Selection into Medicine*

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Abstract

This paper examines how selection into medicine in the United States influences physician practice styles. We exploit macroeconomic conditions at the time of medical school application as an exogenous shock to the applicant pool and find that labor market downturns in other prestigious fields increase medical school applications, particularly from students with non–pre-medical backgrounds. This shift in applicant composition leads to cohorts of physicians who are more likely to work in lucrative, small group practices and to bill Medicare more per beneficiary, even after accounting for experience, specialty choice, and patient risk scores. Our findings highlight selection into medicine as a previously overlooked channel that shapes physician practice styles and health care delivery.

Preliminary; please do not circulate

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I Introduction

Physician decision-making plays a central role in health care delivery. Physicians influence treatment choices, the adoption of new technologies, and the use of high-cost procedures, all of which contribute to regional and provider-level variation in health care expenditures (Cutler et al., 2019; Badinski et al., 2023). While a large literature examines how factors such as financial incentives (Clemens and Gottlieb, 2014), organizational structures (Molitor, 2018; Doyle and Staiger, 2025), and training (Epstein and Nicholson, 2009; Schnell and Currie, 2018) shape physician behavior, most existing work takes the population of practicing physicians as given. This paper investigates a fundamental but understudied question: how do individuals sort into the medical profession, and how does this selection process affect the delivery of care? These questions are particularly important in countries like the United States, where physicians' high earnings raise concerns that financial motivation, rather than patient welfare, may attract some individuals to the profession (Li et al., 2017; Gottlieb et al., 2025).

To examine how selection into medicine influences the delivery of care, this paper exploits macroeconomic conditions at the time of medical school application as an exogenous shock to the applicant pool. By limiting alternative employment opportunities, economic downturns may influence the decision of highly skilled individuals to enter medicine rather than pursue careers in other high-paying, prestigious fields. In line with this, we find that over the past three decades, more people applied to medical school when unemployment in other high-skill occupations was higher. These downturns also changed the composition of entering medical school classes, with more matriculants having majored in non-traditional pre-medical fields. Strikingly, cohort-level differences based on entry conditions persist decades later: physicians who applied to medical school during downturns in competing occupations bill more to Medicare and are more likely to practice in smaller, higher-earning settings. Despite treating healthier patients on average, we find suggestive evidence that their patients, if anything, experience higher mortality. Taken together, these findings indicate that selection into the medical profession has enduring implications for the delivery and effectiveness of health care.

We begin by constructing a business cycle measure that captures economic conditions

relevant to potential physicians. Because few undergraduates deciding whether to apply to medical school are choosing between medicine and low-skill occupations, aggregate unemployment rates may be a poor proxy for the economic conditions they face. We therefore develop a "medical-school-applicant-relevant" business cycle that reflects downturns in occupations plausibly considered by students contemplating medicine. Using data from the Current Population Survey (CPS), the American Community Survey (ACS), and the Association of American Medical Colleges (AAMC) Applicant Matriculant File, we link occupations to undergraduate majors and compute an annual weighted unemployment rate that reflects the labor market conditions facing students in majors common among medical school applicants. Averaged over a four-year window to capture conditions throughout college, this measure provides a more targeted proxy for the outside options facing potential medical school applicants than the overall business cycle.

We then examine the contemporaneous impact of the medical-school-applicant-relevant business cycle on the number and composition of medical school applicants and matriculants. Using data on medical school applications and matriculations from the AAMC's Applicant Matriculant File, we find that a one-percentage-point increase in unemployment in competing fields between 1989 and 2007 was associated with an increase of 0.69 applicants per available spot—a 30 percent rise relative to the mean of 2.3 applicants per spot. Although this increase occurs among both pre-medical and non-pre-medical students, the composition of matriculants shifts during downturns in competing occupations: a one-percentage-point increase in the applicant-relevant unemployment rate raises the share of matriculants with non-pre-medical undergraduate majors by 3.9 percentage points (12.6 percent relative to the mean composition of 31 percent).[1] Similar patterns emerge when exploiting state-level variation, with both the number and composition of applicants responding counter-cyclically to local economic conditions. Together, these results suggest that economic downturns expand the pool of potential physicians by drawing in individuals who might otherwise have pursued alternative professional paths, thereby altering the composition of the future physician

[1] Using survey data from Li et al. (2022) measuring the social preferences of practicing physicians, we show suggestive evidence that those from non-pre-medical backgrounds exhibit lower levels of altruism. Notably, the magnitude of the difference across undergraduate major groups is similar to that observed between male and female physicians.

workforce.

We are ultimately interested in how selection into medicine over the business cycle affects the provision of health care. During economic downturns, two offsetting forces may arise. As more students apply per spot, medical school selectivity increases, potentially improving the average ability of future physicians. At the same time, downturns may attract applicants with different preferences—such as those who are more financially motivated—which could lead to more costly or less patient-oriented care. Consistent with the latter mechanism, data from the AAMC's Matriculating Student Questionnaire show that medical school matriculants are somewhat less likely to express interest in primary care or service in underserved areas when competing occupations contract, although findings are noisy. In contrast, there is little association between average MCAT scores and the medical-school-applicant-relevant business cycle. Taken together, these findings suggest that economic downturns may draw less altruistically motivated individuals into medicine.

Finally, we examine how economic conditions during one's undergraduate studies affect the practice styles of physicians years later. Using data from the public-use Medicare Part B files from 2013 to 2019, we find that, conditional on specialty and outcome-year fixed effects, cohorts facing higher unemployment at the time of medical school application bill nearly twelve dollars more per patient annually. While higher spending could reflect greater patient need, we instead find that Medicare patients of recession-cohort physicians have lower average risk scores and are substantially less likely to be dually eligible for Medicaid. Moreover, data from the Centers for Medicare & Medicaid Services (CMS) Physician Compare database and from IQVIA's SK&A Office-Based Physician Database indicate that recession-cohort physicians are more likely to practice in smaller groups and in settings less likely to offer salaried contracts, allowing these providers to potentially earn more.

This paper builds on four literatures. First, we contribute to the extensive literature examining the determinants of physician behavior. Numerous studies document that providers vary widely in the intensity and type of care they deliver, with important implications for health care costs and patient outcomes (e.g., Currie et al., 2016; Parys, 2016; Currie and Zhang, 2023; Gowrisankaran et al., 2023; Ginja et al., 2024). Building on this evidence, subsequent research has sought to uncover the sources of such variation, examining how dif-

ferences in financial incentives (Clemens and Gottlieb, 2014; Alexander and Schnell, 2024), organizational structures and peer environments (Molitor, 2018; Doyle and Staiger, 2025), training (Epstein and Nicholson, 2009; Schnell and Currie, 2018), skills (Currie and MacLeod, 2017, 2020; Chan et al., 2022), and beliefs (Cutler et al., 2019) shape provider behavior. In contrast to this literature, which treats the composition of the physician workforce as given, we show that part of the variation in clinical behavior arises from who becomes a physician in the first place. By endogenizing entry into medicine, our analysis identifies selection into the profession as an important but often overlooked determinant of heterogeneity in clinical decision-making.

Second, our work builds on the broad literature examining the determinants of occupational choice. A long tradition in labor economics, beginning with Roy (1951) and extended by dynamic frameworks (McCall, 1970; Keane and Wolpin, 1997), studies how individuals select into professions based on expected earnings, non-pecuniary attributes, and preferences (Willis and Rosen, 1979; Heckman and Sedlacek, 1985). Related research on signaling and screening emphasizes how education and training reveal and filter worker ability and motivation (Spence, 1973; Stiglitz, 1975), while more recent work highlights the role of intrinsic and mission-driven motives in shaping who selects into public-service and health-related occupations (Besley and Ghatak, 2005; Delfgaauw and Dur, 2007; Bó et al., 2013). Building on these insights, our paper examines how macroeconomic conditions influence who applies to and matriculates in medical school, shaping the composition of future physicians. In contrast to prior work, which typically examines occupational choice in isolation, we study how this selection process affects subsequent job performance across physician cohorts. Our findings suggest that screening in medicine is imperfect: if medical schools could fully identify applicants with the attributes they seek, cohort performance would not decline during labor market downturns when the pool of applicants to medical school expands.

More specifically, our work contributes to research examining how macroeconomic conditions influence career entry and long-run occupational outcomes. A large body of evidence shows that graduating in a recession leads to persistently lower earnings, slower career advancement, and worse life outcomes (Kahn, 2010; Oreopoulos et al., 2012; Schwandt and

von Wachter, 2019).[2] Recognizing that such downturns can also shape behavior before labor-market entry, subsequent work examines how macroeconomic conditions influence educational and occupational choices (Böhm and Watzinger, 2015; Blom et al., 2021; Weinstein, 2022; Cotofan et al., 2023). These studies emphasize that recessions can have enduring effects not only through early labor-market scarring but also through shifts in human capital investment and career trajectories. Our paper offers a complementary perspective by showing that macroeconomic shocks affect who enters medicine—a recession-resistant profession (Dillender et al., 2021)—with persistent consequences for physician practice styles and health care delivery.

Finally, our work relates to the literature examining how macroeconomic conditions affect health. A large body of research documents that health outcomes fluctuate with the business cycle, with mortality typically declining during recessions and rising during expansions (Ruhm, 2000; Stevens et al., 2015). Subsequent work highlights the heterogeneous effects of macroeconomic shocks across populations and mechanisms, including changes in income, time use, stress, access to care, and pollution (Dehejia and Lleras-Muney, 2004; Miller et al., 2009; Charles and DeCicca, 2008; Finkelstein et al., 2025). Whereas this prior work largely focuses on the contemporaneous health effects of economic fluctuations—or long-run effects on the health of affected individuals themselves (Schwandt and von Wachter, 2020)—we show that macroeconomic conditions can have persistent consequences for population health through their impact on the composition of the physician workforce. By demonstrating that cyclical variation in labor market opportunities influences who enters medicine and, in turn, how care is delivered years later, we link the macroeconomic environment to long-run supply-side determinants of health care quality and costs.

The remainder of the paper is organized as follows. Section II outlines the construction of a business cycle measure that captures macroeconomic fluctuations relevant to high-skilled undergraduates. Section III examines how these fluctuations affect both the number and

[2]While much of this literature focuses on macroeconomic conditions at the time of college graduation, similar patterns emerge in professional labor markets. For example, using data on PhD economists from seven programs, Oyer (2006) shows that those graduating into weaker academic job markets experience worse initial placements, which in turn reduce subsequent research productivity. Similarly, using survey data from the Stanford Graduate School of Business, Oyer (2008) finds that favorable stock market conditions at the time of MBA graduation increase the likelihood of entering investment banking, leading to persistent increases in Wall Street employment and substantially higher lifetime earnings.

characteristics of individuals applying to and matriculating into medical school. In Section IV, we explore how these shifts in cohort composition are associated with cohort-level practice styles, and Section V provides a discussion of potential mechanisms. Section VI concludes.

II Constructing the relevant business cycle

We begin by constructing a business cycle measure that captures economic conditions relevant to potential physicians. Because few undergraduates who might become physicians are also considering careers in fields such as construction, downturns in those sectors are not relevant for our analysis. Accordingly, we construct a "medical-school-applicant-relevant" business cycle to capture the economic conditions faced by individuals on the margin of applying to medical school. As outlined below, this measure is a weighted average of unemployment rates in the occupations that graduates of specific undergraduate majors typically enter, where the weights reflect the proportion of medical school applicants from each major.

We construct this business cycle in four steps using three data sources. First, we use unemployment rate data by occupation from the Current Population Survey (CPS), accessed via IPUMS (Flood et al., 2023). The underlying data are at the individual level but are aggregated to the occupation-year level (or occupation-state-year level for state-level analyses) using survey weights. Occupations are defined using the IPUMS harmonized 2010 occupation codes.[3] These data offer three key advantages: (1) they allow us to examine historical trends dating back to the 1970s, (2) they enable the construction of unemployment rates at the occupation level rather than the broader industry level, and (3) they align with the series used in official U.S. unemployment statistics.

Second, we combine unemployment rate data at the occupation-year level with information on the occupations that graduates of different majors ultimately enter, using data from the American Community Survey (ACS) from 2009–2019. Specifically, we start with a

[3]We construct unemployment rates at the occupation level rather than the industry level, as occupation-based measures better capture the employment prospects of high-skilled professions within an industry. In particular, unemployment rates can vary substantially between high-skilled occupations (e.g., lawyers or physicians) and lower-skilled roles that constitute the majority of employment within an industry (e.g., administrative assistants or home health workers). As in official U.S. unemployment statistics, we restrict the data to individuals aged 16 or older and in the labor force.

list of all undergraduate majors represented among medical school applicants in the AAMC data described below. We then map this list to the ACS and use k-means clustering to group undergraduate majors based on the similarity of the occupations they lead to. This clustering procedure generates seven major clusters: biology/chemistry, engineering, computer science/math/physics, earth sciences, humanities, pre-law/business/economics, and education.[4] As nearly half of all medical school applicants over the last three decades come from the biology/chemistry cluster, we refer to it as the "traditional pre-medical" cluster throughout.

For each major cluster, we construct a corresponding annual unemployment rate as a weighted average of occupation-specific annual unemployment rates from the CPS, where the fixed weights reflect the share of individuals in that major cluster who enter each occupation on average over all years available in the ACS.[5] We use average weights constructed using all available data rather than year-specific weights both because year-specific weights would introduce endogeneity concerns, since the share of a given major cluster entering each occupation is partly driven by contemporaneous labor market conditions, and because the ACS is not available over our entire sample. Nevertheless, as shown in Figure A1(a), the medical-school-applicant-relevant business cycle is very similar when we use weights from a single ACS year applied to the entire period, rather than average weights constructed over 2009–2019.

Third, we combine major cluster–year unemployment rates with information on the share of medical school applicants coming from each major cluster, using data from the AAMC's Applicant Matriculant Data File. This dataset contains detailed information on applicants and matriculants to U.S. medical schools for application cycles from 1989 to 2019, including undergraduate major. To construct the medical-school-applicant-relevant unemployment rate in a given year, we compute a weighted average across all seven major cluster–year unemployment rates, where the fixed weights reflect the share of medical school applicants

[4] See Table A1 for a full list of the majors in each cluster.

[5] In particular, we use occupation weights constructed from all one-year ACS samples with detailed education information that overlap with our study period (2009–2019). As an example of this methodology, suppose that an average of 30 percent of individuals in the engineering major cluster become aerospace engineers and an average of 70 percent become mechanical engineers. Then the unemployment rate for the engineering cluster in a given year would be $0.3 * U_y^{aero} + 0.7 * U_y^{mech}$.

from each major cluster averaged over 1989–2019. As with the occupation weights within each major cluster, we use average weights to aggregate across major clusters because year-specific weights would introduce endogeneity concerns, as contemporaneous labor market conditions affect the distribution of undergraduate majors among medical school applicants in a given year. Nevertheless, as shown in Figure A1(b), the business cycle relevant for medical school applicants is similar when major cluster weights from a single application cycle are applied to the entire period, rather than average weights constructed over 1989–2019.

We aim to capture labor market conditions toward the end of a potential applicant's undergraduate degree, when marginal students are most likely deciding whether to apply to medical school. Two factors complicate the timing of our analysis. First, while specific coursework is not always formally required, applicants typically complete key pre-medical courses during college to prepare for the MCAT and strengthen their applications. This motivates consideration of economic conditions prior to the completion of undergraduate education. Second, many students take one or more gap years after graduating, and we observe only the year in which they apply to medical school. This motivates a consideration of economic conditions after undergraduate completion. To capture both forces, we construct the medical-school-applicant-relevant business cycle as the average unemployment rate relevant to potential medical school applicants in the application year and the three preceding years. We denote this measure by $\bar{U}_y$ for application year y. We further examine the robustness of our results to alternative timing assumptions in Section IV.D.

Figure 1(a) plots the economy-wide unemployment rate, the national unemployment rate for physicians, and the medical-school-applicant-relevant business cycle from 1979 to 2019.[6] Because majors that commonly lead to medical school tend to feed into occupations with relatively low unemployment rates, it is unsurprising that the applicant-relevant business cycle consistently falls below the overall economy-wide measure. While recessions are visible across all series, the relative severity of downturns differs for those considering medicine compared to the broader labor market. Notably, physicians stand out from other high-earning

[6]Because detailed occupation-level information is available in the CPS beginning in 1976, and our baseline measure averages the medical-school-applicant-relevant unemployment rate in the application year and the three preceding years, this measure can be constructed starting in 1979.

occupations, displaying an essentially flat unemployment profile over the business cycle—unlike other high-income or high-prestige occupations, which exhibit much more pronounced cyclicality. Finally, as shown in Figure 1(b), there is substantial cross-state variation in the applicant-relevant business cycle, with certain states experiencing more pronounced effects during specific recessions than others.

III Medical school applicants and matriculants

III.A Data

As outlined above, data on medical school applicants and matriculants come from the AAMC's Applicant Matriculant Data File covering 1989–2019. These data report the number of unique applicants and matriculants to U.S. MD-granting medical schools at the state–year–major level, where state indicates the applicant's legal residence at the time of application, year corresponds to the year of application (i.e., the year before potential matriculation), and major reflects the applicant's detailed undergraduate field of study. In what follows, we limit the sample to applicants residing in the United States and the District of Columbia, as they are expected to be more sensitive to the business cycle fluctuations that we consider.

To examine how both the number and characteristics of future physicians respond to business cycle fluctuations, we consider three key sets of outcomes from the AAMC data. First, to analyze how the number of individuals seeking to pursue a career in medicine changes when there are downturns in competing occupations, we examine the total number of applicants, both nationally and by state. Second, to study the types of individuals who respond to such shocks, we examine the number of applicants—again, both nationally and by state—by undergraduate major grouping and gender. Finally, to assess how business cycle fluctuations affect the composition of future physicians, we consider the characteristics of individuals who matriculate to medical school.

We focus on how the distribution of matriculants across traditional and non-traditional pre-medical majors and by gender varies with economic conditions. This focus reflects the idea that both undergraduate major and gender proxy for underlying applicant "types." While

direct measures of individual preferences are unavailable in standard data sources, major choice provides an informative signal of such preferences, capturing heterogeneity in, for example, enjoyment of coursework and the relative importance individuals attach to expected earnings and non-pecuniary job attributes (Arcidiacono, 2004; Zafar, 2013; Kirkeboen et al., 2016; Wiswell and Zafar, 2015).[7] Similarly, differences in preferences by gender are well documented (Croson and Gneezy, 2009). Whether we see more applicants—and, in turn, matriculants—from particular undergraduate majors and genders over the business cycle may therefore reflect changes in selection into medicine across cohorts.

Consistent with this logic, survey evidence on the social preferences of practicing physicians provides suggestive evidence of differences in preferences by undergraduate major and gender. Specifically, Li et al. (2022) conduct a survey experiment to measure altruism among 284 physicians. In the publicly available data from this experiment, physicians who reported a traditional pre-medical undergraduate major exhibit higher levels of altruism than those from non-traditional majors.[8] Although statistical precision is limited due to the small sample size, the gap in altruism between physicians with traditional versus non-traditional undergraduate majors is sizable (see Figure A2(a)). Notably, the average difference in altruism by undergraduate major is similar in magnitude to the gap between male and female physicians observed in the same data (Figure A2(b)), a gap in social preferences that has been widely documented across many settings (Croson and Gneezy, 2009; Falk and Hermle, 2018; Burbano et al., 2024). Importantly, the similarity of these differences is not driven by a correlation between undergraduate major and gender: differences in social preferences across undergraduate majors exist within both men and women, and differences by gender are also present within traditional and non-traditional majors (Figure A2(c)).

[7] In our setting, applicants that always intended to apply to medical school—and thus chose a traditional pre-medical major—will likely have different average underlying preferences from applicants who did not. For example, students who always wanted to go into medicine may exhibit higher altruism; students who shifted into medicine because of poor labor markets elsewhere may exhibit stronger financial motivation.

[8] When using the data from Li et al. (2022), we define traditional pre-medical majors as biology (including molecular biology, cellular biology, and neurobiology), chemistry, biochemistry, and nursing. The major categories published in these data are more coarse than in our main analysis, and thus we cannot construct groups that perfectly match our main categorization of traditional and non-traditional majors.

III.B National patterns

We begin by examining aggregate patterns in the number of applicants at the national level. Figure 2(a) plots the time series of the total number of applicants per available spot alongside the medical-school-applicant-relevant business cycle from 1989 to 2019. Applications to medical school are strongly countercyclical, with more students applying when outside options weaken due to poor economic conditions. The magnitude of this relationship is sizable: Figure 2(b) plots the number of applicants per spot against the medical-school-applicant-relevant unemployment rate and shows that a one-percentage-point increase in $\bar{U}_y$ is associated with 0.12 additional applicants per spot—an increase of 5.2 percent relative to the average of 2.3 applicants per spot over the period (see Table A2). These patterns are consistent with findings from the education literature showing that educational attainment tends to rise when young adults face adverse labor market conditions.[9]

Figure 2(b) also presents the relationship between applicants per spot and the medical-school-applicant-relevant unemployment rate for the period 1989–2007. We examine this earlier period separately for two reasons. First, when analyzing eventual practice styles in the next section, we restrict attention to physicians who have completed training. Given the timing of our outcome data, this restriction requires limiting the sample to those who applied between 1989 and 2007. Second, the timing of the relationship appears somewhat different around the Great Recession. Notably, the magnitude of the relationship is larger in these earlier years, with a one-percentage-point increase in $\bar{U}_y$ associated with 0.69 additional applicants per spot, an increase of 30 percent relative to the average (Table A2).

Scatterplots of the number of applicants per spot by undergraduate major grouping and gender against the corresponding group-specific unemployment rate are shown in Figure A3. The patterns mirror those observed in the aggregate data: applications to medical school rise when outside options weaken, with countercyclical responses evident across both major groups and genders. For undergraduate major, both traditional and non-traditional pre-medical majors respond counter-cyclically, although the percent increase is larger for

[9]For example, Barr and Turner (2015) and Betts and McFarland (1995) show that college enrollment is countercyclical, while Cascio and Narayan (2022) find that local booms in low-skill jobs decreased high school graduation rates. Although there is less work on graduate school enrollment specifically, the existing literature suggests that enrollment is generally countercyclical (Bedard and Herman, 2008; Johnson, 2013).

non-traditional majors. For gender, men respond more strongly than women. From 1989 to 2007, a one-percentage-point increase in $\bar{U}_y$ was associated with 0.47 additional male applicants per spot (a 36.2 percent increase relative to the mean of 1.3) and 0.22 additional female applicants per spot (a 22 percent increase relative to the mean of 1.0).

While the previous figures show that the composition of applicants varies over the business cycle, whether these fluctuations translate into changes in the composition of physician cohorts depends on whether the composition of matriculants also changes during downturns in competing fields. If medical schools admit the same types of students regardless of the applicant pool, then we would not expect the business cycle to affect the delivery of care years later. In contrast, Figure 3(a) shows that the share of matriculants entering medical school from non-traditional pre-medical majors varies systematically with the business cycle. Over the period 1989–2019, a one-percentage-point increase in $\bar{U}_y$ is associated with a 1.25-percentage-point increase in the share of the cohort coming from non-traditional majors, a 4 percent increase relative to the mean of 31.2 percent (Table A2(d)).[10] By contrast, the gender composition of matriculants does not vary with the business cycle. Although the increase in applicants is more pronounced among men (Figure A3), these fluctuations do not systematically translate into differences in the gender makeup of matriculating classes (see Figure 3(b) and Table A2(d)).

III.C State-level analysis

In addition to examining the association between $\bar{U}_y$, applicant behavior, and cohort composition at the national level, we can also exploit state-level variation in economic conditions. Using deviations from the national business cycle at the state level for identification allows us to include flexible time controls and leverage additional, distinct sources of variation. Specifically, this approach tests whether students in states where alternative occupations experienced more severe downturns respond more strongly than students applying in the same year but from states where these occupations were less affected.

[10] As before, this pattern is more pronounced prior to the Great Recession. From 1989 to 2007, a one-percentage-point increase in $\bar{U}_y$ was associated with a 3.88 percentage point increase in the share of the cohort coming from non-traditional majors, corresponding to a 12.6 percent increase relative to the mean.

To do so, we estimate regressions of the following form using data at the state-year level:

$$Outcome_{sy} = \beta \cdot \bar{U}_{sy} + \lambda_s + \lambda_y + \epsilon_{sy} \tag{1}$$

where $Outcome_{sy}$ denotes the number of applicants or matriculants—overall and by type—per 100,000 state residents from state s in year y; $\bar{U}_{sy}$ is the medical-school-relevant unemployment rate constructed at the state level; and λ_s and λ_y are state and year fixed effects, respectively.[11] Observations are weighted by state population, and standard errors are clustered at the state level.

Results from estimation of equation (1) are shown in Table 1. Consistent with the national results, column (2) of Panel (a) shows that applications to medical school are strongly countercyclical: a one-percentage-point increase in the relevant state-level unemployment rate is associated with 0.40 additional applicants per 100,000 residents, a 3 percent increase relative to the mean. The number of matriculants from a given state rises more modestly and is not statistically significant when both state and year fixed effects are included (column (4) of Panel (a)). This pattern is intuitive: while applicant behavior is likely to respond to local economic shocks, admissions decisions are made in what is effectively a national market. As a result, matriculant patterns should depend more heavily on national economic conditions.[12]

The remainder of Table 1 focuses on responses in the number of applicants by undergraduate major grouping (Panel (b)) and gender (Panel (c)). As in the national data, both traditional and non-traditional majors respond counter-cyclically, with somewhat larger proportional increases among non-traditional majors. Similarly, while applications by both men and women increase during downturns, the response is again stronger among men.

[11] As shown in Figure 1(b), there is considerable variation in $\bar{U}_{sy}$ across states and over time.

[12] For this reason, we do not analyze impacts on the composition of matriculants using state-level data.

IV Physician practice style and organization

IV.A Data

To examine how selection into medicine across the business cycle affects physician practice styles, we use four data sources. First, we draw on the public-use Medicare Part B files at the physician-year level from 2013 to 2019. We construct three outcomes from these data. The first is the average annual Medicare spending per beneficiary, which serves as a proxy for treatment intensity. We calculate this measure by dividing the total standardized Medicare payment reported for each physician-year by the number of unique beneficiaries treated.[13] The second outcome is the average risk score of patients treated by each physician, which provides a summary measure of patient health based on CMS's Hierarchical Condition Category model. Higher risk scores correspond to sicker patient populations and greater expected spending. Finally, because beneficiaries who are dually eligible for Medicaid tend to be sicker, and because physicians are reimbursed at lower rates for treating such patients in most states, we also examine the share of each physician's Medicare patients who are dually eligible for Medicaid.

We also use data on practice organizations from two sources. First, we use information on the size of each physician's practice from CMS's Physician Compare database. We construct this measure for the period 2014 to 2019 as the average annual number of clinicians reported in each organization with which the physician is affiliated.[14] Recent work using administrative tax data documents a strong negative relationship between physician income and firm size (Gottlieb et al., 2025), suggesting that physicians with stronger financial motivation may prefer to practice in smaller organizations.[15]

[13] Standardized payments exclude geographic adjustments and special program payments unrelated to resource use, allowing for comparisons across providers that reflect only differences in care decisions and intensity. We first winsorize the number of beneficiaries at the 99th percentile to limit the influence of likely data errors—or incident-to billing where care is delivered by a different provider—associated with exceptionally large patient panels.

[14] We use December snapshots of the Physician Compare files for all years except 2015, for which only a November snapshot is available. Practice size is based on the number of clinicians affiliated with each Group Practice PAC ID, a unique identifier assigned in CMS's Provider Enrollment, Chain, and Ownership System (PECOS). Medicare defines group membership using the Medicare Data on Provider Practice and Specialty (MD-PPAS) file, which links providers to practices based on their National Provider Identifier (NPI) and Tax Identification Number (TIN).

[15] Gottlieb et al. (2025) show that average annual earnings for physicians peak at approximately $470,000

We supplement this information with data on practice environments from IQVIA's SK&A Office-Based Physician Database from 2008 to 2016. The SK&A data provide information on practice ownership and health system affiliation for office-based physicians in the United States, allowing us to distinguish among physician practices that are independent and unaffiliated, independent and hospital-affiliated, and hospital- or system-owned.[16] Compensation models differ systematically across these ownership types: physicians in hospital- and system-owned practices are more likely to be salaried, whereas those in independent practices—most of which are affiliated with hospitals—are typically paid on a fee-for-service basis (AMA, 2025). As a result, more financially motivated providers may systematically sort away from hospital- or system-owned practices and into independent ones.

Finally, to examine impacts on patient outcomes, we use a 20 percent sample of patient-level Medicare claims from 2001 to 2016. We use these data to construct both predicted and actual one- and three-year mortality for the patients seen by each physician in each year. Following Chan et al. (2023), we predict individual-level mortality at the visit level based on patient demographics and Elixhauser comorbidities, capturing expected mortality given observable health status at the time of treatment.[17] We then aggregate these visit-level statistics to the physician-year level by taking an average across visits with each physician in each year.

We make a series of restrictions to move from the raw data to our final analysis sample. First, we limit the sample to physicians who trained in the United States, as they are most likely to have been exposed to the U.S. business cycle when making the decision to attend medical school. Second, we restrict the sample to individuals who applied to medical school during the period covered by our application data (1989–2019), allowing us to link cohort-

in firms with eight to ten clinicians before declining as firm size increases. This pattern likely reflects the additional business income earned through ownership in smaller group practices.

[16]We define four mutually exclusive practice categories: independent and hospital-affiliated, independent and unaffiliated, hospital- or health system-owned, and other. Approximately 20 percent of providers report more than one practice location in a given year.

[17]Specifically, we generate Elixhauser comorbidities using ICD diagnosis codes from the carrier, outpatient, and inpatient claims files. We merge these data with the Master Beneficiary Summary File to incorporate age, sex, and race. For each beneficiary-visit and Elixhauser condition, we construct indicators for whether the condition ever appeared and whether it occurred within the past year. We then regress actual one- and three-year mortality on these indicators, ten age-bin dummies, sex, and race. Predicted mortality at the visit-level is the prediction from this model.

level variation in practice outcomes to cohort-level variation in applicant and matriculant characteristics. Finally, to account for strong life-cycle effects in physician behavior, we further restrict the sample to physician-year observations where at least seven years have elapsed since medical school graduation. This restriction ensures that we are capturing long-run practice patterns rather than transitory behaviors associated with early-career training or transitions. Given the time coverage of our outcome data, this final restriction limits our analysis to physicians who applied to medical school between 1989 and 2007 when using the public-use Medicare data, between 1989 and 2004 when using the SK&A data, and between 1989 and 2004 (2003) when examining one-year (three-year) mortality in the restricted-use Medicare data.

IV.B Empirical specification

Our goal is to analyze how variation in physician-level practice outcomes relates to the business cycle at the time of medical school application. To do so, we regress measures of physician-year practice outcomes on the medical-school-applicant-relevant unemployment rate at the time of application while controlling for physician experience, specialty, and outcome year. Specifically, we estimate specifications of the following form:

$$Outcome_{it} = \beta \cdot \bar{U}_{y(i)} + \lambda_{specialty} + \lambda_{experience} + \lambda_t + \epsilon_{it} \tag{2}$$

where $Outcome_{it}$ is an outcome measure for physician i in year t; $\bar{U}_{y(i)}$ is the medical-school-applicant-relevent unemployment rate for application year y; $\lambda_{specialty}$ and $\lambda_{experience}$ denote fixed effects for the specialty and number of years since medical school graduation for physician i, respectively; and λ_t denote outcome year fixed effects.[18] P-values and confidence intervals are calculated using a wild cluster bootstrap clustered by application cohort (Cameron et al., 2008).

Estimation of equation (2) delivers a single estimate summarizing the relationship between the economic conditions in competing occupations at the time of medical school ap-

[18]Since medical school is four years, and applicants apply the year before matriculation, we subtract five from the year of medical school graduation available in different data sources to assign application year y to practicing physicians.

plication and practice outcomes for physicians later in their careers. To examine how the effect size varies across the distribution of observed economic conditions, we further estimate versions that replace the continuous medical-school-applicant-relevant unemployment rate with indicators for quartiles of this measure. Letting $\bar{Q}_q$ denote the range of values of unemployment rates in quartile q, we estimate the following regression:

$$Outcome_{it} = \sum_{q=1}^{4} \beta_q \cdot \mathbb{1}\left\{\bar{U}_{y(i)} \in Q_q\right\} + \lambda_{specialty} + \lambda_{experience} + \lambda_t + \epsilon_{it} \tag{3}$$

where is an indicator denoting whether the medical-school-applicant-relevent unemployment rate for application year y was in quartile q over 1989 through 2007, and all other variables are defined as in equation (2). Figure A4(a) illustrates the binning procedure, showing how application years are grouped into quartiles based on the medical-school-applicant-relevant unemployment rate.

IV.C Results

Table 2 reports results from estimation of equation (2) using measures of spending and patient composition from the public-use Medicare files (panel a) and measures of physician practice organization and affiliation from the SK&A data (panel b) as the outcome. Focusing first on results using the Medicare data, column (1) in the top panel shows that physicians who applied to medical school during downturns in competing occupations bill more to Medicare per beneficiary years later. Notably, a one-percentage-point increase in $\bar{U}_{y(i)}$ leads to \$14.7 increase in average annual Medicare spending per beneficiary (p-value < 0.001), corresponding to a 4.9 percent increase relative to the mean of \$296.7. As shown in Figure 4(a) which plots the coefficients on quartiles of $\bar{U}_{y(i)}$ from estimation of equation (3) this effect is not driven by any single quartile of the unemployment rate in competing occupations; rather, average spending per beneficiary increases steadily as employment in alternative occupations declines.

We provide a back-of-the-envelope calculation to benchmark the size of this spending effect. Over 1989–2007, a one percentage point increase in applicant-relevant unemployment increases the share of matriculants from non-traditional majors by 4.5 percentage points

(Figure 3(a)) and raises average Medicare spending per beneficiary by $14.7 (Table 2(a)). Under the strong assumptions that (1) the change in matriculants from non-pre-medical majors fully captures the share of marginal entrants and (2) only marginal entrants change their behavior, the implied spending increase among marginal entrants is $14.7 / 0.045 ≈ $326.7 per beneficiary, or roughly 110% of the mean ($296.7). While a useful mechanical benchmark, this calculation likely overstates behavioral changes among these marginal entrants. First, some individuals may switch majors in response to labor market conditions (e.g., from economics to pre-med), in which case a portion of truly marginal entrants would be classified as inframarginal in this calculation. Second, if inframarginal physicians also respond—for example, through peer effects (see Section V)—then part of the observed average increase in spending will reflect changes among inframarginal physicians, mechanically implying a smaller effect among marginal entrants.

Higher spending per beneficiary could reflect either greater patient need or higher intensity of physician practice styles. While equation (2) includes controls for outcome year, physician experience, and physician specialty—which account for secular trends in patient need and average differences in patient severity across experience and specialty profiles—we directly examine whether the composition of patients treated by a physician varies with labor market conditions at the time the physician applied to medical school. As shown in Table 2 and Figure 4, if anything, physicians who applied to medical school when outside options were more limited treat healthier patients. Specifically, column (2) of Table 2(a) shows that a one-percentage-point increase in $\bar{U}_{y(i)}$ leads to a 0.0096 reduction in the average risk score of Medicare beneficiaries seen by the average physician (p-value = 0.036), corresponding to a 0.6 percent decline relative to the mean of 1.73. Similarly, column (3) shows that a one-percentage-point increase in $\bar{U}_{y(i)}$ leads to a 0.39 percentage-point reduction (p-value $<$ 0.001) in the share of Medicare beneficiaries who are dually eligible for Medicaid—a population that is typically sicker and more medically complex than Medicare-only beneficiaries (MedPAC, 2023)—which corresponds to a 1.6 percent decline relative to the mean of 24.4 percent.[19] Together, these patterns suggest that higher spending per beneficiary among co-

[19]The negative relationship between $\bar{U}_{y(i)}$ and the share of dually eligible Medicare beneficiaries is also consistent with greater financial motivation among individuals entering medicine during economic downturns, given that physicians face lower reimbursement rates and higher administrative burdens when treating dually

horts with lower outside options reflects greater practice and/or billing intensity rather than greater patient need.

The business cycle at the time of application to medical school also affects the practice environments in which physicians ultimately work. As shown in column (4) of Table 2(a) and Figure 4(d), physicians who applied to medical school during downturns practice in smaller organizations: a one-percentage-point increase in $\bar{U}_{y(i)}$ leads to a reduction of 14.4 other providers at the average physician's practice (p-value < 0.001), a nearly 3 percent decline relative to the mean. As physician compensation is generally decreasing in firm size (Gottlieb et al., 2025), this pattern is consistent with greater financial motivation among individuals entering medicine during periods when outside options are weaker.

Results from the SK&A data shed additional light on how physicians sort across organizational forms as a function of labor market conditions at entry. Focussing on the two dominant organizational forms, Table 2(b) and Figure 5 shows that cohorts who applied to medical school when outside options were limited are significantly more likely to work in hospital-affiliated independent practices and significantly less likely to work in hospital- or health-system-owned facilities.[20] These practice environments differ meaningfully in their compensation structures: physicians in independent practices typically face stronger links between effort, billing intensity, and earnings, whereas compensation in hospital- or system-owned settings is more likely to be salaried or subject to revenue smoothing. These findings therefore suggest that physicians who enter medicine when alternative labor market opportunities are weak are more likely to sort into practice environments with higher-powered financial incentives.

Our baseline specification includes experience, outcome year, and specialty fixed effects. Although residency slots—which largely determine cohort specialty composition—do not

eligible patients (Li, 2023).

[20]We do not observe differential sorting into independent, non-affiliated practices. This likely reflects the limited prevalence of such practices during our sample period: independent, non-affiliated practices account for only 6.6 percent of physician-year observations, compared with 49.8 percent for independent but hospital-affiliated practices (see Table 2(b)). The rarity of fully independent practices reflects the substantial fixed costs and administrative burdens of remaining unaffiliated in the modern health care environment, making hospital affiliation the dominant organizational form even among nominally independent practices. We also observe an increase in physicians practicing in "other" arrangements as outside options at medical school application decline, although this category is also relatively rare, accounting for only 8.1 percent of physician-year observations.

vary with entry conditions, and thus differences in specialty mix across entry cohorts are limited, controlling for specialty may nonetheless constitute a "bad control" (Angrist and Pischke, 2009). Reassuringly, Figures A5 and A6 show that results in the public-use Medicare data and the SK&A data, respectively, are very similar when specialty fixed effects are excluded. Moreover, these figures demonstrate that the results remain highly stable when additionally controlling for physician sex and practice ZIP code fixed effects. Together, these patterns indicate that the impacts of entry conditions on physician practice styles and organization are not driven by changes in specialty, gender, or location choices across cohorts, but rather reflect differences in behavior within specialty and market.

By sex We next examine heterogeneity in these patterns by physician gender. As shown in Section III.B, labor market conditions at the time of application do not affect the gender composition of medical school matriculants: across cohorts, the share of women among matriculating physicians is stable with respect to business cycle conditions in competing occupations (see Figure 3(b) Table A2(d)). At the same time, application behavior differs by gender, with the number of male applicants per available medical school seat increasing somewhat more than the number of female applicants per seat during economic downturns (Table 1(c), Table A2(c), and Figure A3(b)). As a result, even though the observed gender composition of matriculants remains unchanged, the pool of men who ultimately matriculate may be more differentially selected during downturns than the corresponding pool of women.

Consistent with this pattern, we observe heterogeneity by gender in subsequent practice outcomes. As shown in Table 3(a) and Figure A7(a), estimated effects of $\bar{U}_{y(i)}$ on Medicare spending per beneficiary are over twice as large for male physicians as for female physicians, although the difference is not statistically significant (p-value = 0.260). Gender differences are particularly pronounced in practice organization: as shown in Table 3(b), the increase in employment in hospital-affiliated independent practices and the corresponding decline in hospital- or health-system-owned employment associated with higher $\bar{U}_{y(i)}$ are almost entirely concentrated among male physicians, with the difference in responsiveness between male and female physicians being highly significant ($p < 0.001$ for both outcomes). These gender differences are confirmed in Figure A8, which shows that the monotonic increase

(decrease) in the share practicing in hospital-affiliated (hospital- or system-owned) practices as outside options at medical school application decline are substantially more pronounced among male physicians than female physicians.

IV.D Robustness

The impacts of entry conditions on practice styles, patient composition, and practice organization are not sensitive to a wide range of empirical choices.

Table A3 summarizes results using alternative specifications and samples for outcomes in the public-use Medicare data. Column (1) reports our baseline results for reference. Column (2) additionally controls for average patient risk scores; because cohorts who entered medicine during economic downturns tend to see slightly healthier patients, the gradient in spending per beneficiary is modestly larger when controlling for patient risk. Column (3) weights observations by the total number of beneficiaries at the provider-year level to reduce noise from providers with relatively few Medicare patients; although estimates are somewhat attenuated, qualitative patterns remain unchanged. Finally, columns (4)–(7) vary the sample. Column (4) requires at least 10 years since medical school graduation, rather than seven in our baseline specification, to further ensure completion of residency and fellowship training and focus on more established practice patterns. Column (5) extends the outcome period to include the COVID-19 years (2020–2023), rather than ending the sample in 2019. Column (6) includes application cohorts who applied before the start of the AAMC data in 1989.[21] Results are robust across these alternative samples.

Tables A4 and A5 report results using alternative measures of economic conditions as the independent variable of interest for outcomes in the public-use Medicare data and SK&A data, respectively. Column (1) again reports our baseline results from estimation of equation (2) for reference, which use the medical-school-applicant-relevant business cycle averaged over the year of application to medical school and the three preceding years (years 0–3). As shown in column (2), using the overall business cycle—also averaged over the year of application

[21] We exclude physicians with more than 30 years of experience since medical school graduation to avoid changes in practice patterns associated with retirement decisions. This restriction allows us to include physicians who applied to medical school from 1978 onward in this exercise.

and the three preceding years—yields smaller estimates for both sets of outcome measures, consistent with the idea that some fluctuations in the overall economy are not relevant for individuals on the margin of applying to medical school. Because increased unemployment among physicians should have opposite theoretical implications from increased unemployment in other high-skilled occupations, column (3) constructs the applicant-relevant business cycle holding physician employment fixed. Results using this alternative measure are very similar to the baseline, and in some cases more pronounced. Finally, columns (4)–(6) use the baseline medical-school-applicant-relevant unemployment rate but vary the averaging window. Estimates are substantially attenuated for both sets of outcomes when only employment conditions in the year of application are considered (column (4)), consistent with the idea that students require time to adjust their coursework in order to pivot toward medicine. In contrast, results are very similar when averaging over the year of application and the two preceding years (column (5)) or the four preceding years (column (6)).

Finally, because different application cohorts mechanically contribute observations at different experience levels in different outcome years, our baseline sample has an unbalanced cohort–year–experience structure. As a result, cohort-driven differences may be partially absorbed by the year or experience fixed effects, and cohorts that disproportionately populate certain cells may exert greater influence on the estimated effects. Tables A6 and A7 report results using alternative estimation samples in the public-use Medicare data and SK&A data, respectively, to address these concerns. Column (2) restricts the sample to ensure adequate support across cohorts, experience levels, and outcome years, requiring that each cohort, outcome year, and experience level be observed with at least four values along the other two dimensions (see Figures A9(b) and A10(b)). Columns (3) and (4) impose balance restrictions: column (3) requires balance across outcome years and application cohorts (Figures A9(c) and A10(c)), ensuring that differential cohort representation across outcome years does not influence the year fixed effects, while column (4) requires balance across outcome years and experience profiles (Figures A9(d) and A10(d)), ensuring that the results are not driven by shifts in experience composition over time. Column (5) drops the cohorts with the highest and lowest values of $\bar{U}_y$, so that the effects are not disproportionately influenced by a small number of cohorts at the extremes of the labor market distribution. Lastly, column (6)

weights observations by the inverse share of physician-year observations in each experience–outcome year cell so that heavily represented cells do not receive greater implicit weight in estimation. Reassuringly, the results for both sets of outcomes are robust across all of these alternative restrictions and weighting schemes.

V Potential mechanisms

When the medical-school-applicant-relevant unemployment rate is higher, at least two things change that could affect the performance of the resulting physician cohort. First, as shown in Figure 2, more individuals apply for a largely fixed number of medical school slots, reducing acceptance rates and increasing selectivity. If medical schools can effectively screen on clinical aptitude, heightened selectivity during downturns in competing occupations could raise the average skill of matriculating students, thereby leading to improved cohort performance. Second, as shown in Figure 3, the composition of matriculating classes shifts, with a higher share of students from non-traditional pre-medical backgrounds enrolling when outside labor market options weaken. This channel could instead affect future performance by changing the distribution of physician preferences: individuals entering medicine during downturns may place different weight on financial returns or other career attributes, leading to systematic differences in practice styles even conditional on skill.

Importantly, both of these channels could affect not only the marginal physicians themselves, but also their "always-taker" peers through peer effects. Even if an individual would have attended medical school regardless of outside labor market conditions, the characteristics of their classmates may change when unemployment is high. As outlined above, increased selectivity may alter the distribution of skills within a cohort, while compositional shifts may change the distribution of career ambitions, financial motivations, or risk-taking behavior. These cohort-level changes could influence training environments, peer learning, professional networks, and ultimately practice norms. As a result, the effects of labor market conditions at entry may propagate beyond marginal entrants and shape the behavior of inframarginal physicians as well.

The empirical findings shown in Section IV.C are more consistent with changes in physi-

cian preferences—potentially amplified through peer effects—than with changes in clinical skill. Cohorts entering medicine when outside options are weak bill more per beneficiary despite treating healthier patients, and they sort into smaller, more lucrative practice settings (Table 2). However, their patients do not experience better outcomes. If heightened selectivity were primarily raising clinical skill, one might expect improvements in patient outcomes or a greater willingness to manage more complex patients. Instead, the patterns suggest that physicians entering during downturns exhibit stronger financial motivation, sorting into practice environments where financial incentives are greater and practicing medicine in ways that generate higher revenue without measurable improvements in patient outcomes.

To assess the extent to which these channels account for the reduced-form relationship between unemployment at the time of medical school application and physician outcomes, we implement a regression-based mediation analysis similar in the spirit of Heckman et al. (2013).[22] The objective is to quantify how much of the total reduced-form effect of applicant-relevant unemployment on physician practice outcomes is statistically accounted for by observed changes in admissions selectivity and cohort composition. We emphasize that this exercise provides a regression-based decomposition of the reduced-form relationship rather than a fully causal mediation analysis. A causal interpretation of the indirect components would require strong assumptions about the absence of unobserved cohort-level confounders affecting both the mediators and physician outcomes.[23] Our goal is therefore more modest: to quantify the extent to which observable changes in selectivity and cohort composition statistically account for the reduced-form relationship between unemployment at application and downstream practice outcomes. We consider two cohort-level mediators: the medical school acceptance rate, M_y^{acc}, capturing changes in selectivity (and thus potential differences in skill), and the share of matriculants from non-traditional pre-medical backgrounds, M_y^{nontrad}, capturing one dimension of compositional shifts potentially related

[22]Similar regression-based decompositions have long been used in sociology and related fields and, more recently, in empirical economics. For example, they have been used to quantify how distinct channels contribute to intergenerational wealth persistence (Fagereng et al., 2021) and to changes in victimization following criminal justice reforms (Gonçalves et al., forthcoming).

[23]These assumptions would be violated if, for example, contemporaneous changes in admissions policies, class sizes, or federal financing of medical education independently influenced cohort selectivity and composition, as well as downstream physician outcomes, even conditional on applicant-relevant unemployment rates.

to preferences.

Recall our primary estimating equation, displayed as equation (2) in Section IV:

$$Outcome_{it} = \beta \cdot \bar{U}_{y(i)} + \lambda_{specialty} + \lambda_{experience} + \lambda_t + \epsilon_{it}$$

where i indexes physicians, $y(i)$ indexes application cohorts, and t indexes outcome years. The coefficient β captures the reduced-form effect of the applicant-relevant unemployment rate on downstream physician outcomes.

To implement the mediation analysis, we begin by estimating first-stage regressions of each mediator on the applicant-relevant unemployment rate:

$$M_y^k = \delta_k \cdot \bar{U}_y + \eta_{ky}, \quad k \in \{acc, nontrad\} \tag{4}$$

Because both $\bar{U}_y$ and the mediators vary only at the cohort level, we estimate these first-stage equations at the cohort level. To maintain consistency with the physician–year outcome specification above, each cohort is weighted by the number of physician–year observations it contributes to the estimation sample, aligning the first-stage estimates with the implicit weighting of cohorts in the reduced-form regression.

Next, we estimate the outcome equation including both mediators:

$$\begin{aligned} Outcome_{it} =& \gamma \cdot \bar{U}_{y(i)} + \theta_{acc} \cdot M_{y(i)}^{acc} + \theta_{nontrad} \cdot M_{y(i)}^{nontrad} \\ &+ \lambda_{specialty} + \lambda_{experience} + \lambda_t + \varepsilon_{it} \end{aligned} \tag{5}$$

The contribution of mediator k to the total reduced-form effect is given by the product $\delta_k \theta_k$. The sum $\delta_{\text{acc}}\theta_{\text{acc}} + \delta_{\text{nontrad}}\theta_{\text{nontrad}}$ represents the portion of the overall unemployment effect that is statistically accounted for by observed changes in selectivity and cohort composition. The remaining portion (i.e., the "residual" component) is given by γ, the coefficient on unemployment in the outcome equation that conditions on both mediators. Intuitively, this captures the portion of the reduced-form effect that is not statistically mediated by observed changes in selectivity or our measured proxy of cohort composition.[24]

[24]By construction, the total reduced-form effect equals $\beta = \delta_{acc}\theta_{acc} + \delta_{nontrad}\theta_{nontrad} + \gamma$.

Inference in the main specification uses a wild cluster bootstrap at the cohort level. In the mediation setting, the objects of interest include nonlinear combinations of estimated coefficients, such as products of first-stage and second-stage estimates. We therefore implement a cohort-level cluster bootstrap procedure: in each replication, we resample application cohorts with replacement, re-estimate the reduced form (equation (2)), the weighted cohort-level first stages (equation (4)), and the mediation regression (equation (5)), and recompute each component. We report percentile confidence intervals from the bootstrap distribution.

Figures A12 and A13 report results from the mediation analysis for outcomes in the public-use Medicare data and SK&A data, respectively. The decomposition reveals that the relative importance of the two mediators—the acceptance rate and the share of matriculants from non-traditional pre-medical majors—differs across outcomes. For measures most directly tied to physician income, such as Medicare spending per beneficiary and choice of practice affiliation and ownership, the compositional channel plays an important role, with changes in the share of matriculants from non-traditional pre-medical backgrounds accounting for a meaningful share of the reduced-form effect of unemployment on these income-related margins.

Admissions selectivity, in contrast, plays a more prominent role in explaining differences in patient composition, with cohorts entering during periods of higher selectivity treating patients with lower average risk scores. This pattern is somewhat surprising, as one might instead expect more selective cohorts to manage more complex patients. Rather, these results indicate that an increase in applicants for a fixed number of spots does not necessarily translate into behavior consistent with higher clinical aptitude, suggesting that the screening process for medical school admissions may be imperfect at identifying such potential clinicians.

Taken together, the results indicate that outside labor market conditions shape physician behavior through multiple channels. From a policy perspective, these findings suggest that different levers for influencing the physician workforce may operate through distinct mechanisms. Policies that alter the number of medical school spots, and thus admissions selectivity, may change sorting patterns across patient populations. In contrast, policies that affect the relative attractiveness of medicine compared to other occupations—such as

changes in physician reimbursement or the cost of medical education—may influence who chooses to apply and matriculate, shifting the distribution of preferences within cohorts and, in turn, influencing downstream practice patterns and spending.

VI Conclusion

Little is currently known about the process of selection into medicine, and how physician type influences practice style. In this paper, we first show that poor economic conditions prior to application to medical school changes the composition of physicians in a cohort. We find that a one-percentage-point increase in the medical-school-relevant unemployment rate leads to a four percent increase in the share of medical students coming from non-traditional backgrounds in the matriculating class. This estimate is likely an underestimate of the true effect of economic conditions on the composition of medical school class sizes, as some students will likely change their undergraduate major in response to poor economic conditions—and thus look like traditional medical students in our data (Blom et al., 2021).

We next show that this shift in the composition of incoming medical students away from those from traditional backgrounds leads to differences in practice style decades later, in ways that are suggestive of these physicians being more profit-motivated. Being exposed to a higher medical-school-relevant unemployment rate prior to applying is associated with physicians practicing medicine more intensively, as proxied by Medicare spending per beneficiary, and working in smaller practices. While both the composition of medical school classes and competition for medical school slots increase during downturns, our results suggest changes in share of incoming medical students coming from non-traditional backgrounds is the most important factor.

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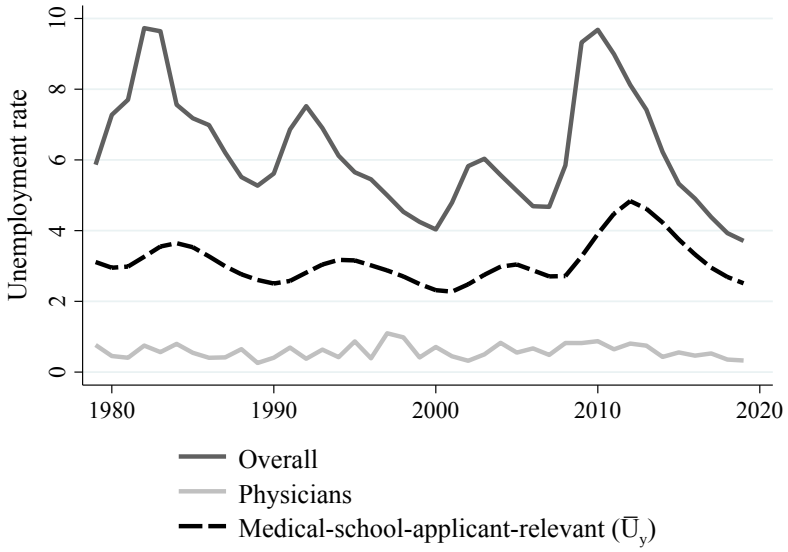
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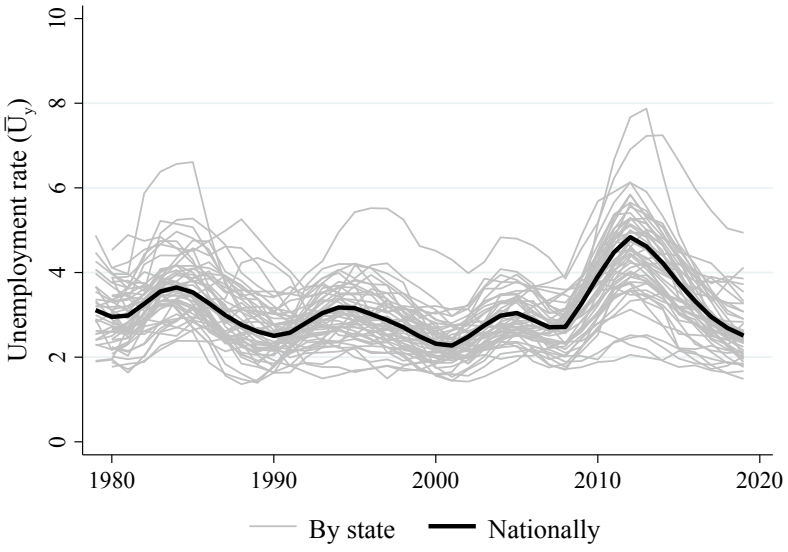
VII Figures

Figure 1: Unemployment rates overall and by state over time

(a) Overall and by occupation nationally



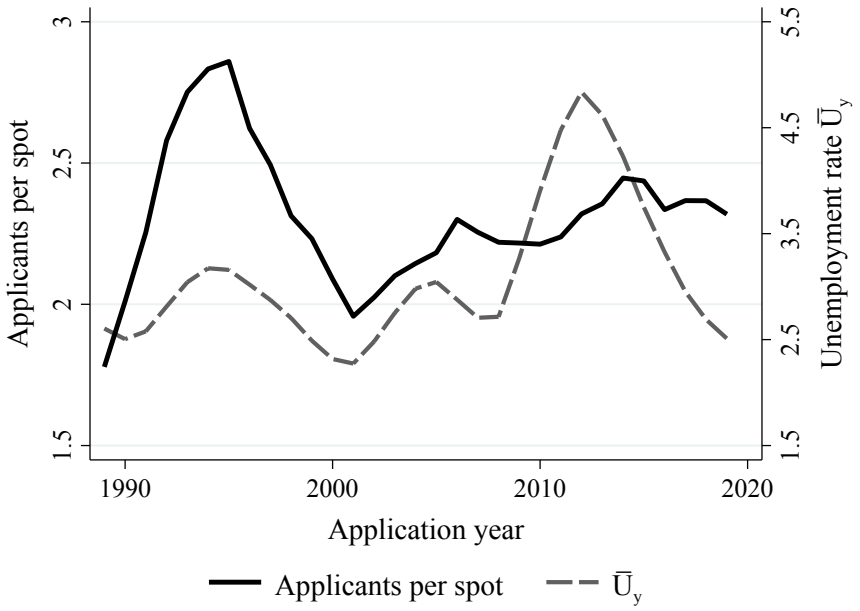
(b) Medical-school-relevant unemployment by state



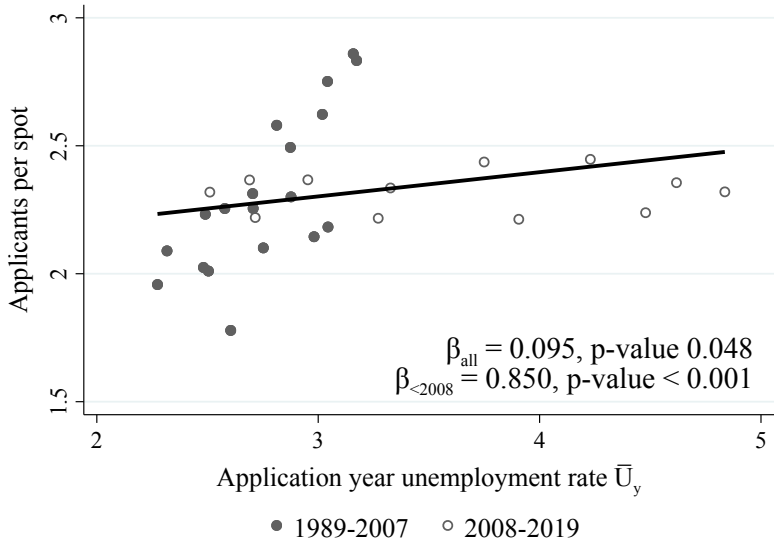
Notes: The above figures plot unemployment rates nationally (subfigure (a)) and by state (subfigure (b)). Subfigure (a) shows the economy-wide unemployment rate, the national unemployment rate for physicians, and the medical-school-applicant-relevant business cycle ($\bar{U}_t$) from 1980 to 2019; see Section II for details on the construction of $\bar{U}_y$. Subfigure (b) plots $\bar{U}_t$ at both the national and state levels from 1989 to 2019. All unemployment rates are constructed using data from the CPS.

Figure 2: Entry conditions and medical school applicants per spot

(a) Applicants per spot and unemployment over time



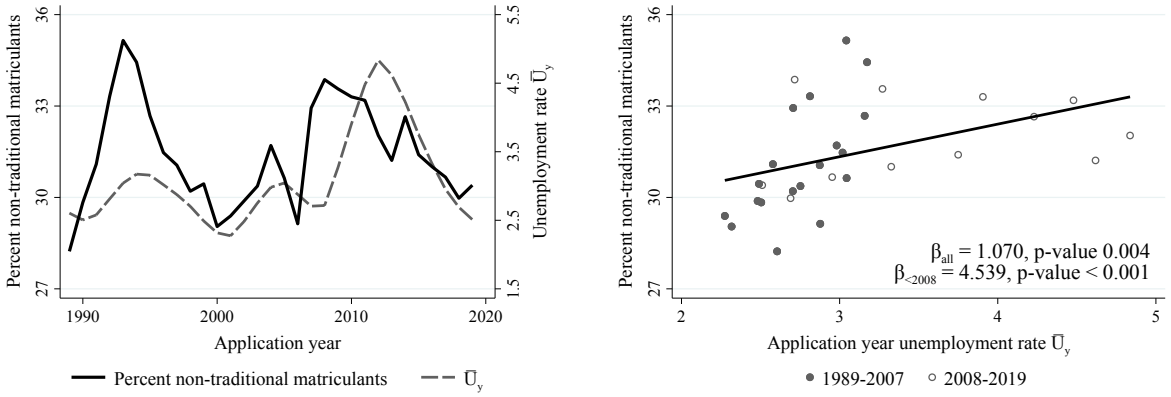
(b) Applicants per spot versus relevant unemployment



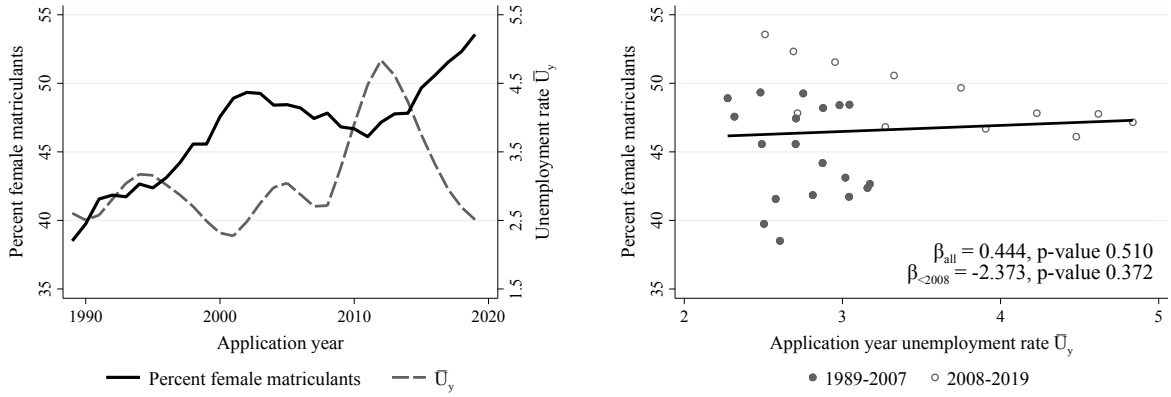
Notes: The above figures show how the annual number of applicants to medical school, divided by the number of matriculants ("spots"), covaries with the medical-school-applicant-relevant business cycle ($\bar{U}_t$) from 1989 to 2019. Subfigure (a) presents the raw time series of these variables, while subfigure (b) shows a scatterplot of their relationship. In subfigure (b), the relationship is shown separately for the period before the Great Recession (1989–2007; solid circles) and the period after (2008–2019; hollow circles). The betas and p-values reported in subfigure (b) come from bivariate regressions of applicants per spot on $\bar{U}_t$ with robust standard errors. See Section II for details on the construction of $\bar{U}_y$. Data on applicants and matriculants are from the AAMC.

Figure 3: Entry conditions and the composition of medical school matriculants

(a) Percent of matriculants from non–pre-med majors



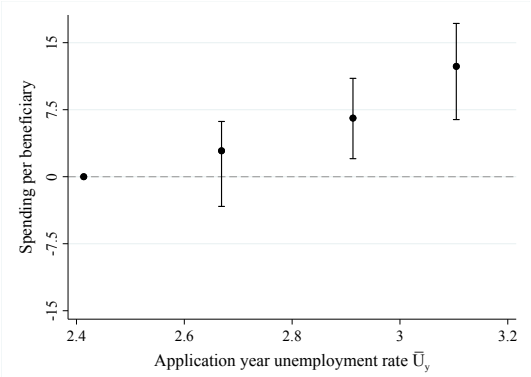
(b) Percent female among matriculants



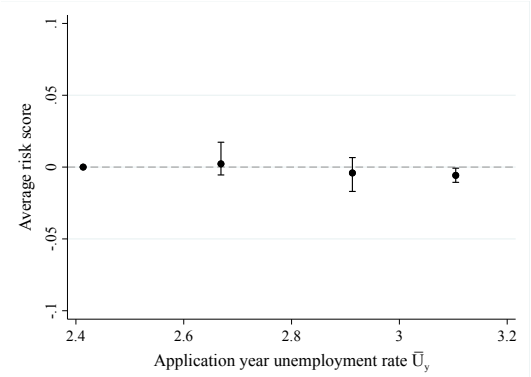
Notes: The above figures show how the annual percent of medical school matriculants with non-traditional undergraduate majors (subfigure (a)) and the percent who are female (subfigure (b)) covary with the medical-school-applicant-relevant business cycle ($\bar{U}_t$) from 1989 to 2019. In each subfigure, the left subplot presents the raw time series of these variables, while the right subplot shows a scatterplot of their relationship. In the right subplots, the relationship is shown separately for the period before the Great Recession (1989–2007; solid circles) and the period after (2008–2019; hollow circles). The betas and p-values reported in the right subplots come from bivariate regressions of the percent of non-traditional or female matriculants on $\bar{U}_t$ with robust standard errors. See Section II for details on the construction of $\bar{U}_y$. Data on matriculants are from the AAMC.

Figure 4: Entry conditions, physician practice styles, and patient composition

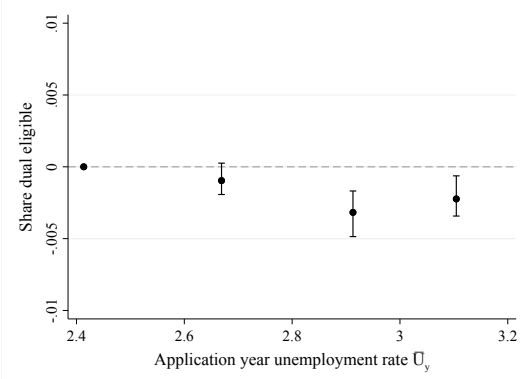
(a) Average Medicare spending per beneficiary



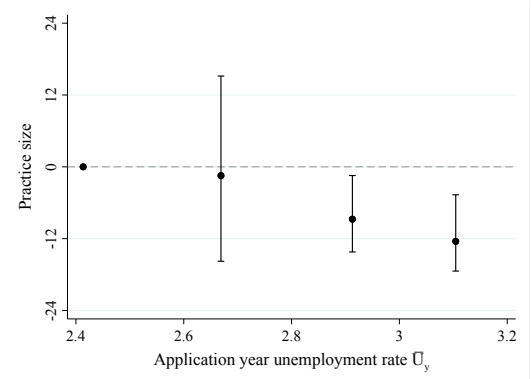
(b) Average patient risk scores



(c) Share Medicare beneficiaries dually eligible

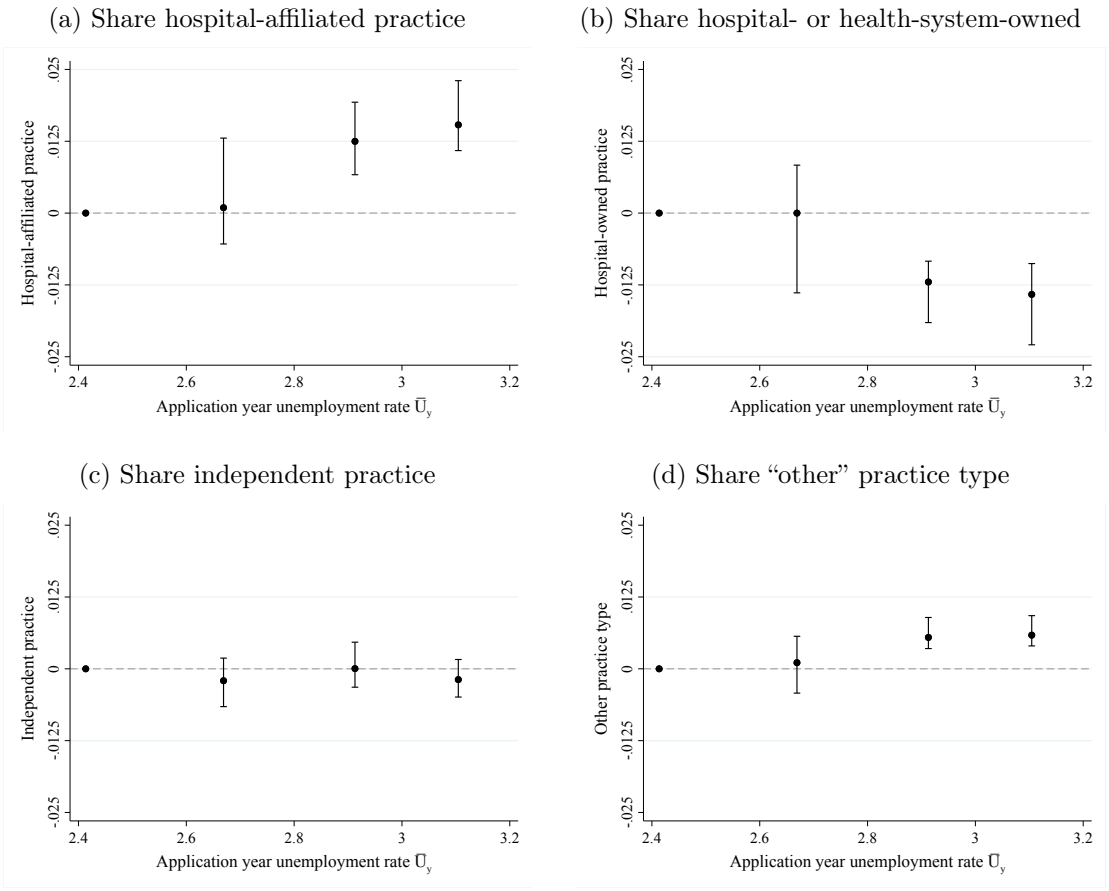


(d) Practice size



Notes: The above figures present results from estimation of equation (3) using average annual billing per Medicare beneficiary (subfigure (a)), average risk scores among Medicare beneficiaries (subfigure (b)), share Medicare beneficiaries that are dually eligible for Medicaid (subfigure (c)), and physician practice size (subfigure (d)) as outcomes. Confidence intervals are calculated using a wild cluster bootstrap clustered by graduation cohort (Cameron et al., 2008).The y-axes are scaled to span from –5 percent to +5 percent of the outcome mean. All regressions include specialty, experience, and year fixed effects. The sample is restricted to physicians who completed their initial medical education in the United States, applied to medical school in or after 1989, and have at least seven years of experience in a given outcome year. See Section II for details on the construction of $\bar{U}_y$. Outcome data are drawn from the public-use Part B Medicare files from 2013–2019 and the public-use Medicare Physician Compare files from 2014–2019; data on physician characteristics come from the AMA Masterfile.

Figure 5: Entry conditions and physician practice ownership and affiliation



Notes: The above figures present results from estimation of equation (3) using as outcomes the share of physicians in each mutually exclusive practice category: independent but hospital affiliated (subfigure (a)), hospital- or health-system-owned (subfigure (b)), independent and unaffiliated (subfigure (c)), and "other" (subfigure (d)). Confidence intervals are calculated using a wild cluster bootstrap clustered by graduation cohort (Cameron et al., 2008). All regressions include specialty, experience, and year fixed effects. The sample is restricted to physicians who completed their initial medical education in the United States, applied to medical school in or after 1989, and have at least seven years of experience in a given outcome year. See Section II for details on the construction of $\bar{U}_y$. Outcome data are drawn from the SK&A data from 2008–2016; data on physician characteristics come from the AMA Masterfile.

VIII Tables

Table 1: Relevant unemployment and medical school applicants and matriculants by state

a. Overall	Applicants per 100,000		Matriculants per 100,000	
	(1)	(2)	(3)	(4)
Unemployment rate $\bar{U}_{sy}$	0.73***	0.38**	0.19***	0.09
	(0.14)	(0.18)	(0.06)	(0.10)
R^2	0.67	0.86	0.82	0.87
Mean dependent variable	13.5	13.5	5.8	5.8
Percent of mean	5.4	2.8	3.3	1.6
b. Applicants by major group	Pre-medical applicants per 100,000		Other applicants per 100,000	
	(1)	(2)	(3)	(4)
Unemployment rate $\bar{U}_{sy}$	0.24***	0.18	0.22***	0.16**
	(0.08)	(0.12)	(0.04)	(0.07)
R^2	0.68	0.84	0.64	0.81
Mean dependent variable	8.3	8.3	3.7	3.7
Percent of mean	2.9	2.2	5.9	4.3
c. Applicants by sex	Male applicants per spot		Female applicants per spot	
	(1)	(2)	(3)	(4)
Unemployment rate $\bar{U}_{sy}$	0.45***	0.23**	0.28***	0.15*
	(0.08)	(0.11)	(0.06)	(0.08)
R^2	0.63	0.86	0.67	0.86
Mean dependent variable	7.1	7.1	6.3	6.3
Percent of mean	6.3	3.2	4.4	2.4
Observations	1,530	1,530	1,530	1,530
State fixed effects	✓	✓	✓	✓
Year fixed effects		✓		✓

Notes: The above table shows output from estimation of equation (1) using data at the state-year level from 1990–2019. Outcomes are expressed per 100,000 state residents, and observations are weighted by state population. Standard errors clustered by state. See Section II for details on the construction of $\bar{U}_{sy}$. Data on applicants and matriculants are from the AAMC, and data on annual state population are from the U.S. Census Bureau's intercensal population estimates.

Table 2: Impacts of entry conditions on physician practice styles and organization

a. Public Medicare files (2013–2019)	Spending per beneficiary (1)	Average risk score (x100) (2)	Dual eligible benes. (%) (3)	Practice size (4)
Unemployment rate $\bar{U}_y$	14.68***	-0.96**	-0.39***	-14.42***
	(2.85)	(0.36)	(0.07)	(3.54)
	[<0.001]	[0.036]	[<0.001]	[<0.001]
Observations	1,380,583	1,380,583	1,380,583	1,079,734
R^2	0.12	0.20	0.09	0.02
Mean dependent variable	296.7	173.1	24.4	489.2
Percent of mean	4.9	-0.6	-1.6	-2.9
b. SK&A data (2006–2018)	Hospital affiliated (%) (1)	Hospital or system owned (%) (2)	Independent practice (%) (3)	Other practice type (%) (4)
Unemployment rate $\bar{U}_y$	2.45***	-2.29***	-0.14	0.92***
	(0.26)	(0.31)	(0.18)	(0.12)
	[<0.001]	[<0.001]	[0.470]	[<0.001]
Observations	1,073,439	1,073,439	1,073,439	1,073,439
R^2	0.05	0.05	0.01	0.04
Mean dependent variable	49.8	42.9	6.6	8.1
Percent of mean	4.9	-5.3	-2.1	11.4
Specialty fixed effects	✓	✓	✓	✓
Experience fixed effects	✓	✓	✓	✓
Outcome year fixed effects	✓	✓	✓	✓

Notes: The above table shows output from estimation of equation (2) using data at the physician-year level. Standard errors, clustered by cohort, are shown in parentheses; p-values, calculated using a wild cluster bootstrap (Cameron et al., 2008) clustered by cohort, are shown in brackets. See Section II for details on the construction of $\bar{U}_y$. Outcome data in panel a are drawn from public-use Medicare files from 2013–2019; outcome data in panel b are drawn from the SK&A data from 2008–2016.

Table 3: Heterogeneity by sex: impacts on physician practice styles and organization

a. Public Medicare files (2013–2019)	Spending per beneficiary (1)	Average risk score (x100) (2)	Dual eligible benes. (%) (3)	Practice size (4)
$\bar{U}_y$: male physicians	18.16**	-0.84	-0.48***	-14.32**
	(5.08)	(0.60)	(0.12)	(5.61)
	[0.026]	[0.222]	[0.002]	[0.044]
$\bar{U}_y$: female physicians	8.68***	-1.07	-0.22	-8.54
	(2.82)	(0.83)	(0.16)	(9.34)
	[0.002]	[0.314]	[0.206]	[0.408]
Observations	1,363,385	1,363,385	1,363,385	1,078,842
Mean outcome: males	327.1	177.5	24.8	460.6
Mean outcome: females	251.7	165.1	23.4	535.4
Percent of mean: males	5.6	-0.5	-1.9	-3.1
Percent of mean: females	3.4	-0.6	-0.9	-1.6
P-value on difference	[0.260]	[0.930]	[0.406]	[0.730]
b. SK&A data (2006–2018)	Hospital affiliated (%) (1)	Hospital or system owned (%) (2)	Independent practice (%) (3)	Other practice type (%) (4)
$\bar{U}_y$: male physicians	3.25***	-3.01***	0.10	0.88***
	(0.43)	(0.42)	(0.29)	(0.18)
	[<0.001]	[<0.001]	[0.810]	[0.002]
$\bar{U}_y$: female physicians	0.91*	-0.59	-0.52***	0.84**
	(0.40)	(0.41)	(0.20)	(0.22)
	[0.076]	[0.258]	[0.008]	[0.016]
Observations	954,416	954,416	954,416	954,416
Mean outcome: males	53.1	41.5	6.8	7.7
Mean outcome: females	43.3	48.3	6.3	7.7
Percent of mean: males	6.1	-7.3	1.5	11.4
Percent of mean: females	2.1	-1.2	-8.3	10.9
P-value on difference	[<0.001]	[<0.001]	[0.134]	[0.850]
Specialty fixed effects	✓	✓	✓	✓
Experience fixed effects	✓	✓	✓	✓
Outcome year fixed effects	✓	✓	✓	✓

Notes: The above table shows output from estimation of equation (2) using data at the physician-year level. Regressions are estimated separately for male and female physicians; physicians with missing gender information in the AMA Masterfile are excluded from this analysis. Standard errors, clustered by cohort, are shown in parentheses; p-values, calculated using a wild cluster bootstrap (Cameron et al., 2008) clustered by cohort, are shown in brackets. See Section II for details on the construction of $\bar{U}_y$. Outcome data in panel a are drawn from public-use Medicare files from 2013–2019; outcome data in panel b are drawn from the SK&A data from 2008–2016.

Online Appendix

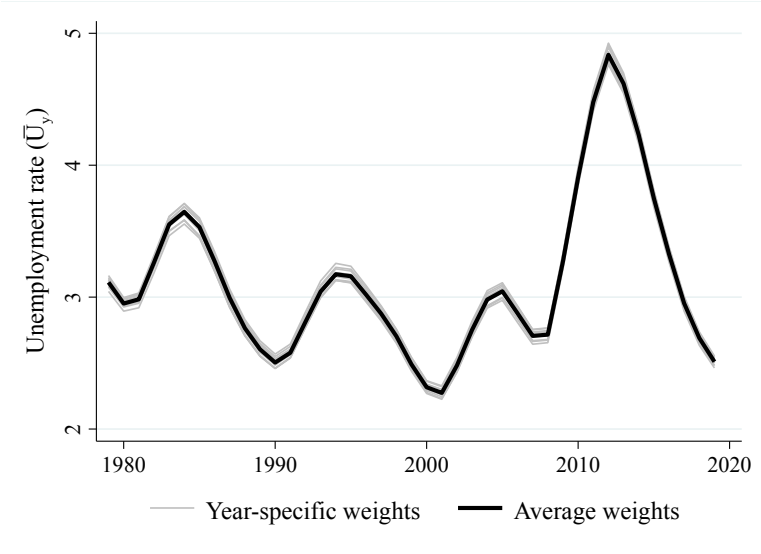
Selection into Medicine

Alexander and Schnell (2026)

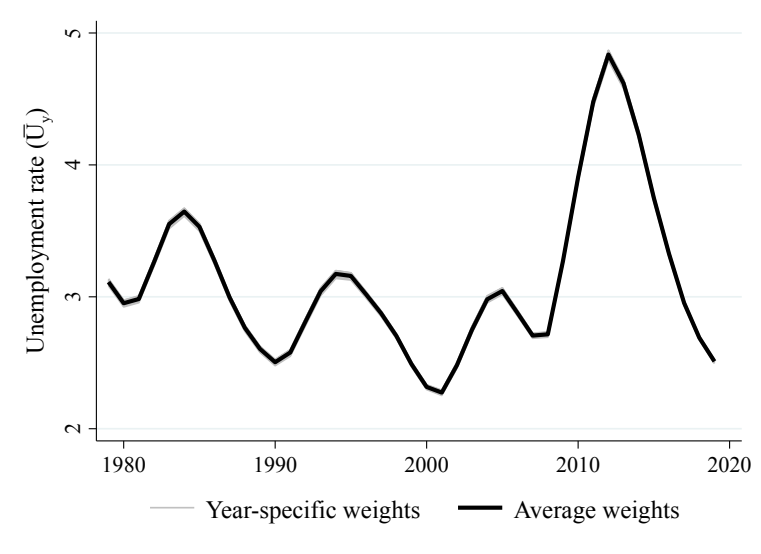
A Supplementary figures

Figure A1: Medical-school-applicant-relevent unemployment rate: alternative weights

(a) Alternative within–major-cluster, across-occupation weights



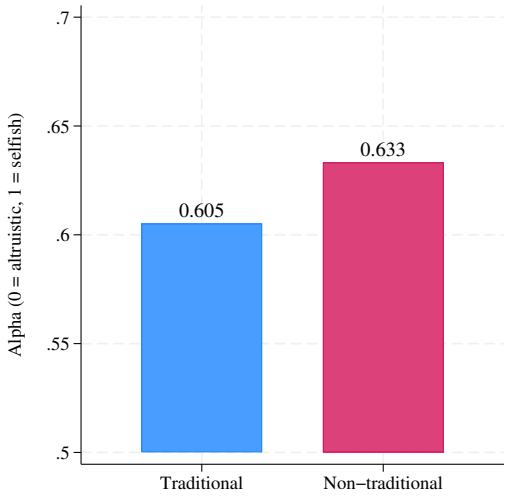
(b) Alternative across–major-cluster weights



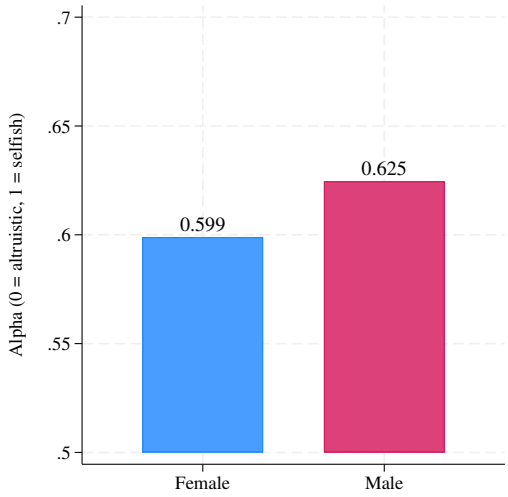
Notes: The above figures plot the medical-school-applicant-relevant business cycle ($\bar{U}_t$) from 1979 to 2019 constructed using alternative weights. Subfigure (a) plots $\bar{U}_t$ constructed using the shares of individuals in each major cluster entering each occupation from a single year of ACS data, applied to the entire period (thin, gray lines), rather than average weights constructed over all years available in the ACS (2009–2019; thick, black line). Subfigure (b) plots $\bar{U}_t$ constructed using the shares of medical school applicants coming from each major cluster from a single application cycle in the AAMC data, applied to the entire period (thin, gray lines), rather than average weights constructed over all years available in the AAMC data (1989–2019; thick, black line). See Section II for details on the construction of $\bar{U}_y$. All unemployment rates are constructed using data from the CPS.

Figure A2: Social preferences by undergraduate major and sex

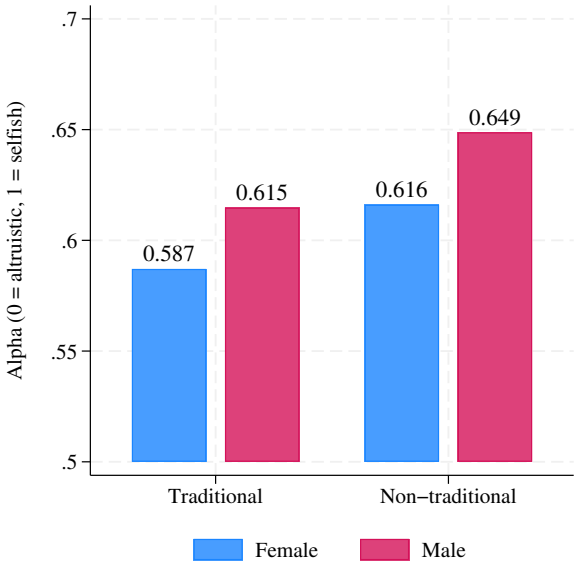
(a) By undergraduate major category



(b) By sex



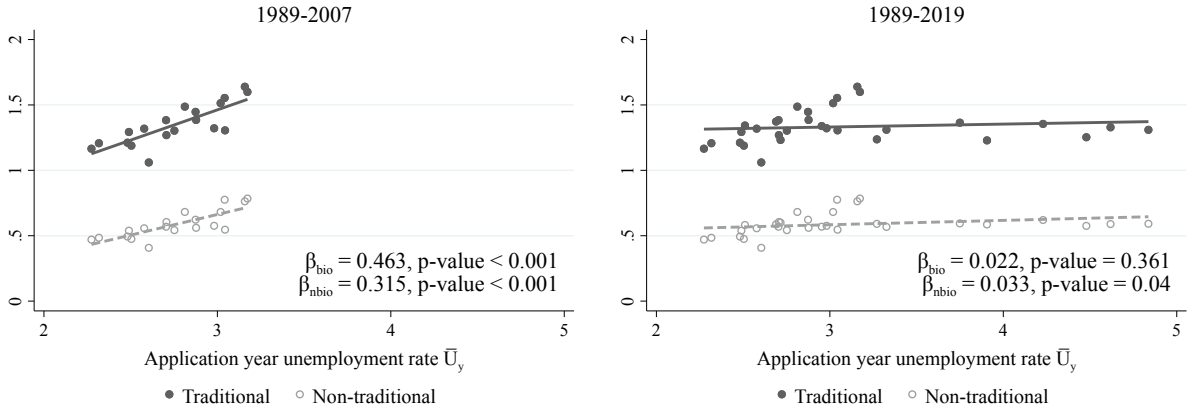
(c) By undergraduate major category and sex



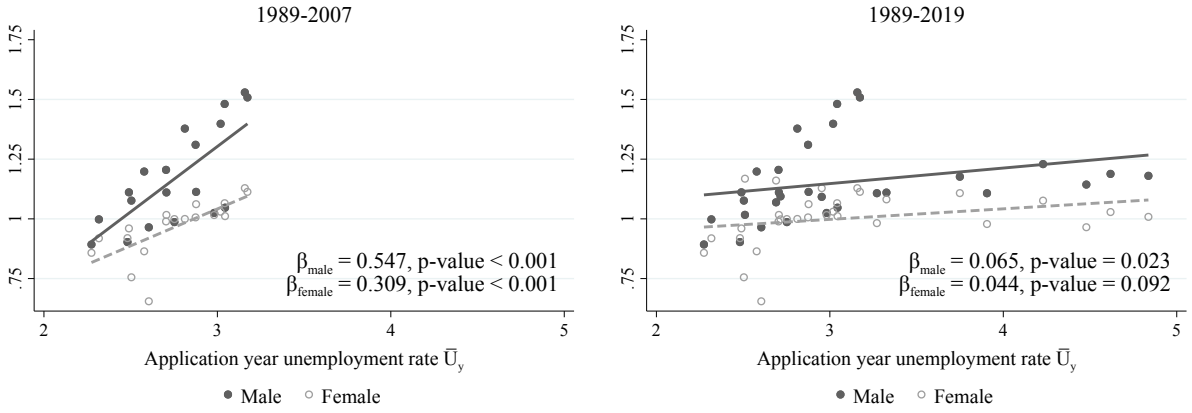
Notes: The above figures plot average measures of social preferences across undergraduate major groupings (subfigure (a)), sex (subfigure (b)), and both undergraduate major grouping and sex (subfigure (c)). Social preferences come from Li et al. (2022) and are measured using an incentivized choice experiment that elicits physicians' willingness to trade off personal income between themselves and others; "0" denotes full altruism (allocating all money to others), whereas "1" denotes full selfishness (allocating all money to oneself). "Traditional" undergraduate majors for individuals entering medicine are defined as those in the traditional pre-medical cluster (see Table A1).

Figure A3: Medical school applicants per spot over time by type

(a) By undergraduate major grouping



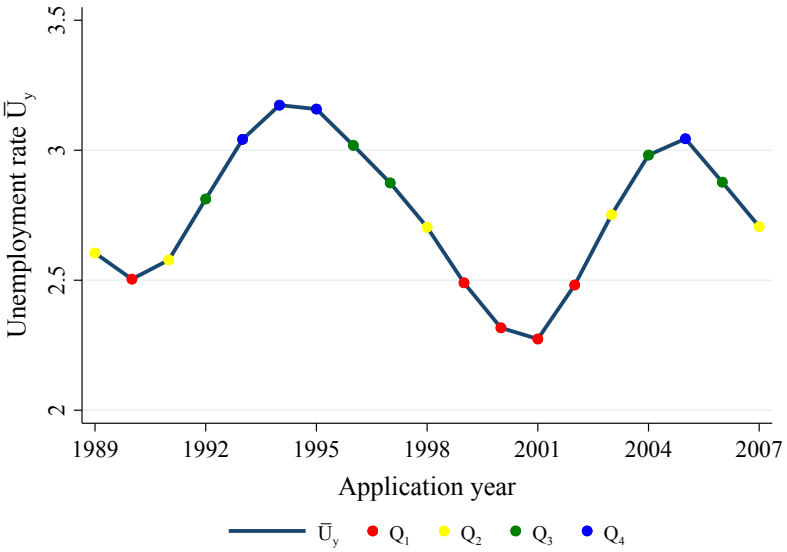
(b) By sex



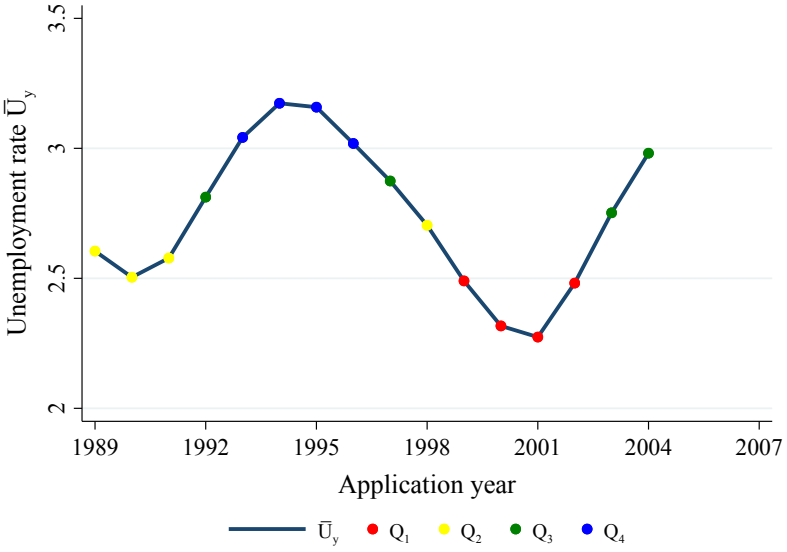
Notes: The above figures show how the annual number of applicants to medical school, divided by the number of matriculants ("spots"), covaries with the medical-school-applicant-relevant business cycle ($\bar{U}_t$) from 1989 to 2007 (left panels) and from 1989 to 2019 (right panels). Subfigure (a) separates applicants by undergraduate major grouping, while subfigure (b) separates them by sex. "Traditional" undergraduate majors for individuals entering medicine are defined as those in the traditional pre-medical cluster (see TableA1). Reported betas and p-values come from bivariate regressions of applicants per spot on $\bar{U}_t$ with robust standard errors. See Section 2 for details on the construction of $\bar{U}_t$. Data on applicants and matriculants are from the AAMC.

Figure A4: Medical-school-applicant-relevant unemployment quartile groupings

(a) Primary groupings: 1989–2007

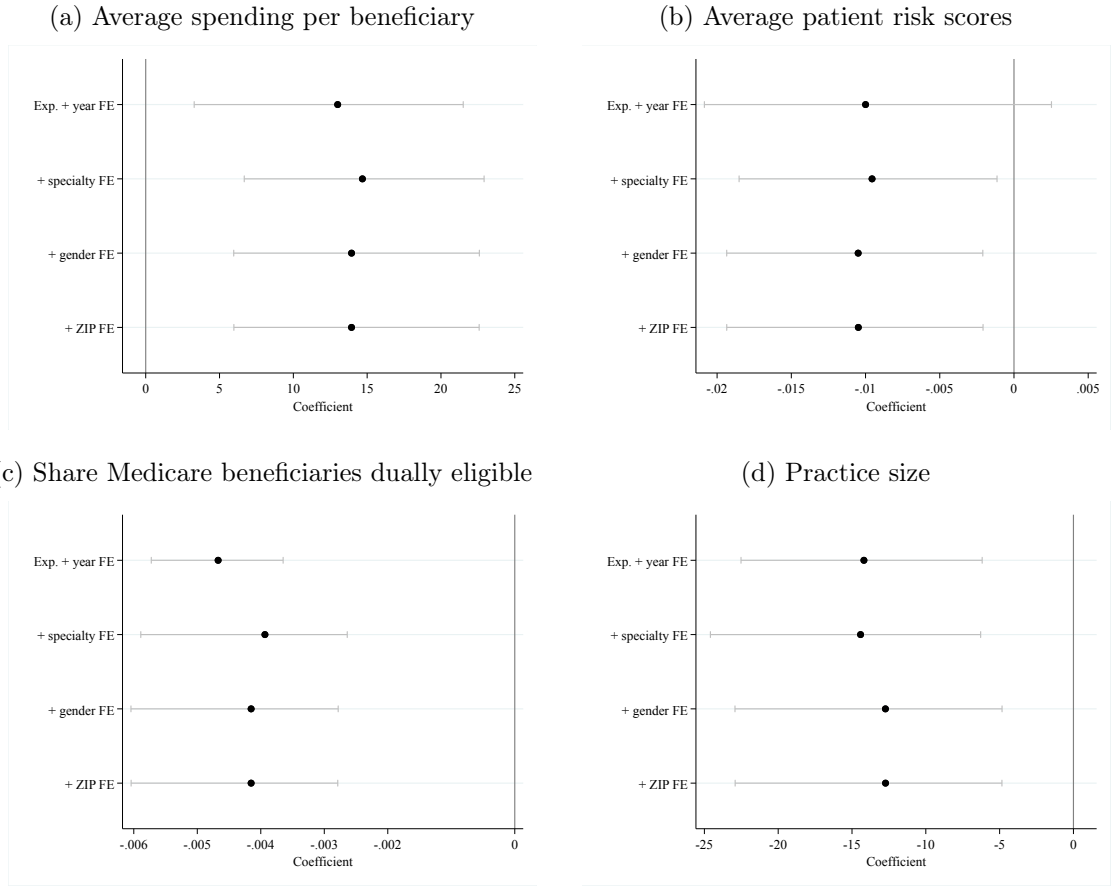


(b) Alternative groupings: 1989–2004



Notes: The above figures show how the medical-school-applicant-relevant business cycle ($\bar{U}_t$) is divided into quartiles when using data from 1989–2007 (subfigure (a)) and from 1989–2004 (subfigure (b)). These groupings are subsequently used for analyses relying on estimation of equation (3). See Section 2 for details on the construction of $\bar{U}_t$.

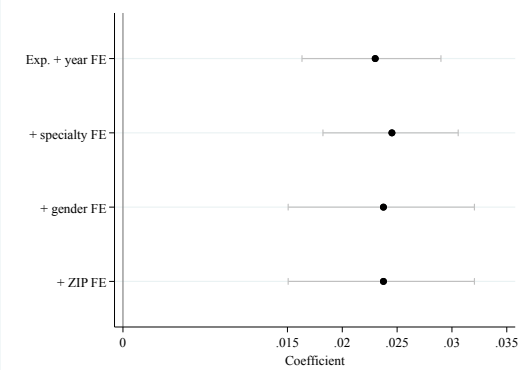
Figure A5: Alternative controls: practice styles and patient composition



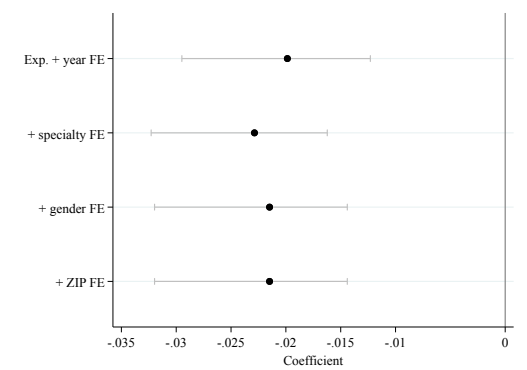
Notes: The above figures present results from estimation of analogs of equation (2) using average annual billing per Medicare beneficiary (subfigure (a)), average risk scores among Medicare beneficiaries (subfigure (b)), share Medicare beneficiaries that are dually eligible for Medicaid (subfigure (c)), and physician practice size (subfigure (d)) as outcomes. Confidence intervals are calculated using a wild cluster bootstrap clustered by graduation cohort (Cameron et al., 2008). All regressions include experience and year fixed effects. The second row in each subfigure additionally includes specialty fixed effects; the third additionally includes physician sex fixed effects (male, female, and missing); and the final row additionally includes practice ZIP code fixed effects. The sample is restricted to physicians who completed their initial medical education in the United States, applied to medical school in or after 1989, and have at least seven years of experience in a given outcome year. See Section II for details on the construction of $\bar{U}_y$. Outcome data are drawn from the public-use Part B Medicare files from 2013–2019 and the public-use Medicare Physician Compare files from 2014–2019; data on physician characteristics come from the AMA Masterfile.

Figure A6: Alternative controls: practice ownership and affiliation

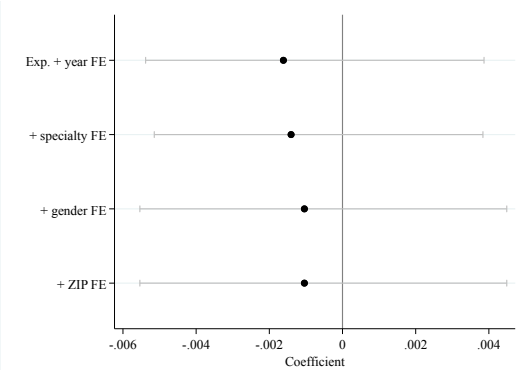
(a) Share hospital-affiliated practice



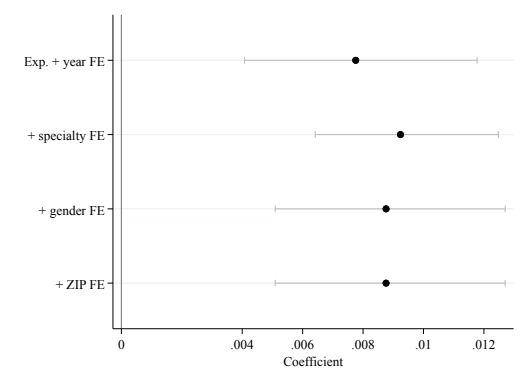
(b) Share hospital- or health-system-owned



(c) Share independent practice

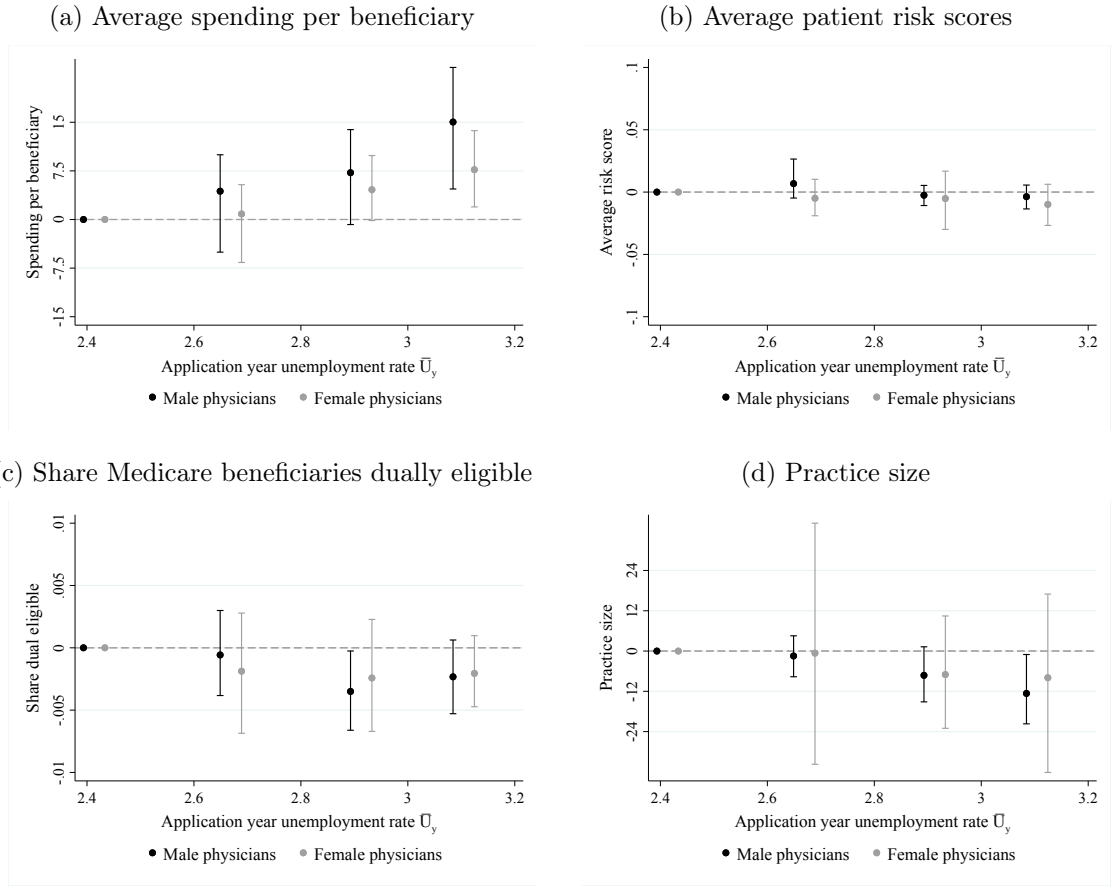


(d) Share "other" practice type



Notes: The above figures present results from estimation of equation (2) using as outcomes the share of physicians in each mutually exclusive practice category: independent but hospital affiliated (subfigure (a)), hospital- or health-system-owned (subfigure (b)), independent and unaffiliated (subfigure (c)), and "other" (subfigure (d)). Confidence intervals are calculated using a wild cluster bootstrap clustered by graduation cohort (Cameron et al., 2008). All regressions include experience and year fixed effects. The second row in each subfigure additionally includes specialty fixed effects; the third additionally includes physician sex fixed effects (male, female, and missing); and the final row additionally includes practice ZIP code fixed effects. The sample is restricted to physicians who completed their initial medical education in the United States, applied to medical school in or after 1989, and have at least seven years of experience in a given outcome year. See Section II for details on the construction of $\bar{U}_y$. Outcome data are drawn from the SK&A data from 2008–2016; data on physician characteristics come from the AMA Masterfile.

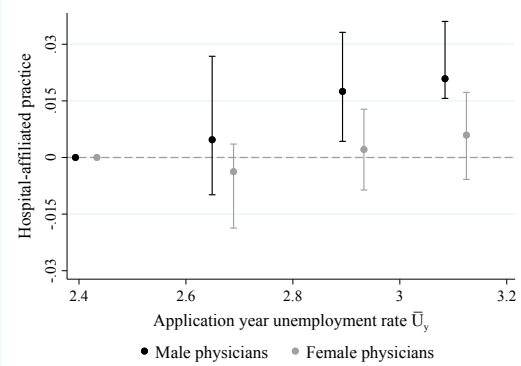
Figure A7: Heterogeneity by physician sex: practice styles and patient composition



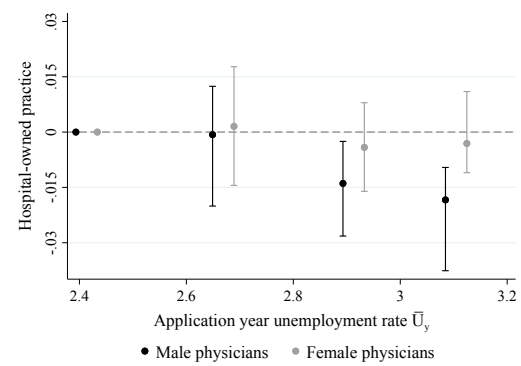
Notes: The above figures present results from estimation of equation (3) using average annual billing per Medicare beneficiary (subfigure (a)), average risk scores among Medicare beneficiaries (subfigure (b)), share Medicare beneficiaries that are dually eligible for Medicaid (subfigure (c)), and physician practice size (subfigure (d)) as outcomes. Results are shown separately for male physicians (black dots and lines) and female physicians (gray dots and lines). Confidence intervals are calculated using a wild cluster bootstrap clustered by graduation cohort (Cameron et al., 2008). The y-axes are scaled to span from –5 percent to +5 percent of the outcome mean. All regressions include specialty, experience, and year fixed effects. The sample is restricted to physicians who completed their initial medical education in the United States, applied to medical school in or after 1989, and have at least seven years of experience in a given outcome year. See Section II for details on the construction of $\bar{U}_y$. Outcome data are drawn from the public-use Part B Medicare files from 2013–2019 and the public-use Medicare Physician Compare files from 2014–2019; data on physician characteristics come from the AMA Masterfile.

Figure A8: Heterogeneity by physician sex: practice ownership and affiliation

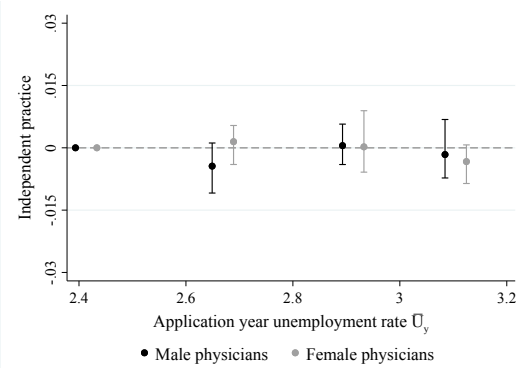
(a) Share hospital-affiliated practice



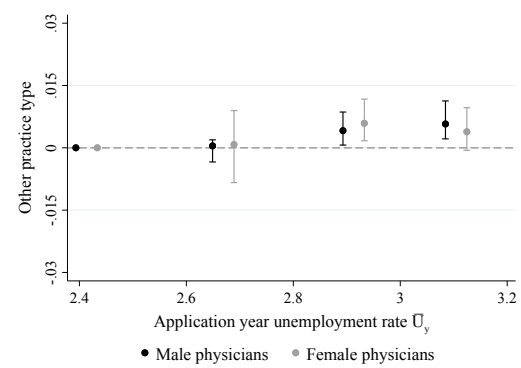
(b) Share hospital- or health-system-owned



(c) Share independent practice



(d) Share "other" practice type



Notes: The above figures present results from estimation of equation (3) using as outcomes the share of physicians in each mutually exclusive practice category: independent but hospital affiliated (subfigure (a)), hospital- or health-system-owned (subfigure (b)), independent and unaffiliated (subfigure (c)), and "other" (subfigure (d)). Results are shown separately for male physicians (black dots and lines) and female physicians (gray dots and lines). Confidence intervals are calculated using a wild cluster bootstrap clustered by graduation cohort (Cameron et al., 2008). All regressions include specialty, experience, and year fixed effects. The sample is restricted to physicians who completed their initial medical education in the United States, applied to medical school in or after 1989, and have at least seven years of experience in a given outcome year. See Section II for details on the construction of $\bar{U}_y$. Outcome data are drawn from the SK&A data from 2008–2016; data on physician characteristics come from the AMA Masterfile.

Figure A9: Alternative sample definitions: public-use Medicare data (2013–2019)

(a) Main sample

Application year (cohort)	Outcome year 2013	2014	2015	2016	2017	2018	2019
1989	19	20	21	22	23	24	25
1990	18	19	20	21	22	23	24
1991	17	18	19	20	21	22	23
1992	16	17	18	19	20	21	22
1993	15	16	17	18	19	20	21
1994	14	15	16	17	18	19	20
1995	13	14	15	16	17	18	19
1996	12	13	14	15	16	17	18
1997	11	12	13	14	15	16	17
1998	10	11	12	13	14	15	16
1999	9	10	11	12	13	14	15
2000	8	9	10	11	12	13	14
2001	7	8	9	10	11	12	13
2002	6	7	8	9	10	11	12
2003	5	6	7	8	9	10	11
2004	4	5	6	7	8	9	10
2005	3	4	5	6	7	8	9
2006	2	3	4	5	6	7	8
2007	1	2	3	4	5	6	7
2008	0	1	2	3	4	5	6

(b) 4+ observations per cell

Application year (cohort)	Outcome year 2013	2014	2015	2016	2017	2018	2019
1989	19	20	21	22	23	24	25
1990	18	19	20	21	22	23	24
1991	17	18	19	20	21	22	23
1992	16	17	18	19	20	21	22
1993	15	16	17	18	19	20	21
1994	14	15	16	17	18	19	20
1995	13	14	15	16	17	18	19
1996	12	13	14	15	16	17	18
1997	11	12	13	14	15	16	17
1998	10	11	12	13	14	15	16
1999	9	10	11	12	13	14	15
2000	8	9	10	11	12	13	14
2001	7	8	9	10	11	12	13
2002	6	7	8	9	10	11	12
2003	5	6	7	8	9	10	11
2004	4	5	6	7	8	9	10
2005	3	4	5	6	7	8	9
2006	2	3	4	5	6	7	8
2007	1	2	3	4	5	6	7
2008	0	1	2	3	4	5	6

(c) Balance: outcome years and cohort

Application year (cohort)	Outcome year 2013	2014	2015	2016	2017	2018	2019
1989	19	20	21	22	23	24	25
1990	18	19	20	21	22	23	24
1991	17	18	19	20	21	22	23
1992	16	17	18	19	20	21	22
1993	15	16	17	18	19	20	21
1994	14	15	16	17	18	19	20
1995	13	14	15	16	17	18	19
1996	12	13	14	15	16	17	18
1997	11	12	13	14	15	16	17
1998	10	11	12	13	14	15	16
1999	9	10	11	12	13	14	15
2000	8	9	10	11	12	13	14
2001	7	8	9	10	11	12	13
2002	6	7	8	9	10	11	12
2003	5	6	7	8	9	10	11
2004	4	5	6	7	8	9	10
2005	3	4	5	6	7	8	9
2006	2	3	4	5	6	7	8
2007	1	2	3	4	5	6	7
2008	0	1	2	3	4	5	6

(d) Balance: outcome years and experience

Application year (cohort)	Outcome year 2013	2014	2015	2016	2017	2018	2019
1989	19	20	21	22	23	24	25
1990	18	19	20	21	22	23	24
1991	17	18	19	20	21	22	23
1992	16	17	18	19	20	21	22
1993	15	16	17	18	19	20	21
1994	14	15	16	17	18	19	20
1995	13	14	15	16	17	18	19
1996	12	13	14	15	16	17	18
1997	11	12	13	14	15	16	17
1998	10	11	12	13	14	15	16
1999	9	10	11	12	13	14	15
2000	8	9	10	11	12	13	14
2001	7	8	9	10	11	12	13
2002	6	7	8	9	10	11	12
2003	5	6	7	8	9	10	11
2004	4	5	6	7	8	9	10
2005	3	4	5	6	7	8	9
2006	2	3	4	5	6	7	8
2007	1	2	3	4	5	6	7
2008	0	1	2	3	4	5	6

Notes: The figures present alternative samples used to estimate equation (3) using the public-use Medicare data from 2013–2019. Subfigure (a) shows the main sample, which limits the data to physicians who applied to medical school in or after 1989 and had at least seven years of experience following medical school in a given outcome year. Starting from this main sample, subfigure (b) additionally requires at least four cohort–experience–outcome year cells within each included cohort, experience profile, and outcome year; subfigure (c) requires balance across outcome years and application cohorts; and subfigure (d) requires balance across outcome years and experience profiles. Results for these alternative samples are reported in Table A6.

Figure A10: Alternative sample definitions: SK&A data (2008–2016)

(a) Main sample

Application year (cohort) \ Outcome year	2008	2009	2010	2011	2012	2013	2014	2015	2016
1989	14	15	16	17	18	19	20	21	22
1990	13	14	15	16	17	18	19	20	21
1991	12	13	14	15	16	17	18	19	20
1992	11	12	13	14	15	16	17	18	19
1993	10	11	12	13	14	15	16	17	18
1994	9	10	11	12	13	14	15	16	17
1995	8	9	10	11	12	13	14	15	16
1996	7	8	9	10	11	12	13	14	15
1997	6	7	8	9	10	11	12	13	14
1998	5	6	7	8	9	10	11	12	13
1999	4	5	6	7	8	9	10	11	12
2000	3	4	5	6	7	8	9	10	11
2001	2	3	4	5	6	7	8	9	10
2002	1	2	3	4	5	6	7	8	9
2003	0	1	2	3	4	5	6	7	8
2004	-1	0	1	2	3	4	5	6	7
2005	-2	-1	0	1	2	3	4	5	6

(b) 4+ observations per cell

Application year (cohort) \ Outcome year	2008	2009	2010	2011	2012	2013	2014	2015	2016
1989	14	15	16	17	18	19	20	21	22
1990	13	14	15	16	17	18	19	20	21
1991	12	13	14	15	16	17	18	19	20
1992	11	12	13	14	15	16	17	18	19
1993	10	11	12	13	14	15	16	17	18
1994	9	10	11	12	13	14	15	16	17
1995	8	9	10	11	12	13	14	15	16
1996	7	8	9	10	11	12	13	14	15
1997	6	7	8	9	10	11	12	13	14
1998	5	6	7	8	9	10	11	12	13
1999	4	5	6	7	8	9	10	11	12
2000	3	4	5	6	7	8	9	10	11
2001	2	3	4	5	6	7	8	9	10
2002	1	2	3	4	5	6	7	8	9
2003	0	1	2	3	4	5	6	7	8
2004	-1	0	1	2	3	4	5	6	7
2005	-2	-1	0	1	2	3	4	5	6

(c) Balance: outcome years and cohort

Application year (cohort) \ Outcome year	2008	2009	2010	2011	2012	2013	2014	2015	2016
1989	14	15	16	17	18	19	20	21	22
1990	13	14	15	16	17	18	19	20	21
1991	12	13	14	15	16	17	18	19	20
1992	11	12	13	14	15	16	17	18	19
1993	10	11	12	13	14	15	16	17	18
1994	9	10	11	12	13	14	15	16	17
1995	8	9	10	11	12	13	14	15	16
1996	7	8	9	10	11	12	13	14	15
1997	6	7	8	9	10	11	12	13	14
1998	5	6	7	8	9	10	11	12	13
1999	4	5	6	7	8	9	10	11	12
2000	3	4	5	6	7	8	9	10	11
2001	2	3	4	5	6	7	8	9	10
2002	1	2	3	4	5	6	7	8	9
2003	0	1	2	3	4	5	6	7	8
2004	-1	0	1	2	3	4	5	6	7
2005	-2	-1	0	1	2	3	4	5	6

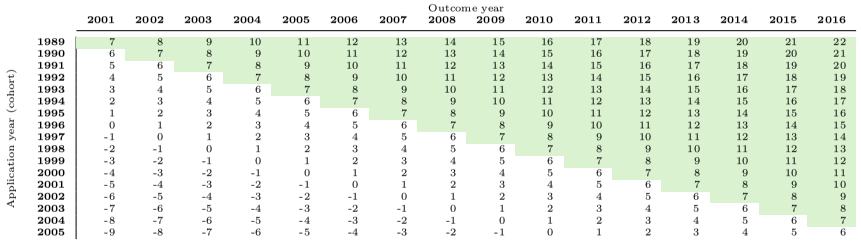
(d) Balance: outcome years and experience

Application year (cohort) \ Outcome year	2008	2009	2010	2011	2012	2013	2014	2015	2016
1989	14	15	16	17	18	19	20	21	22
1990	13	14	15	16	17	18	19	20	21
1991	12	13	14	15	16	17	18	19	20
1992	11	12	13	14	15	16	17	18	19
1993	10	11	12	13	14	15	16	17	18
1994	9	10	11	12	13	14	15	16	17
1995	8	9	10	11	12	13	14	15	16
1996	7	8	9	10	11	12	13	14	15
1997	6	7	8	9	10	11	12	13	14
1998	5	6	7	8	9	10	11	12	13
1999	4	5	6	7	8	9	10	11	12
2000	3	4	5	6	7	8	9	10	11
2001	2	3	4	5	6	7	8	9	10
2002	1	2	3	4	5	6	7	8	9
2003	0	1	2	3	4	5	6	7	8
2004	-1	0	1	2	3	4	5	6	7
2005	-2	-1	0	1	2	3	4	5	6

Notes: The figures present alternative samples used to estimate equation (3) using the SK&A data from 2008–2016. Subfigure (a) shows the main sample, which limits the data to physicians who applied to medical school in or after 1989 and had at least seven years of experience following medical school in a given outcome year. Starting from this main sample, subfigure (b) additionally requires at least four cohort–experience–outcome year cells within each included cohort, experience profile, and outcome year; subfigure (c) requires balance across outcome years and application cohorts; and subfigure (d) requires balance across outcome years and experience profiles. Results for these alternative samples are reported in Table A6.

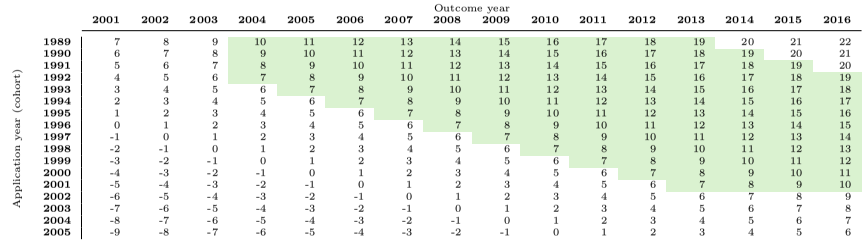
Figure A11: Alternative sample definitions: restricted Medicare data (2001–2016)

(a) Main sample



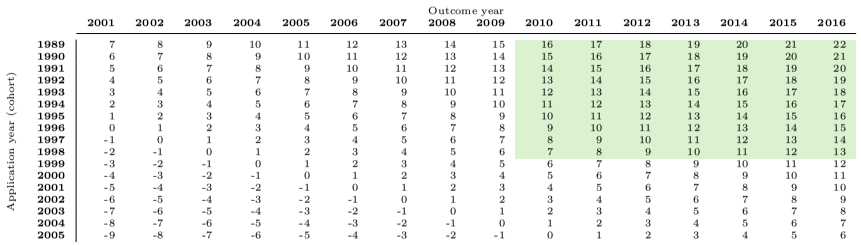
	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
1989	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22
1990	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21
1991	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1992	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
1993	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
1994	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1995	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1996	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1997	-1	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1998	-2	-1	0	1	2	3	4	5	6	7	8	9	10	11	12	13
1999	-3	-2	-1	0	1	2	3	4	5	6	7	8	9	10	11	12
2000	-4	-3	-2	-1	0	1	2	3	4	5	6	7	8	9	10	11
2001	-5	-4	-3	-2	-1	0	1	2	3	4	5	6	7	8	9	10
2002	-6	-5	-4	-3	-2	-1	0	1	2	3	4	5	6	7	8	9
2003	-7	-6	-5	-4	-3	-2	-1	0	1	2	3	4	5	6	7	8
2004	-8	-7	-6	-5	-4	-3	-2	-1	0	1	2	3	4	5	6	7
2005	-9	-8	-7	-6	-5	-4	-3	-2	-1	0	1	2	3	4	5	6

(b) 4+ observations per cell



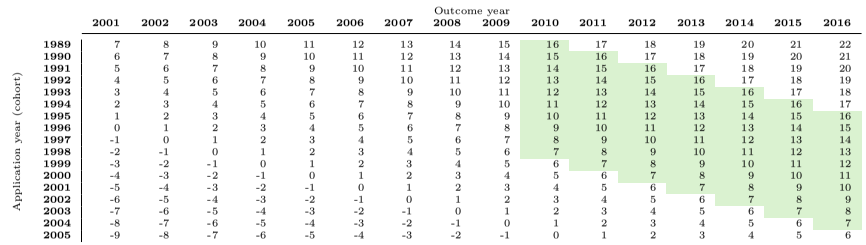
	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
1989	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22
1990	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21
1991	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1992	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
1993	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
1994	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1995	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1996	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1997	-1	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1998	-2	-1	0	1	2	3	4	5	6	7	8	9	10	11	12	13
1999	-3	-2	-1	0	1	2	3	4	5	6	7	8	9	10	11	12
2000	-4	-3	-2	-1	0	1	2	3	4	5	6	7	8	9	10	11
2001	-5	-4	-3	-2	-1	0	1	2	3	4	5	6	7	8	9	10
2002	-6	-5	-4	-3	-2	-1	0	1	2	3	4	5	6	7	8	9
2003	-7	-6	-5	-4	-3	-2	-1	0	1	2	3	4	5	6	7	8
2004	-8	-7	-6	-5	-4	-3	-2	-1	0	1	2	3	4	5	6	7
2005	-9	-8	-7	-6	-5	-4	-3	-2	-1	0	1	2	3	4	5	6

(c) Balance: outcome years and cohort



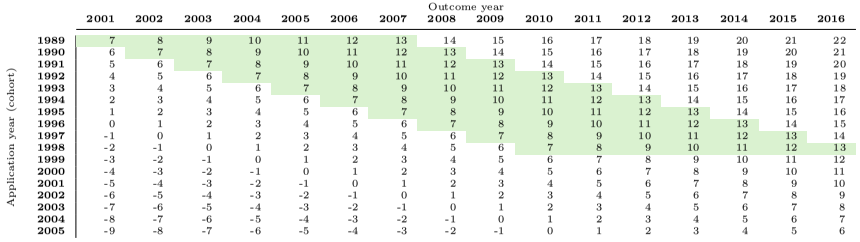
	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
1989	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22
1990	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21
1991	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1992	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
1993	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
1994	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1995	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1996	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1997	-1	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1998	-2	-1	0	1	2	3	4	5	6	7	8	9	10	11	12	13
1999	-3	-2	-1	0	1	2	3	4	5	6	7	8	9	10	11	12
2000	-4	-3	-2	-1	0	1	2	3	4	5	6	7	8	9	10	11
2001	-5	-4	-3	-2	-1	0	1	2	3	4	5	6	7	8	9	10
2002	-6	-5	-4	-3	-2	-1	0	1	2	3	4	5	6	7	8	9
2003	-7	-6	-5	-4	-3	-2	-1	0	1	2	3	4	5	6	7	8
2004	-8	-7	-6	-5	-4	-3	-2	-1	0	1	2	3	4	5	6	7
2005	-9	-8	-7	-6	-5	-4	-3	-2	-1	0	1	2	3	4	5	6

(d) Balance: outcome years and experience



	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
1989	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22
1990	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21
1991	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1992	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
1993	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
1994	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1995	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1996	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1997	-1	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1998	-2	-1	0	1	2	3	4	5	6	7	8	9	10	11	12	13
1999	-3	-2	-1	0	1	2	3	4	5	6	7	8	9	10	11	12
2000	-4	-3	-2	-1	0	1	2	3	4	5	6	7	8	9	10	11
2001	-5	-4	-3	-2	-1	0	1	2	3	4	5	6	7	8	9	10
2002	-6	-5	-4	-3	-2	-1	0	1	2	3	4	5	6	7	8	9
2003	-7	-6	-5	-4	-3	-2	-1	0	1	2	3	4	5	6	7	8
2004	-8	-7	-6	-5	-4	-3	-2	-1	0	1	2	3	4	5	6	7
2005	-9	-8	-7	-6	-5	-4	-3	-2	-1	0	1	2	3	4	5	6

(e) Balance: experience and cohort

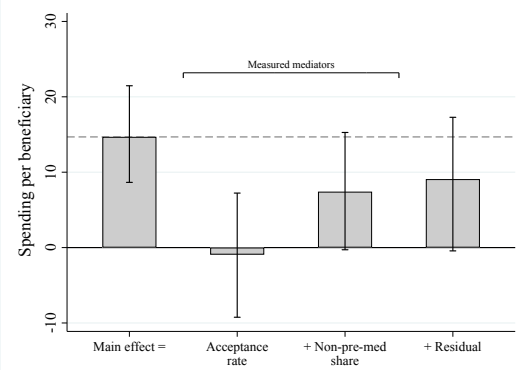


	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
1989	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22
1990	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21
1991	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1992	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
1993	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
1994	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1995	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1996	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1997	-1	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1998	-2	-1	0	1	2	3	4	5	6	7	8	9	10	11	12	13
1999	-3	-2	-1	0	1	2	3	4	5	6	7	8	9	10	11	12
2000	-4	-3	-2	-1	0	1	2	3	4	5	6	7	8	9	10	11
2001	-5	-4	-3	-2	-1	0	1	2	3	4	5	6	7	8	9	10
2002	-6	-5	-4	-3	-2	-1	0	1	2	3	4	5	6	7	8	9
2003	-7	-6	-5	-4	-3	-2	-1	0	1	2	3	4	5	6	7	8
2004	-8	-7	-6	-5	-4	-3	-2	-1	0	1	2	3	4	5	6	7
2005	-9	-8	-7	-6	-5	-4	-3	-2	-1	0	1	2	3	4	5	6

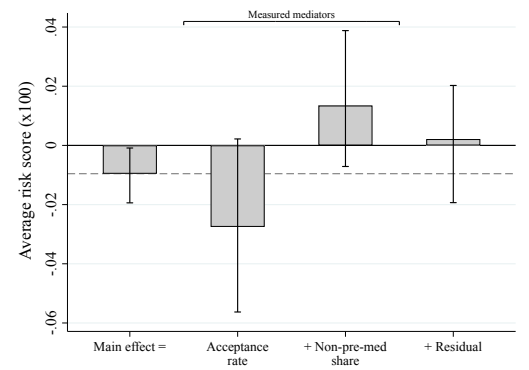
Notes: The figures present alternative samples used to estimate equation (3) using the restricted Medicare data from 2001–2016. Subfigure (a) shows the main sample, which limits the data to physicians who applied to medical school in or after 1989 and had at least seven years of experience following medical school in a given outcome year. Starting from this main sample, subfigure (b) additionally requires at least four cohort–experience–outcome year cells within each included cohort, experience profile, and outcome year; subfigure (c) requires balance across outcome years and application cohorts; subfigure (d) requires balance across outcome years and experience profiles; and subfigure (e) requires balance across experience profiles and cohorts. Results for these alternative samples are reported in Table A6.

Figure A12: Mediation analysis: practice styles and patient composition

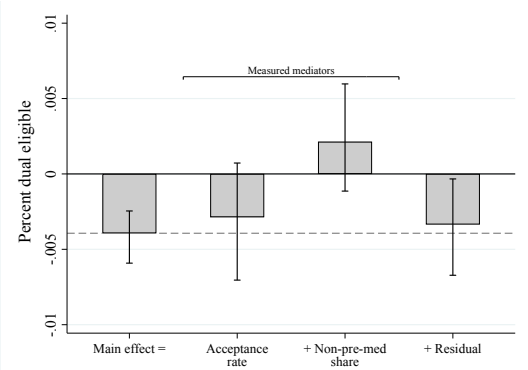
(a) Average spending per beneficiary



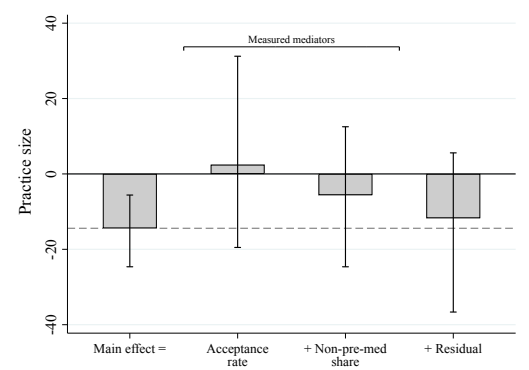
(b) Average patient risk scores



(c) Share Medicare beneficiaries dually eligible



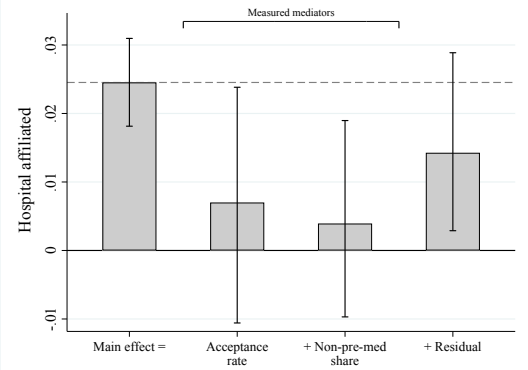
(d) Practice size



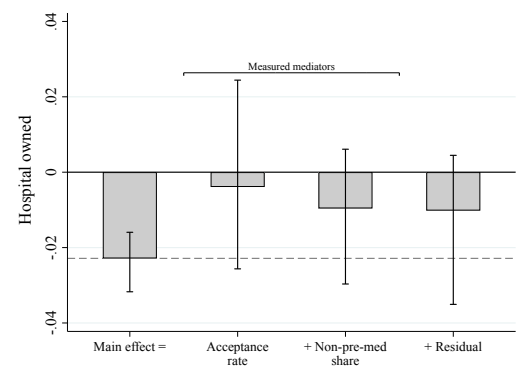
Notes: The above figures present regression-based decompositions of the reduced-form effect of the applicant-relevant unemployment rate at the time of medical school application on average annual billing per Medicare beneficiary (subfigure (a)), average risk scores among Medicare beneficiaries (subfigure (b)), share Medicare beneficiaries that are dually eligible for Medicaid (subfigure (c)), and physician practice size (subfigure (d)). The total reduced-form effect ("Main effect") corresponds to the coefficient β from equation (2). The mediator components are computed using the first-stage and mediation regressions in equations (4) and (5). Specifically, the "Acceptance rate" and "Share non-pre-med" bars equal $\delta_k\theta_k$, where δ_k is the coefficient from the cohort-level first-stage regression (equation (4)) and θ_k is the corresponding coefficient from the outcome equation including both mediators (equation (5)). The "Residual" component corresponds to the coefficient γ from equation (5). By construction, the sum of the mediator components and the residual equals the total reduced-form effect. Confidence intervals are calculated using a cohort-level cluster bootstrap that resamples application cohorts with replacement and re-estimates equations (2), (4), and (5) in each replication. See Section II for details on the construction of $\bar{U}_y$. Outcome data are drawn from the public-use Part B Medicare files from 2013–2019 and the public-use Medicare Physician Compare files from 2014–2019; data on applicants and matriculants are from the AAMC.

Figure A13: Mediation analysis: practice ownership and affiliation

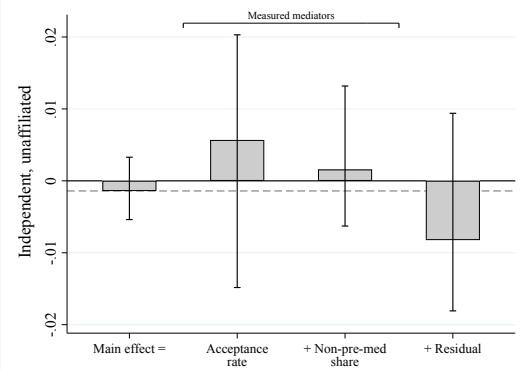
(a) Share hospital-affiliated practice



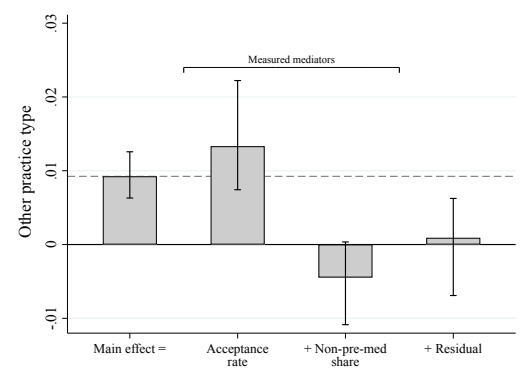
(b) Share hospital- or health-system-owned



(c) Share independent practice

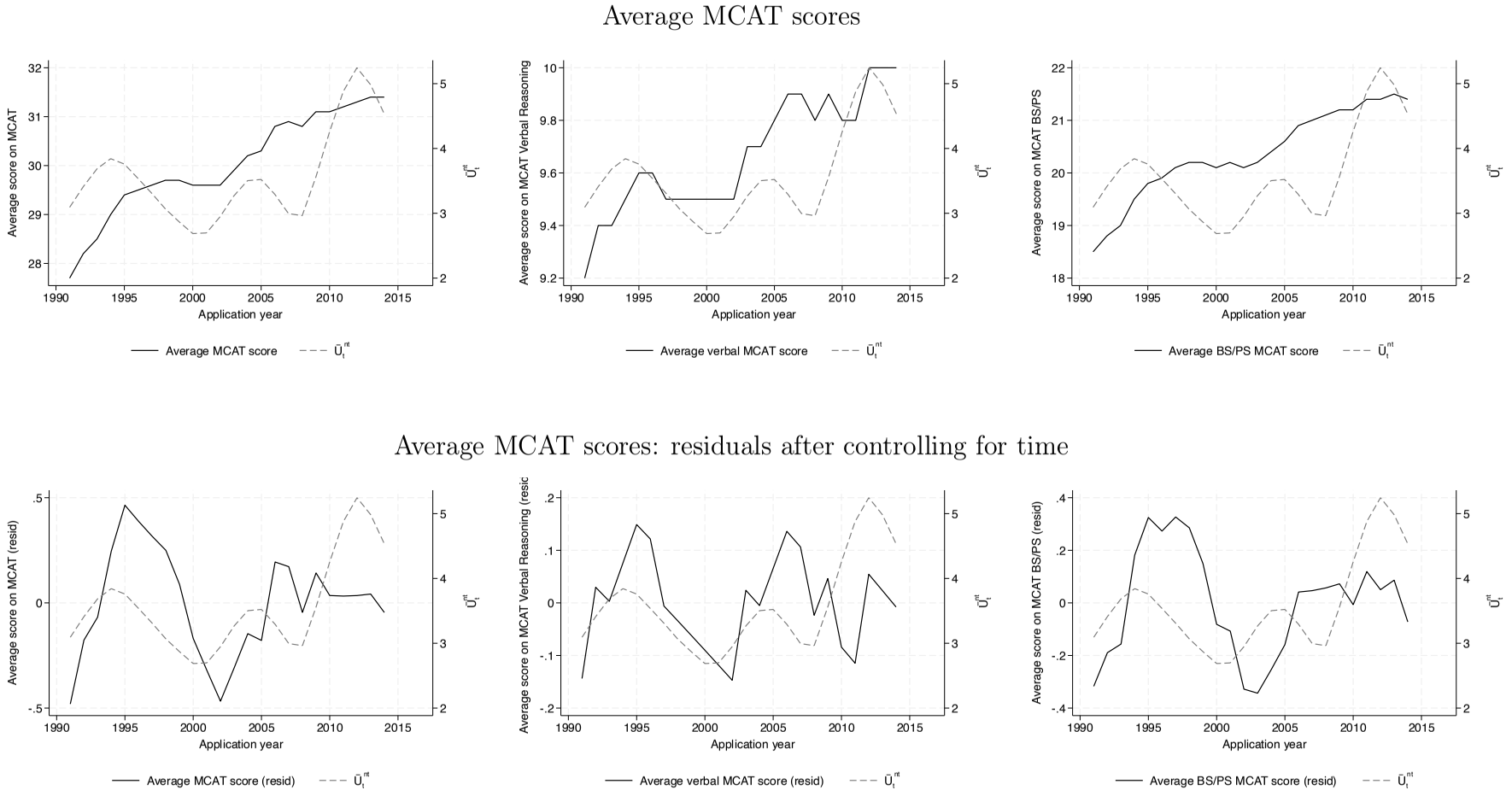


(d) Share "other" practice type



Notes: The above figures present regression-based decompositions of the reduced-form effect of the applicant-relevant unemployment rate at the time of medical school application on the share of physicians in each mutually exclusive practice category: independent but hospital affiliated (subfigure (a)), hospital- or health-system-owned (subfigure (b)), independent and unaffiliated (subfigure (c)), and "other" (subfigure (d)). The total reduced-form effect ("Main effect") corresponds to the coefficient β from equation (2). The mediator components are computed using the first-stage and mediation regressions in equations (4) and (5). Specifically, the "Acceptance rate" and "Share non-pre-med" bars equal $\delta_k\theta_k$, where δ_k is the coefficient from the cohort-level first-stage regression (equation (4)) and θ_k is the corresponding coefficient from the outcome equation including both mediators (equation (5)). The "Residual" component corresponds to the coefficient γ from equation (5). By construction, the sum of the mediator components and the residual equals the total reduced-form effect. Confidence intervals are calculated using a cohort-level cluster bootstrap that resamples application cohorts with replacement and re-estimates equations (2), (4), and (5) in each replication. See Section II for details on the construction of $\bar{U}_y$. Outcome data are drawn from the public-use Part B Medicare files from 2013–2019 and the public-use Medicare Physician Compare files from 2014–2019; data on applicants and matriculants are from the AAMC.

Figure A14: Average qualifications of matriculants: MCAT scores



Notes: MCAT residuals after controlling for time. Application years in which students applied after having taken the old MCAT (administered prior to 2015). The left column reports total MCAT scores, the middle column scores for the verbal reasoning section, and the right column scores on the biological and physical sciences sections.

B Supplementary tables

Table A1: Clusters of undergraduate majors from k-means clustering

Cluster 1: Traditional Pre-Medical Majors	
Biochemical Sciences	Molecular Biology
Biology	Neuroscience
Biomedical Engineering	Nursing
Chemistry	Pharmacology
Genetics	Pharmacy, Pharmaceutical Sciences
Health and Medical Preparatory Programs	Physiology
Microbiology	Zoology
Cluster 2: Engineering	
Aerospace Engineering	Electrical Engineering
Biological Engineering	General Engineering
Chemical Engineering	Mechanical Engineering
Civil Engineering	
Cluster 3: Computer Science, Math, Physics	
Astronomy and Astrophysics	Mathematics
Computer Science	Physics
Management Information Systems and Statistics	
Cluster 4: Earth Sciences	
Animal Sciences	Geology and Earth Science
Architecture	Geosciences
Atmospheric Sciences and Meteorology	Medical Technologies Technicians
Botany	Military Technologies
Environmental Science	Miscellaneous Biology
Forestry	Oceanography
General Agriculture	Oceanography
Geography	
Cluster 5: Humanities and Applied Social Sciences	
Anthropology and Archeology	Library Science
Communications	Linguistics and Comparative Language
Community and Public Health	Miscellaneous Business and Medical Admin.
Composition and Speech	Miscellaneous Health Medical Professions
Drama and Theater Arts	Miscellaneous Social Sciences
English Language and Literature	Music
Fine Arts	Nutrition Sciences
French, German, Latin, and Other Common Languages	Psychology
General Social Sciences	Social Work
Humanities	Sociology
Journalism	Treatment Therapy Professions
Liberal Arts	
Cluster 6: Business, Economics, Political Science	
Accounting	International Relations
Economics	Philosophy and Religious Studies
General Business	Political Science and Government
History	Pre-Law and Legal Studies
Cluster 7: Education	
General Education	Physical and Health Education Teaching
Interdisciplinary and Multi-Disciplinary Studies	

Notes: The above table shows the grouping of undergraduate majors into seven clusters. Groupings are obtained via k-means clustering based on the similarity in the occupational distributions of graduates across majors as reported in one-year ACS from 2009–2019. See Section II for additional details.

Table A2: Unemployment and medical school applicants and matriculants nationally

a. Overall	Applicants per spot		Total matriculants (10,000s)	
	1989–2019	1989–2007	1989–2019	1989–2007
	(1)	(2)	(3)	(4)
Unemployment rate $\bar{U}_y$	0.09**	0.85***	0.16***	0.08*
	(0.05)	(0.17)	(0.03)	(0.04)
R^2	0.07	0.57	0.26	0.09
Mean dependent variable	2.3	2.3	1.7	1.5
Percent of mean	3.9	37.0	9.4	5.3
b. Applicants by major group	Pre-medical applicants per spot		Other applicants per spot	
	1989–2019	1989–2007	1989–2019	1989–2007
	(1)	(2)	(3)	(4)
Unemployment rate $\bar{U}_y$	0.01	0.45***	0.03*	0.32***
	(0.02)	(0.09)	(0.02)	(0.06)
R^2	0.00	0.57	0.05	0.58
Mean dependent variable	1.4	1.5	0.6	0.6
Percent of mean	0.7	30.0	5.0	53.3
c. Applicants by sex	Male applicants per spot		Female applicants per spot	
	1989–2019	1989–2007	1989–2019	1989–2007
	(1)	(2)	(3)	(4)
Unemployment rate $\bar{U}_y$	0.06**	0.55***	0.04	0.30***
	(0.03)	(0.13)	(0.03)	(0.07)
R^2	0.05	0.47	0.05	0.47
Mean dependent variable	1.2	1.3	1.1	1.0
Percent of mean	5.0	42.3	3.6	30.0
d. Matriculant composition	Percent non-pre-medical		Percent female	
	1989–2019	1989–2007	1989–2019	1989–2007
	(1)	(2)	(3)	(4)
Unemployment rate $\bar{U}_y$	1.07***	4.54***	0.44	-2.37
	(0.35)	(1.00)	(0.66)	(2.59)
R^2	0.18	0.44	0.01	0.03
Mean dependent variable	31.4	31.1	46.5	45.0
Percent of mean	3.4	14.6	0.9	-5.3
Observations	31	19	31	19

Notes: The above table shows output from estimation of an analog of equation (1) using national data at the annual level. Columns (1) and (3) in each panel use data from 1989–2019, while columns (2) and (4) restrict the sample to 1989–2007. Standard errors are robust. See Section II for details on the construction of $\bar{U}_y$. Data on applicants and matriculants are from the AAMC.

Table A3: Impacts of entry conditions: alternative specifications and samples

a. Spending per beneficiary	(1)	(2)	(3)	(4)	(5)	(6)
Unemployment rate $\bar{U}_y$	14.68***	14.98***	7.58**	15.89***	11.99***	6.92**
	(2.85)	(2.90)	(2.24)	(3.65)	(3.31)	(2.53)
	[<0.001]	[<0.001]	[0.014]	[<0.001]	[<0.001]	[0.022]
Observations	1,380,583	1,380,583	1,380,583	1,104,017	2,294,882	1,989,740
Mean dependent variable	296.7	296.7	268.5	304.8	294.9	302.2
Percent of mean	4.9	5.0	2.8	5.2	4.1	2.3
b. Average risk score (x100)	(1)	(2)	(3)	(4)	(5)	(6)
Unemployment rate $\bar{U}_y$	-0.96**	-0.96**	0.45	-1.99***	-0.65**	-0.95*
	(0.36)	(0.36)	(0.51)	(0.36)	(0.29)	(0.47)
	[0.036]	[0.036]	[0.390]	[<0.001]	[0.040]	[0.074]
Observations	1,380,583	1,380,583	1,380,583	1,104,017	2,294,882	1,989,740
Mean dependent variable	173.1	173.1	174.9	170.6	171.1	167.1
Percent of mean	-0.6	-0.6	0.3	-1.2	-0.4	-0.6
c. Percent dual eligible	(1)	(2)	(3)	(4)	(5)	(6)
Unemployment rate $\bar{U}_y$	-0.39***	-0.39***	-0.41*	-0.40***	-0.39***	-0.30**
	(0.07)	(0.07)	(0.16)	(0.08)	(0.07)	(0.08)
	[<0.001]	[<0.001]	[0.050]	[0.002]	[<0.001]	[0.010]
Observations	1,380,583	1,380,583	1,380,583	1,104,017	2,294,882	1,989,740
Mean dependent variable	24.4	24.4	24	23.7	22.3	23.5
Percent of mean	-1.6	-1.6	-1.7	-1.7	-1.7	-1.3
d. Practice size	(1)	(2)	(3)	(4)	(5)	(6)
Unemployment rate $\bar{U}_y$	-14.42***	-12.50***	-13.73**	-14.46***	-17.23***	-15.40***
	(3.54)	(3.56)	(4.73)	(4.00)	(3.39)	(5.01)
	[<0.001]	[<0.001]	[0.018]	[0.002]	[<0.001]	[0.002]
Observations	1,079,734	1,079,734	1,079,734	867,484	1,913,146	1,516,644
Mean dependent variable	489.2	489.2	328.5	476.3	584.9	445.7
Percent of mean	-2.9	-2.6	-4.2	-3.0	-2.9	-3.5
Outcome years	2013–2019	2013–2019	2013–2019	2013–2019	2013–2023	2013–2019
Experience restriction	≥ 7	≥ 7	≥ 7	≥ 10	≥ 7	7–30
Application years	1989–2007	1989–2007	1989–2007	1989–2004	1989–2007	1978–2007
Control for avg. risk score		✓				
Weight by beneficiaries			✓			

Notes: The above table shows output from estimation of analogs of equation (2) using data at the physician-year level. Standard errors, clustered by cohort, are shown in parentheses; p-values, calculated using a wild cluster bootstrap (Cameron et al., 2008) clustered by cohort, are shown in brackets. Results from the baseline specification—in which outcome data cover 2013–2019, physician-year observations occur at least seven years after medical school graduation, and all observations receive equal weight—are shown in column (1). Column (2) additionally controls for the average patient risk score at the physician-year level, and column (3) weights observations by the total number of beneficiaries. Column (4) restricts the sample to physician-year observations at least ten years after medical school graduation, while column (5) extends the outcome data to include years 2020–2023. See Section II for details on the construction of $\bar{U}_y$. Outcome data are drawn from public-use Medicare files.

Table A4: Impacts of entry conditions: alternative unemployment measures (Medicare)

a. Spending per beneficiary	(1)	(2)	(3)	(4)	(5)	(6)
Unemployment rate $\bar{U}_y$	14.68***	7.38***	14.43***	7.02***	13.03***	14.44***
	(2.85)	(1.13)	(2.85)	(1.70)	(2.24)	(3.80)
	[<0.001]	[<0.001]	[<0.001]	[0.004]	[<0.001]	[0.004]
Observations	1,380,583	1,380,583	1,380,583	1,380,583	1,380,583	1,380,583
Mean dependent variable	296.7	296.7	296.7	296.7	296.7	296.7
Percent of mean	4.9	2.5	4.9	2.4	4.4	4.9
b. Average risk score (x100)	(1)	(2)	(3)	(4)	(5)	(6)
Unemployment rate $\bar{U}_y$	-0.96**	-0.23	-0.88**	0.00	-0.59*	-1.43**
	(0.36)	(0.14)	(0.35)	(0.24)	(0.28)	(0.53)
	[0.036]	[0.138]	[0.046]	[0.992]	[0.062]	[0.026]
Observations	1,380,583	1,380,583	1,380,583	1,380,583	1,380,583	1,380,583
Mean dependent variable	173.1	173.1	173.1	173.1	173.1	173.1
Percent of mean	-0.6	-0.1	-0.5	0.0	-0.3	-0.8
c. Percent dual eligible	(1)	(2)	(3)	(4)	(5)	(6)
Unemployment rate $\bar{U}_y$	-0.39***	-0.17***	-0.39***	-0.13	-0.29***	-0.52***
	(0.07)	(0.03)	(0.07)	(0.06)	(0.07)	(0.08)
	[<0.001]	[<0.001]	[<0.001]	[0.112]	[0.002]	[<0.001]
Observations	1,380,583	1,380,583	1,380,583	1,380,583	1,380,583	1,380,583
Mean dependent variable	24.4	24.4	24.4	24.4	24.4	24.4
Percent of mean	-1.6	-0.7	-1.6	-0.5	-1.2	-2.1
d. Practice size	(1)	(2)	(3)	(4)	(5)	(6)
Unemployment rate $\bar{U}_y$	-14.42***	-7.92***	-14.85***	-13.13***	-15.27***	-13.05***
	(3.54)	(2.01)	(3.65)	(2.84)	(3.67)	(3.47)
	[<0.001]	[<0.001]	[<0.001]	[<0.001]	[<0.001]	[0.006]
Observations	1,079,734	1,079,734	1,079,734	1,079,734	1,079,734	1,079,734
Mean dependent variable	489.2	489.2	489.2	489.2	489.2	489.2
Percent of mean	-2.9	-1.6	-3.0	-2.7	-3.1	-2.7
Unemployment measure	Med-specific	Overall	Exclude physicians	Med-specific	Med-specific	Med-specific
Number of included lags	0–3	0–3	0–3	0	0–2	0–4

Notes: The above table shows output from estimation of analogs of equation (2) using physician-year data from 2013–2019. Standard errors, clustered by cohort, are shown in parentheses; p-values, calculated using a wild cluster bootstrap (Cameron et al., 2008) clustered by cohort, are shown in brackets. Results from the baseline specification—which uses the medical-school-applicant-relevant business cycle averaged over the year of application to medical school and the three preceding years (years 0–3)—are shown in column (1). Column (2) instead uses the overall business cycle, while column (3) uses the medical-school-applicant-relevant business cycle holding physician employment fixed; both measures are averaged over year 0–3. Columns (4)–(6) use the baseline medical-school-applicant-relevant unemployment rate but vary the averaging window. Column (4) considers only the year of application to medical school (year 0), column (5) averages over the year of application and the two preceding years (years 0–2), and column (6) averages over the year of application and the four preceding years (years 0–4). See Section II for additional details on the construction of $\bar{U}_y$. Outcome data are drawn from public-use Medicare files from 2013–2019.

Table A5: Impacts of entry conditions: alternative unemployment measures (SK&A)

a. Hospital affiliated	(1)	(2)	(3)	(4)	(5)	(6)
Unemployment rate $\bar{U}_y$	2.45***	1.13***	2.45***	1.24***	2.10***	2.76***
	(0.26)	(0.11)	(0.26)	(0.27)	(0.19)	(0.41)
	[<0.001]	[<0.001]	[<0.001]	[<0.001]	[<0.001]	[<0.001]
Mean dependent variable	49.8	49.8	49.8	49.8	49.8	49.8
Percent of mean	4.9	2.3	4.9	2.5	4.2	5.5
b. Hospital owned	(1)	(2)	(3)	(4)	(5)	(6)
Unemployment rate $\bar{U}_y$	-2.29***	-1.09***	-2.30***	-1.47***	-2.11***	-2.42***
	(0.31)	(0.15)	(0.31)	(0.25)	(0.24)	(0.43)
	[<0.001]	[<0.001]	[<0.001]	[<0.001]	[<0.001]	[0.002]
Mean dependent variable	42.9	42.9	42.9	42.9	42.9	42.9
Percent of mean	-5.3	-2.5	-5.4	-3.4	-4.9	-5.6
c. Independent, unaffiliated	(1)	(2)	(3)	(4)	(5)	(6)
Unemployment rate $\bar{U}_y$	-0.14	-0.04	-0.12	0.31	0.01	-0.24
	(0.18)	(0.09)	(0.18)	(0.14)	(0.18)	(0.20)
	[0.470]	[0.776]	[0.524]	[0.152]	[0.964]	[0.266]
Mean dependent variable	6.6	6.6	6.6	6.6	6.6	6.6
Percent of mean	-2.1	-0.6	-1.8	4.7	0.2	-3.6
d. Other practice type	(1)	(2)	(3)	(4)	(5)	(6)
Unemployment rate $\bar{U}_y$	0.92***	0.40***	0.91***	0.40	0.75***	1.13***
	(0.12)	(0.05)	(0.12)	(0.13)	(0.11)	(0.16)
	[<0.001]	[0.002]	[<0.001]	[0.120]	[<0.001]	[<0.001]
Mean dependent variable	8.1	8.1	8.1	8.1	8.1	8.1
Percent of mean	11.4	4.9	11.2	4.9	9.3	14.0
Observations	1,073,439	1,073,439	1,073,439	1,073,439	1,073,439	1,073,439
Unemployment measure	Med-specific	Overall	Exclude physicians	Med-specific	Med-specific	Med-specific
Number of included lags	0–3	0–3	0–3	0	0–2	0–4

Notes: The above table shows output from estimation of analogs of equation (2) using physician-year data from 2008–2016. Standard errors, clustered by cohort, are shown in parentheses; p-values, calculated using a wild cluster bootstrap (Cameron et al., 2008) clustered by cohort, are shown in brackets. Results from the baseline specification—which uses the medical-school-applicant-relevant business cycle averaged over the year of application to medical school and the three preceding years (years 0–3)—are shown in column (1). Column (2) instead uses the overall business cycle, while column (3) uses the medical-school-applicant-relevant business cycle holding physician employment fixed; both measures are averaged over year 0–3. Columns (4)–(6) use the baseline medical-school-applicant-relevant unemployment rate but vary the averaging window. Column (4) considers only the year of application to medical school (year 0), column (5) averages over the year of application and the two preceding years (years 0–2), and column (6) averages over the year of application and the four preceding years (years 0–4). See Section II for additional details on the construction of $\bar{U}_y$. Outcome data are drawn from the SK&A data.

Table A6: Impacts of entry conditions: alt. support and balance restrictions (Medicare)

a. Spending per beneficiary	(1)	(2)	(3)	(4)	(5)	(6)
Unemployment rate $\bar{U}_y$	14.68***	15.25***	16.66***	12.97***	14.44***	14.93***
	(2.85)	(3.01)	(3.76)	(2.58)	(4.03)	(2.89)
	[<0.001]	[<0.001]	[0.004]	[<0.001]	[<0.001]	[<0.001]
Observations	1,380,583	1,229,774	1,099,797	1,140,541	1,209,178	1,380,583
Mean dependent variable	296.7	298.9	304.3	293.7	296.7	296.7
Percent of mean	4.9	5.1	5.5	4.4	4.9	5.0
b. Average risk score (x100)	(1)	(2)	(3)	(4)	(5)	(6)
Unemployment rate $\bar{U}_y$	-0.96**	-1.21*	-2.53***	-0.80*	-1.12**	-1.01**
	(0.36)	(0.52)	(0.33)	(0.36)	(0.35)	(0.37)
	[0.036]	[0.072]	[<0.001]	[0.064]	[0.010]	[0.032]
Observations	1,380,583	1,229,774	1,099,797	1,140,541	1,209,178	1,380,583
Mean dependent variable	173.1	172.5	169.6	175.3	173.0	173.1
Percent of mean	-0.6	-0.7	-1.5	-0.5	-0.6	-0.6
c. Percent dual eligible	(1)	(2)	(3)	(4)	(5)	(6)
Unemployment rate $\bar{U}_y$	-0.39***	-0.38***	-0.41***	-0.42***	-0.43***	-0.39***
	(0.07)	(0.07)	(0.09)	(0.07)	(0.11)	(0.07)
	[<0.001]	[<0.001]	[<0.001]	[<0.001]	[0.004]	[<0.001]
Observations	1,380,583	1,229,774	1,099,797	1,140,541	1,209,178	1,380,583
Mean dependent variable	24.4	24.5	23.9	24.9	24.3	24.4
Percent of mean	-1.6	-1.6	-1.7	-1.7	-1.8	-1.6
d. Practice size	(1)	(2)	(3)	(4)	(5)	(6)
Unemployment rate $\bar{U}_y$	-14.42***	-12.57***	-12.02**	-14.43***	-17.88***	-14.38***
	(3.54)	(3.86)	(4.53)	(3.16)	(4.55)	(3.58)
	[<0.001]	[<0.001]	[0.010]	[<0.001]	[0.002]	[<0.001]
Observations	1,079,734	947,980	829,674	872,904	949,167	1,079,734
Mean dependent variable	489.2	476.1	459.7	499.0	489.3	489.2
Percent of mean	-2.9	-2.6	-2.6	-2.9	-3.7	-2.9
Outcome years	2013–2019	2013–2019	2013–2019	2013–2019	2013–2019	2013–2019
Experience restriction	≥ 7	7–19	≥ 7	7–19	≥ 7	≥ 7
Application years	1989–2007	1992–2004	1989–2001	1989–2007	Not 1994, 2001	1989–2007
Inverse weighting						✓

Notes: The above table shows output from estimation of equation (2) using physician-year data from 2013–2019. Standard errors, clustered by cohort, are shown in parentheses; p-values, calculated using a wild cluster bootstrap (Cameron et al., 2008) clustered by cohort, are shown in brackets. Results from the baseline sample, which limits the data to physicians who applied to medical school in or after 1989 and had at least seven years of experience following medical school in a given outcome year (see Figure A9(a)), are shown in column (1). Starting from this baseline sample, column (2) additionally requires that each cohort, outcome year, and experience level be observed with at least four values along the other two dimensions, as shown in Figure A9(b); column (3) requires balance across outcome years and application cohorts, as shown in Figure A9(c); and column (4) requires balance across outcome years and experience profiles, as shown in Figure A9(d). Column (5) drops the application cohorts with the highest and lowest values of $\bar{U}y$ (1994 and 2001, respectively), while column (6) weights observations by the inverse of the share of physician-year observations accounted for by each experience–outcome year cell. See Section II for details on the construction of $\bar{U}y$. Outcome data are drawn from public-use Medicare files.

Table A7: Impacts of entry conditions: alternative support and balance restrictions (SK&A)

a. Hospital affiliated	(1)	(2)	(3)	(4)	(5)	(6)
Unemployment rate $\bar{U}_y$	2.45***	2.49***	2.59**	2.32***	2.42***	2.50***
	(0.26)	(0.27)	(0.49)	(0.29)	(0.33)	(0.27)
	[<0.001]	[<0.001]	[0.034]	[<0.001]	[<0.001]	[<0.001]
Mean dependent variable	49.8	50.6	50.0	48.3	49.9	49.8
Percent of mean	4.9	4.9	5.2	4.8	4.8	5.0
b. Hospital owned	(1)	(2)	(3)	(4)	(5)	(6)
Unemployment rate $\bar{U}_y$	-2.29***	-2.29***	-2.51*	-2.24***	-2.25***	-2.28***
	(0.31)	(0.32)	(0.62)	(0.33)	(0.42)	(0.33)
	[<0.001]	[<0.001]	[0.058]	[<0.001]	[<0.001]	[<0.001]
Mean dependent variable	42.9	42.1	42.9	44.7	42.7	42.9
Percent of mean	-5.3	-5.4	-5.9	-5.0	-5.3	-5.3
c. Independent, unaffiliated	(1)	(2)	(3)	(4)	(5)	(6)
Unemployment rate $\bar{U}_y$	-0.14	-0.13	-0.21	-0.12	-0.04	-0.18
	(0.18)	(0.18)	(0.27)	(0.17)	(0.17)	(0.18)
	[0.470]	[0.548]	[0.718]	[0.550]	[0.760]	[0.386]
Mean dependent variable	6.6	6.6	6.3	6.1	6.7	6.6
Percent of mean	-2.1	-2.0	-3.3	-2.0	-0.6	-2.7
d. Other practice type	(1)	(2)	(3)	(4)	(5)	(6)
Unemployment rate $\bar{U}_y$	0.92***	0.92***	0.94*	0.87***	0.87***	0.89***
	(0.12)	(0.12)	(0.27)	(0.16)	(0.13)	(0.12)
	[<0.001]	[<0.001]	[0.076]	[<0.001]	[<0.001]	[<0.001]
Mean dependent variable	8.1	8.1	8.6	8.1	8.2	8.1
Percent of mean	11.4	11.4	10.9	10.7	10.6	11.0
Observations	1,073,439	959,602	773,344	703,786	947,703	1,073,439
Outcome years	2008–2016	2008–2016	2010–2016	2010–2016	2008–2016	2008–2016
Experience restriction	≥ 7	7–19	≥ 7	7–16	≥ 7	≥ 7
Application years	1989–2004	1989–2001	1989–1998	1989–2004	Not 1994, 2001	1989–2004
Inverse weighting						✓

Notes: The above table shows output from estimation of equation (2) using physician-year data. Standard errors, clustered by cohort, are shown in parentheses; p-values, calculated using a wild cluster bootstrap (Cameron et al., 2008) clustered by cohort, are shown in brackets. Results from the baseline sample, which limits the data to physicians who applied to medical school in or after 1989 and had at least seven years of experience following medical school in a given outcome year (see Figure A10(a)), are shown in column (1). Starting from this baseline sample, column (2) additionally requires that each cohort, outcome year, and experience level be observed with at least four values along the other two dimensions, as shown in Figure A10(b); column (3) requires balance across outcome years and application cohorts, as shown in Figure A10(c); and column (4) requires balance across outcome years and experience profiles, as shown in Figure A10(d). Column (5) drops the application cohorts with the highest and lowest values of $\bar{U}y$ (1994 and 2001, respectively), while column (6) weights observations by the inverse of the share of physician-year observations accounted for by each experience–outcome year cell. See Section II for details on the construction of $\bar{U}y$. Outcome data are drawn from Sk&A data from 2008–2016.