dividends. Statistics may not add up across rows due to rounding. The "Positive Earnings" column computes the summary statistics on the sample of individuals with positive values of the respective income component.

Table A.6: Summary Statistics at Medicare Specialty Level (2017)

Specialty category	(1) N	(2) Mean Age	(3) Mean Income ($)	(4) Median Income ($)	(5) Share in Top 1%	(6) Hours per Week	(7) Years of Training	(8) Share US-Degree
Addiction Medicine	250	57.4	240,900	187,500	13%	42.4	4.4	64.3%
Allergy/ Immunology	3,500	51.9	351,900	263,400	32%	44.8	5.2	72.8%
Anesthesiology	49,000	49.9	391,100	359,900	34%	52.2	4.8	70.2%
Back Office	150	56.5	166,500	128,900	9%	38.7	1.0	.
Cardiac Surgery	4,300	53.2	617,800	549,300	62%	64.8	7.3	76.0%
Cardiovascular Disease (Cardiology)	19,500	52.8	491,600	424,300	51%	57.0	6.1	64.7%
Clinical Cardiac Electrophysiology	2,300	49.0	585,300	538,600	65%	60.0	7.0	.
Colorectal Surgery (Proctology)	1,500	49.9	417,700	374,000	40%	60.9	6.9	.
Critical Care (Intensivists)	3,100	48.1	380,800	355,600	32%	57.2	5.5	52.8%
Dermatology	12,000	48.5	588,600	378,500	50%	43.9	4.6	88.4%
Diagnostic Radiology	34,500	50.0	464,900	399,100	46%	49.5	5.7	83.7%
Emergency Medicine	52,000	47.3	319,900	290,200	20%	44.3	3.8	81.4%
Endocrinology	6,500	49.6	276,700	214,500	21%	49.8	5.2	56.5%
Family Practice	119,000	49.6	226,700	199,600	10%	47.8	3.9	59.2%
Gastroenterology	14,000	51.6	544,100	454,700	56%	54.7	5.9	66.2%
General Practice	11,000	50.2	134,500	72,750	5%	43.8	3.7	59.4%
General Surgery	30,500	48.1	363,400	324,900	32%	59.4	6.0	75.0%
Genetics	750	52.5	244,000	195,400	17%	50.6	4.9	.
Geriatric Medicine	3,700	52.7	269,500	214,100	17%	49.8	4.6	43.0%
Gynecological Oncology	1,200	49.7	501,300	435,400	54%	60.9	6.9	.
Hand Surgery	550	50.6	551,000	429,500	52%	57.2	6.4	.
Heart Failure and Transplant Cardiology	350	44.9	431,200	388,200	45%	59.1	6.3	.
Hematology	700	51.7	381,200	321,400	34%	55.9	6.2	59.5%
Hematology-Oncology	10,000	50.2	526,100	384,000	47%	54.2	5.9	59.5%
Hospice and Palliative Care	1,000	47.1	235,400	210,700	13%	49.2	4.5	.
Hospitalist	12,500	42.0	283,900	264,200	14%	53.9	3.6	.
Infectious Disease	7,500	50.2	291,300	233,100	22%	52.9	5.4	61.4%
Internal Medicine	119,000	47.6	261,000	213,600	16%	50.2	4.0	55.0%

Continued on next page...

Specialty category	(1) N	(2) Mean Age	(3) Mean Income ($)	(4) Median Income ($)	(5) Share in Top 1%	(6) Hours per Week	(7) Years of Training	(8) Share US-Degree
...continued from previous page								
Interventional Cardiology	4,300	50.7	627,600	572,700	69%	60.6	6.7	50.2%
Interventional Pain Management	1,800	49.8	613,100	392,900	47%	52.4	5.1	61.9%
Interventional Radiology	2,500	47.7	504,700	450,900	53%	53.9	5.9	82.5%
Maxillofacial Surgery	800	48.1	474,200	394,500	45%	47.5	4.4	.
Medical Oncology	3,300	51.8	515,100	375,500	47%	54.8	5.5	59.5%
Nephrology	9,500	49.7	424,700	322,900	38%	55.8	5.1	45.9%
Neurology	1,700	48.0	268,700	218,000	17%	55.5	6.0	.
Neuropsychiatry	23,000	49.9	285,100	235,800	19%	49.9	5.3	62.7%
Neurosurgery	6,000	48.7	741,900	614,600	64%	63.3	6.5	83.0%
Nuclear Medicine	750	54.3	430,200	273,700	27%	48.6	4.7	.
Obstetrics/ Gynecology	41,500	49.7	345,800	274,400	27%	54.2	4.7	78.3%
Ophthalmology	18,500	50.7	535,300	346,200	44%	47.2	5.1	89.2%
Orthopedic Surgery	26,500	49.3	644,400	518,500	58%	56.7	5.8	87.7%
Osteopathic Manipulative Medicine	850	53.7	244,300	182,500	16%	43.3	4.5	.
Otolaryngology	10,500	49.3	480,700	384,300	44%	53.2	5.6	87.8%
Pain Management	750	51.3	459,200	317,200	37%	49.5	5.1	61.9%
Pathology	16,500	51.3	328,900	265,400	27%	48.4	5.4	66.0%
Pediatric Medicine	80,000	48.1	248,900	191,300	16%	47.9	4.9	68.4%
Peripheral Vascular Disease	3,400	50.6	513,300	430,800	48%	63.0	6.8	77.5%
Physical Medicine and Rehabilitation	12,500	47.4	261,600	204,500	18%	46.1	4.9	61.4%
Plastic and Reconstructive Surgery	4,100	50.8	506,500	341,300	41%	55.4	6.8	86.3%
Preventive Medicine	4,500	55.8	229,700	176,900	10%	43.3	3.9	77.3%
Psychiatry	37,000	51.7	252,900	211,100	13%	44.4	4.7	64.3%
Pulmonary Disease	10,500	51.2	384,000	334,800	34%	56.6	5.8	64.9%
Radiation Oncology	4,800	49.7	563,100	453,300	53%	51.0	5.0	85.1%
Rheumatology	5,200	51.2	334,300	236,700	28%	49.5	5.1	60.2%
Sleep Medicine	600	50.5	339,200	265,400	27%	49.7	4.5	.
Sports Medicine	600	52.1	296,200	205,100	18%	46.1	5.2	.
Surgical Oncology	1,200	48.2	423,200	361,400	41%	61.5	6.8	.
Urology	9,900	50.3	525,600	416,400	47%	56.5	5.8	84.9%

Notes: This Table replicates Table 1 at the Medicare specialty level, see the notes to Table 1 for the variable definition. The sample includes individuals who had a physician National Provider Identifier in the April 2018 version of the National Plan and Provider Enumeration System, had a Census Protected Identification Key, were age 20 to 70 (inclusive) in 2017, and were alive in 2017. Share with U.S. degree is based on external source as described in Appendix A.2 and was not available for all Medicare specialties.

Table A.7: Effect of RVU Changes on Physician Earnings & Labor Supply

Specifications	Estimate (1)	Standard Error (2)	Mean of Dep. Var. (3)	S.D. of Dep. Var. (4)	No. of Unique Physicians (5)	No. of Observations (6)
A. Main outcomes						
Medicare Revenue (first diff. in logs)	0.977	0.203	0.041	0.630	510,000	2,088,000
Earnings (first diff. in logs)	0.324	0.098	0.038	0.516	510,000	2,088,000
Change in Probability of Top 1%	0.035	0.075	0.004	0.317	488,000	1,358,000
Number of RVUs (first diff. in logs, ages 30 to 65)*	0.158	0.160	0.028	0.604	530,000	2,168,000
Number of RVUs (first diff. in logs, ages 56 to 70)	0.426	0.181	-0.071	0.532	212,000	773,000
Probability of Retirement	0.033	0.022	0.036	0.187	214,000	786,000
B. Heterogeneity (Earnings)						
Self employed						
No	0.308	0.119	0.043	0.495	457,000	1,876,000
Yes	0.371	0.203	-0.003	0.677	52,000	210,000
Share Own Specialty/ Size of EIN						
Less of Own Specialty/ Small EIN	-0.391	1.123	0.026	0.569	600	2,400
More of Own Specialty/ Small EIN	0.541	0.185	0.020	0.537	48,500	211,000
Less of Own Specialty/ Large EIN	0.202	0.152	0.068	0.470	189,000	721,000
More of Own Specialty/ Large EIN	0.239	0.270	0.031	0.482	176,000	755,000

* Computed using time-invariant average RVU per service over the whole period of MPUPD data, thus measuring the quantity of care provided.

Notes: The table displays the effects of changes in Medicare reimbursement rates, obtained by estimating equation (2). For each index year included in the estimation (2013–2017), the main outcome variables displayed in Panel A are first differences in: log Medicare revenue that physicians received according to Medicare MPUPD billing records, log professional earnings, probability of being in the top 1% of households by AGI, the log number of RVUs provided, and an indicator for having currently or previously received Form 1099-SSA, which is our measure of retirement. In Panel B, we re-estimate the regressions with log earnings as the outcome variable on several sub-samples as defined in section 4.4. The independent variables are the percent changes in Relative Value Units (RVUs) calculated according to (1) for the index year, two years before ($\tau < 0$), and two years after ($\tau > 0$) the index year. Only coefficients for the index year are displayed. The sample includes physicians in NPPES aged 30–65 or 56–70 (retirement) who billed services to Medicare between 2012 and 2018 and for whom the outcome variables were observed. Regressions include age and Medicare-specialty-by-year fixed effects, with standard errors clustered by Medicare specialty.

Table A.8: Effects of ACA Medicaid Primary Care Fee Bump (Categorical Eligibility)

Specifications	Estimate	Standard Error	Mean of Dep. Var.	S.D. of Dep. Var.	No. of Unique Physicians	No. of Observations
	(1)	(2)	(3)	(4)	(5)	(6)
A. Main outcomes						
Log Earnings	0.087	0.005	12.440	0.800	217,000	1,570,000
Probability of Top 1%	0.021	0.002	0.274	0.446	216,000	1,538,000
Probability of Retirement	-0.002	0.003	0.143	0.350	103,000	589,000
B. Heterogeneity (Earnings)						
Self employed						
No	0.078	0.006	12.450	0.707	198,000	1,307,000
Yes	0.109	0.025	12.450	1.148	57,000	211,000
Share of Own Specialty/ Size of EIN						
Less of Own Specialty/ Small EIN	0.121	0.053	12.340	0.861	4,800	11,500
More of Own Specialty/ Small EIN	0.035	0.014	12.530	0.802	41,500	156,000
Less of Own Specialty/ Large EIN	0.041	0.011	12.400	0.675	109,000	517,000
More of Own Specialty/ Large EIN	0.068	0.008	12.540	0.698	116,000	549,000
Government Employee (ACS)						
No	0.058	0.008	12.480	0.786	35,000	252,000
Yes	0.018	0.025	12.350	0.662	2,600	19,500

Note: The table displays difference-in-differences estimates of the effect of physicians exposure to the Medicaid payment increase for primary care services to match Medicare rates ("fee bump"), implemented in January 2013. In Panel A, the dependent variables are log professional earnings, having AGI in the top percentile of tax units, and an indicator for currently or previously receiving Form 1099-SSA, which is our measure of retirement. In Panel B, we re-estimate the regressions with log earnings as the outcome variable on several sub-samples as defined in section 4.4. The independent variables are the interaction of an indicator for years after the reform with our measure of exposure to the fee bump, as defined in section 4.2. Regression equation (3) also includes age fixed effects, Medicare-specialty-by-year fixed effects, and state fixed effects. Standard errors are clustered at the Medicare specialty level. The sample is physicians aged 30–65 (or 56–70 for retirement) in specialties "categorically eligible" for the fee bump as defined in section 4.2, who appear in the MPUPD in 2012, and who billed at least 50 line items to Medicare. Physicians in nine states where the fee bump was not binding, or where rates changed substantially before 2013, are excluded.

Table A.9: Effects of ACA Medicaid Primary Care Fee Bump (Billing-Based Eligibility)

Specifications	Estimate (1)	Standard Error (2)	Mean of Dep. Var. (3)	S.D. of Dep. Var. (4)	No. of Unique Physicians (5)	No. of Observations (6)
A. Main outcomes						
Log Earnings	0.092	0.007	12.780	0.799	184,000	1,341,000
Probability of Top 1%	0.047	0.003	0.451	0.498	183,000	1,317,000
Probability of Retirement	0.002	0.002	0.142	0.350	85,500	476,000
B. Heterogeneity (Earnings)						
Self employed						
No	0.090	0.005	12.800	0.707	169,000	1,115,000
Yes	0.076	0.024	12.780	1.139	49,500	184,000
Share of Own Specialty/ Size of EIN						
Less of Own Specialty/ Small EIN	1.638	0.441	12.740	1.158	300	450
More of Own Specialty/ Small EIN	0.061	0.012	12.920	0.823	33,500	130,000
Less of Own Specialty/ Large EIN	0.043	0.007	12.670	0.716	82,500	406,000
More of Own Specialty/ Large EIN	0.101	0.008	12.920	0.664	99,500	519,000
Government Employee (ACS)						
No	0.073	0.011	12.840	0.775	30,500	221,000
Yes	-0.006	0.030	12.660	0.678	2,300	17,500

Notes: The table displays difference-in-differences estimates of the effect of physicians likely eligible for increased Medicaid payments for primary care services to match Medicare rates ("fee bump"), implemented in January 2013. In Panel A, the dependent variables are log professional earnings, having AGI in the top percentile of tax units, and an indicator for currently or previously receiving Form 1099-SSA, which is our measure of retirement. In Panel B, we re-estimate the regressions with log earnings as the outcome variable on several sub-samples as defined in section 4.4. The independent variables are the interaction of an indicator for years after the reform with our measure of exposure to the fee bump, as defined in section 4.2. Regression equation (3) also includes age fixed effects, Medicare-specialty-by-year fixed effects, and state fixed effects. Standard errors are clustered at the Medicare specialty level. The sample is physicians aged 30–65 (or 56–70 for retirement) who were not in specialties "categorically eligible" for the fee bump as defined in section 4.2, who appear in the MPUPD in 2012, and who billed at least 50 line items to Medicare. Physicians in nine states where the fee bump was not binding, or where rates changed substantially before 2013, are excluded.

Table A.10: Effect of ACA Expansion on Physician Income & Labor Outcomes

Specifications	Estimate (1)	Standard Error (2)	Mean of Dep. Var. (3)	S.D. of Dep. Var. (4)	No. of Unique Physicians (5)	No. of Observations (6)
A. Main outcomes						
Percent Insured	0.487	0.035	0.881	0.051	500,000	3,047,000
Log Earnings	0.191	0.052	12.320	0.965	500,000	3,047,000
Probability of Top 1%	0.057	0.018	0.275	0.447	500,000	3,020,000
Probability of Retirement	-0.050	0.019	0.196	0.397	197,000	1,074,000
B. Heterogeneity (Earnings)						
Self employed (ACS)						
No	0.217	0.069	12.400	0.846	59,500	384,000
Yes	0.209	0.113	12.550	0.969	17,000	112,000
Share of Own Specialty/ Size of EIN						
Less of Own Specialty/ Small EIN	-0.140	0.765	12.320	1.086	2,400	4,000
More of Own Specialty/ Small EIN	0.383	0.121	12.530	0.908	74,500	258,000
Less of Own Specialty/ Large EIN	0.216	0.074	12.210	0.863	284,000	1,215,000
More of Own Specialty/ Large EIN	0.186	0.091	12.490	0.825	233,000	975,000
Government Employee (ACS)						
No	0.152	0.066	12.460	0.887	68,000	443,000
Yes	0.274	0.133	12.230	0.772	8,500	53,000

Note: The table displays difference-in-differences estimates of the effects of the ACA insurance expansions beginning in 2014. Results are based on physicians in states that expanded Medicaid in 2014 or 2015 (see section 4.3) aged 30-65 (56-70 for retirement). In Panel A, the outcomes are the percent insured in the physician's county, log professional earnings, having AGI in the top percentile of tax units, and an indicator for currently or previously receiving Form 1099-SSA, which is our measure of retirement. In Panel B, we re-estimate the regressions with log earnings as the outcome variable on several sub-samples as defined in section 4.4. The independent variable is the interaction of an indicator for years after the reform with the fraction of population that is insured in a physician's county in 2013. The regression equations include fixed effects for age, county, and year. Standard errors are clustered at the county level.

Table A.11: Long-run Labor Supply

	(1) Income ($1,000)	(2) Income ($1,000)	(3) Share U.S. Degree
Weekly Hours Worked	16.1		
	(2.97)		
Years of Training		106.4	
		(13.65)	
Income ($1,000)			0.07
			(0.01)
Number of Unique Physicians	863,500	863,400	863,500
Number of Specialties	59	58	42
Mean of Independent Variable	52.2	5.3	357.9
S.D. of Independent Variable	6.0	1.1	100.5
Mean of Dependent Variable	401.4	402.4	65.7
S.D. of Dependent Variable	137.6	138.6	12.0
R-Squared	0.34	0.52	0.39

Notes: The table reports the estimates underlying the regression lines in Figure 7. Columns 1, 2, and 3 correspond to Panels A, B, and C, respectively. The regressions are run at the Medicare specialty level, with regression weights that are equal to the number of individuals in each Medicare specialty in our baseline sample. The number of specialties included in the regressions varies across columns, as not all measures were available for all specialties. In column (3) the left and the right hand side variables were first residualized to take out the variation attributable to differences in the average number of work hours and years of training. Years of training is imputed from tax data as described in Appendix A.2. Work hours are computed on the subsample of physicians who are observed in 2005-2017 ACS. The number of unique physicians is not equal to the count in Table 1 due to rounding at the Medicare specialty level.