Selection into Medicine*

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Abstract

This paper examines how selection into medicine in the United States influences physician practice styles using macroeconomic conditions at the time of medical school application as an exogenous shock to the applicant pool. We 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 a cohort of physicians who are more likely to work in lucrative, small group practices and 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 and incomplete; 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 bill more to Medicare and are more likely to practice in smaller, higher-earning settings. Despite treating healthier patients on average, their patients 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.

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 at least 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 differences 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). Recognizing that such downturns can also shape behavior before labor-

market entry, subsequent work examines how macroeconomic conditions influence educational and occupational choices (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 high-skill individuals may buffer themselves from such adverse shocks by switching into recession-resistant professions, such as medicine (Dillender et al., 2021).

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 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. As few undergraduates who might become physicians are also considering careers in fields like construction, for example, downturns in those sectors are not relevant for our analysis. To construct a measure of economic conditions that is relevant to an individual on the margin of applying to medical school, we construct a "medical-school-applicant-relevant" business cycle. This business cycle 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 with 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.[2] These data offer three key advantages: (1) they allow us to examine historical trends dating back to the 1980s, (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). Specifically, we start with a 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,

[2]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.

earth sciences, humanities, education, and pre-law/business/economics.[3] 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 at baseline.[4]

Third, we compute a weighted annual average across six of the major cluster–year unemployment rates, where the weights reflect the share of medical school applicants from each major cluster. Data on medical school applicants come from the AAMC's Applicant Matriculant Data File, covering application cycles from 1989 to 2019. In addition to the number of applicants, the data include information on their undergraduate majors. The majority of medical school applicants come from a set of traditional "pre-medical" majors. According to AAMC data, students who majored in fields such as biology, chemistry, and biochemistry have accounted for nearly half of all medical school applicants over the past three decades. We define "traditional" medical school applicants as those with majors in the biology/chemistry cluster and classify applicants in the other six clusters as "non-traditional" applicants. To construct our medical-school-applicant-relevant unemployment rate, we take a weighted average of the six non-traditional major clusters, using the share of applicants in each cluster as weights.

We aim to capture labor market conditions toward the end of a potential applicant's undergraduate degree, as this is when marginal undergraduates are 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 before one completes their undergraduate education. Second, many students take a gap year or two after graduating, and we only observe the application year. This motivates a consideration of economic conditions after one completes their undergraduate education. To capture both of these forces in our measure of relevant economic conditions, we compute the medical-school-applicant-relevant

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

[4] In particular, we use occupation weights from the first available five-year ACS (2005–2009). As an example of this methodology, suppose that 30 percent of individuals in the engineering major cluster become aerospace engineers and 70 percent become mechanical engineers. Then the unemployment rate for the engineering cluster would be $0.3 * U_y^{aero} + 0.7 * U_y^{mech}$.

unemployment rate as the average unemployment rate in the application year and the three preceding years and denote this unemployment rate as $\bar{U}_y$ for application year y.

Figure 1(a) plots the economy-wide unemployment rate, the national unemployment rate for physicians, and the medical-school-applicant-relevant business cycle from 1980 to 2019. 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 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).[5] 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.[6] 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 A1(a)). Notably, the average difference in al-

[5] 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.

[6] 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.

truism by undergraduate major is similar in magnitude to the gap between male and female physicians observed in the same data (Figure A1(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 A1(c)).

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.[7]

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

[7]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).

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 A2. 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 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 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).[8] 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 A2), these fluctuations do not systematically translate into differences in the gender makeup of matriculating classes (see Figure A3 and Table A2).

[8]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.

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.

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

$$Outcome_{sy} = \beta_0 + \beta_1 \bar{U}_{sy} + \lambda_s + \lambda_y + \epsilon_{sy} \tag{1}$$

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.[9] 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.[10]

The remainder of Table 1 focuses on responses in the number of applicants by under-

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

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

graduate 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.

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.[11] 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.[12] Recent work using administra-

[11]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.

[12]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

tive 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.[13]

We supplement this information on firm size with data on physician organizational affiliation 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 between independent, hospital-owned, and health system–affiliated practices. Compensation models differ systematically across these ownership types: independent physicians are typically paid on a fee-for-service basis, while hospital- and system-employed physicians are more often salaried (AMA, 2025). As a result, more financially motivated providers may systematically sort into smaller, independent practices.

Finally, to examine impacts on patient outcomes, we use a 20 percent sample of patient-level Medicare claims from 1999 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.[14] 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

(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).

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

[14] 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.

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-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 2001 when using the SK&A data, and between 1989 and 2003 (2001) 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:

$$Outcome_{it} = \beta_0 + \beta \cdot \bar{U}_{y(i)} + \lambda_{specialty} + \lambda_{experience} + \lambda_t + \epsilon_{it} \tag{2}$$

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.[15] P-values and confidence intervals are calculated using a wild cluster bootstrap clustered by application cohort (Cameron et al., 2008).

[15]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.

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

$$Outcome_{it} = \beta_0 + \sum_{q=1}^{4} \beta_q \cdot \mathbb{1}\left\{\bar{U}_{y(i)} \in Q_q\right\} + \lambda_{specialty} + \lambda_{experience} + \lambda_t + \epsilon_{it} \tag{3}$$

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 A6(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

Average Medicare spending per beneficiary increases as the level of unemployment experienced at the time of a physician's application to medical school increases. Figure 4(a) plots the coefficients on quartiles of $\bar{U}_{y(i)}$ from estimation of equation (3) and shows a strong relationship between economic conditions in competing occupations during undergraduate years and average Medicare spending per beneficiary decades later. As shown in column (1) of Table 2, which shows results from estimation of equation (2), a one-percentage-point increase in $\bar{U}_{y(i)}$ leads to an increase in average annual Medicare spending per beneficiary of 12.3 dollars, or 4.2 percent relative to the baseline mean of 296.4 dollars.

It does not appear that higher average resource use for those that applied to medical school during economic downturns can be explained by differences in patient severity. Figure 5(a) presents results from estimation of equation (3) using average beneficiary risk score at the physician-year level as the outcome and shows that there is little relationship between patient risk scores and $\bar{U}_{y(i)}$. In anything, higher unemployment in competing occupations at

the time of medical school applications leads physicians to see patients with lower severity: as shown in column (1) of Table A3, a one-percentage-point increase in $\bar{U}_{y(i)}$ leads to a reduction in average patient risk scores by 0.4 percent (a reduction of 0.007 relative to the mean of 1.7). As such, the impacts of $\bar{U}_{y(i)}$ on Medicare spending per beneficiary are very similar regardless of whether we control for average patient severity.

In addition to differences in average Medicare spending, physicians who applied to medical school during periods of high unemployment in competing occupations also tend to practice in smaller practices. As shown in Figure 4(b), practice size is generally decreasing across quartiles of $\bar{U}_{y(i)}$. Notably, physicians who applied to medical school when the medical-school-applicant-relevent unemployment rate was one-percentage-point higher on average practice in practices with 13.7 fewer other physicians, or 2.8 percent relative to the mean of nearly 500.

V Potential mechanisms

When the medical-school-applicant-relevent unemployment rate is high, two things happen. First, as shown in Section III, the composition of matriculating classes shifts to include a higher share of students from non-traditional pre-medical backgrounds. Second, since more individuals apply, whereas the number of slots does not change, the process of getting into medical school becomes more competitive (see Section III). Consistent with an increase in selectivity during economic downturns, Figure A8 provides suggestive evidence that MCAT scores of matriculating students rise slightly when the medical-school-applicant-relevent unemployment rate is high. Thus, changes in practice style associated with poor economic conditions prior to medical school could be the result of differences in preferences or skill levels of individuals who become physicians during economic downturns.

In columns (2) through (4) of Tables 2 and A3, we look at the direct effect on practice style of the share of matriculants from non-traditional majors and the acceptance rate in a physician's cohort rather than $\bar{U}_{y(i)}$. While measures are individually associated with practice style outcomes (columns 2 and 3—not surprising as these measures are negatively correlated), when both measures are included in the same regression in column (4), it appears

that conditional on the share of matriculants coming from non-traditional majors, there is no remaining effect of selectivity.

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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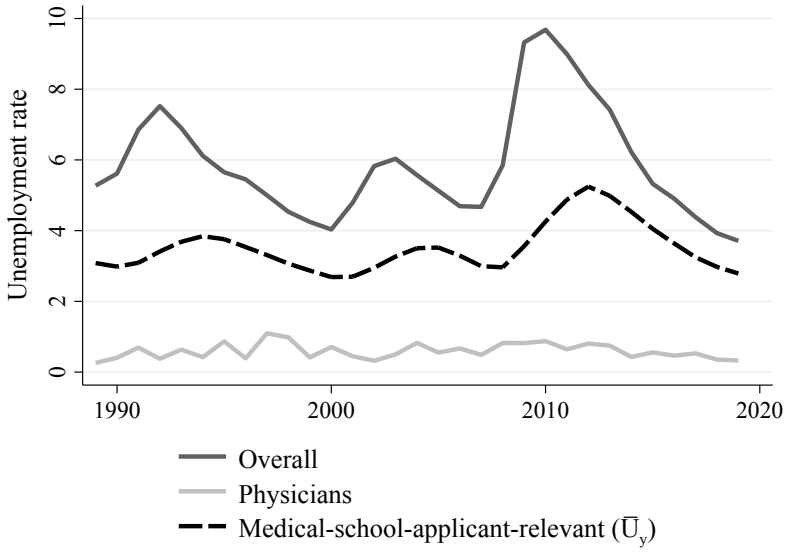
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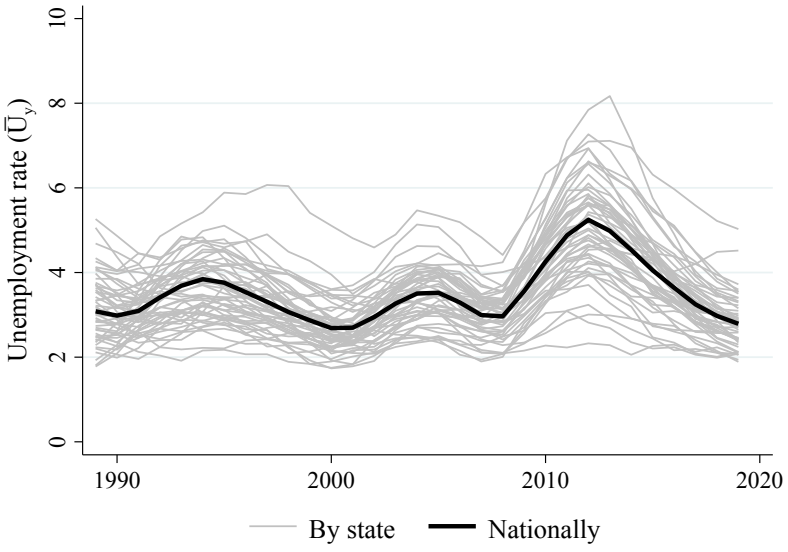
VII Figures

Figure 1: Unemployment rates overall and by state over time

(a) Overall and by occupation nationally



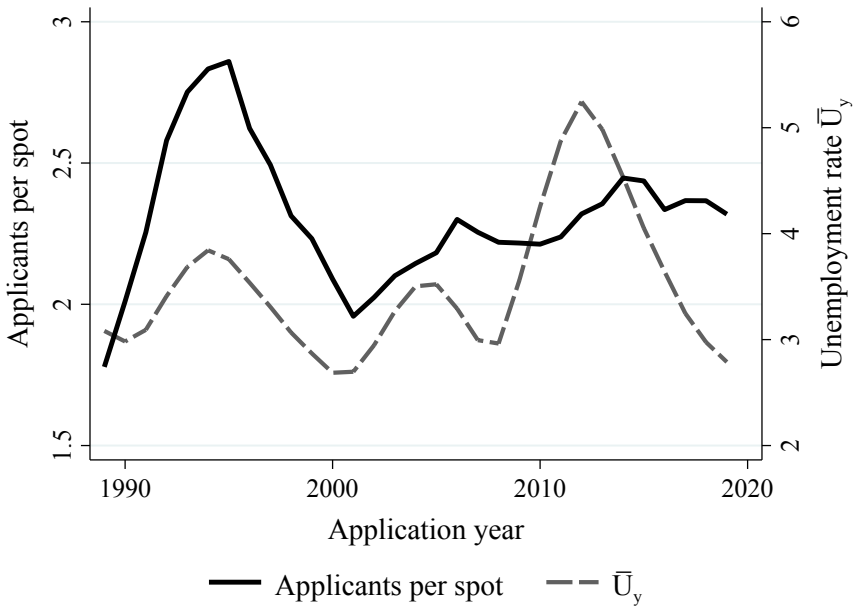
(b) Medical-school-relevant unemployment by state



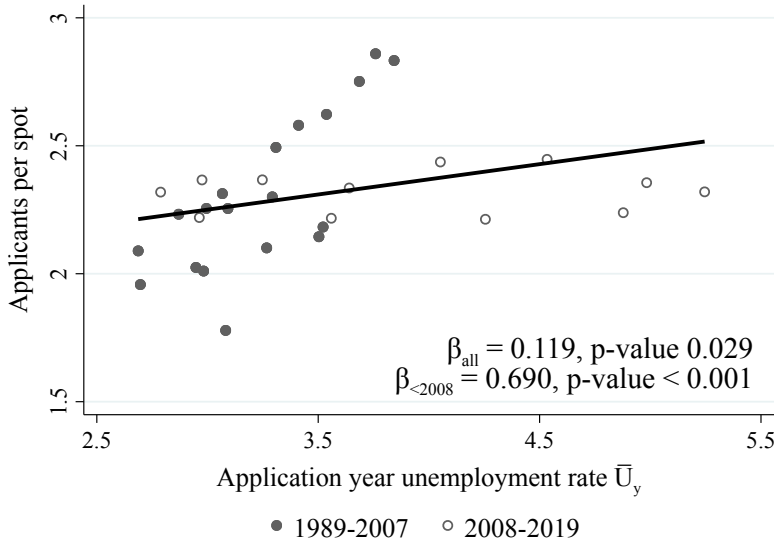
Notes: The above figures plot unemployment rates nationally (subfigure (a)) and by state (subfigure (b)). Subfigure (a) shows the economy-wide unemployment rate, the national unemployment rate for physicians, and the medical-school-applicant-relevant business cycle ($\bar{U}_t$) from 1980 to 2019; see 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: Medical school applicants per spot over time

(a) Applicants per spot and unemployment over time



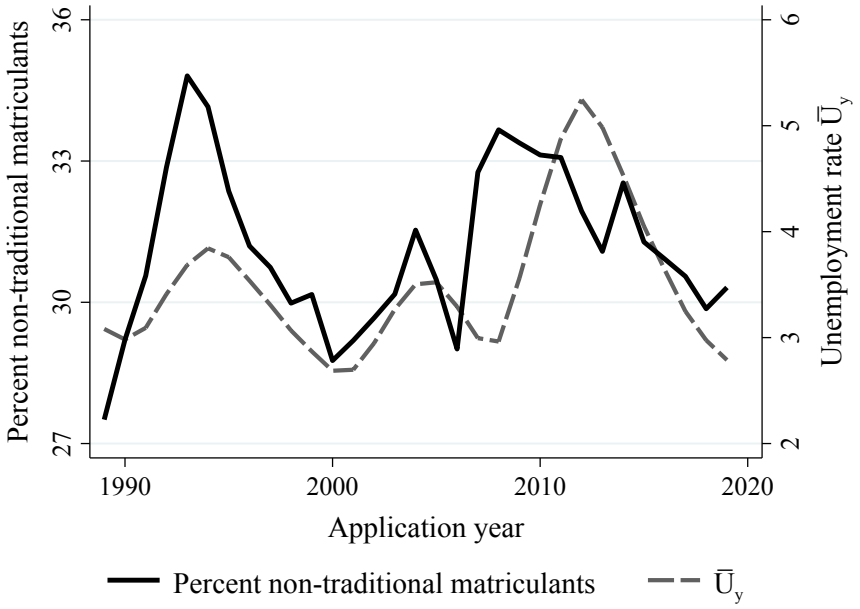
(b) Applicants per spot versus relevant unemployment



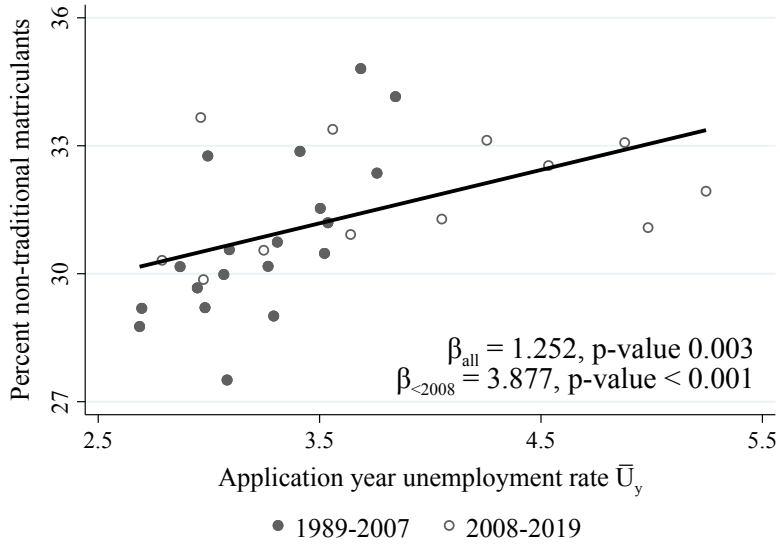
Notes: The above figures show how the annual number of applicants to medical school, divided by the number of matriculants ("spots"), covaries with the medical-school-applicant-relevant business cycle ($\bar{U}_t$) from 1989 to 2019. Subfigure (a) presents the raw time series of these variables, while 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: Percent non-traditional matriculants over time

(a) Percent non-traditional matriculants and unemployment over time



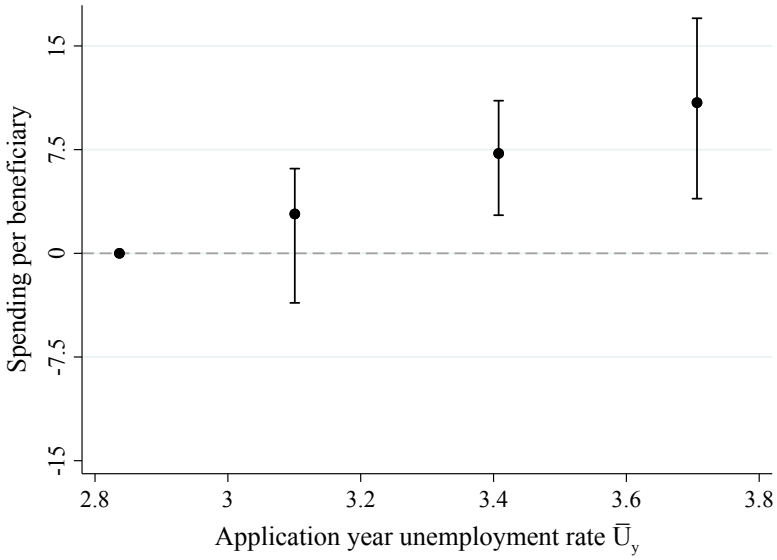
(b) Percent non-traditional matriculants versus relevant unemployment



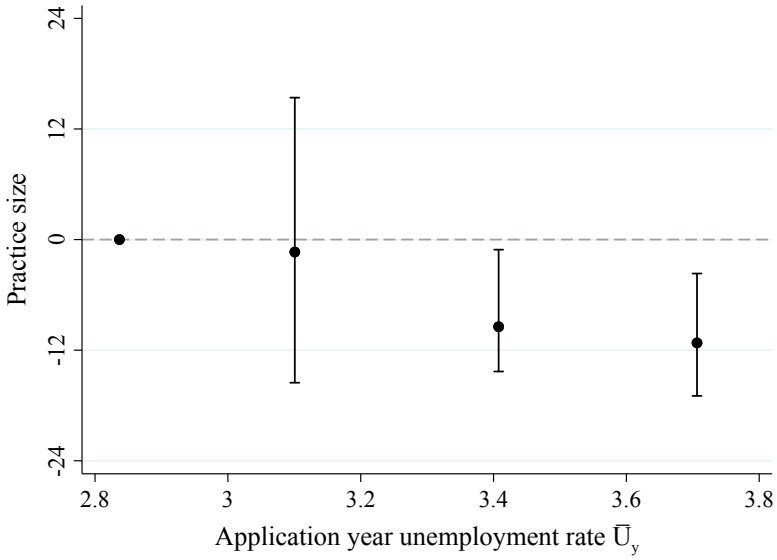
Notes: The above figures show how the annual percent of medical school matriculants with non-traditional undergraduate majors covaries with the medical-school-applicant-relevant business cycle ($\bar{U}_t$) from 1989 to 2019. Subfigure (a) presents the raw time series of these variables, while subfigure (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 the percent of non-traditional 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: Physician billing and practice size versus relevant unemployment

(a) Average Medicare spending per beneficiary



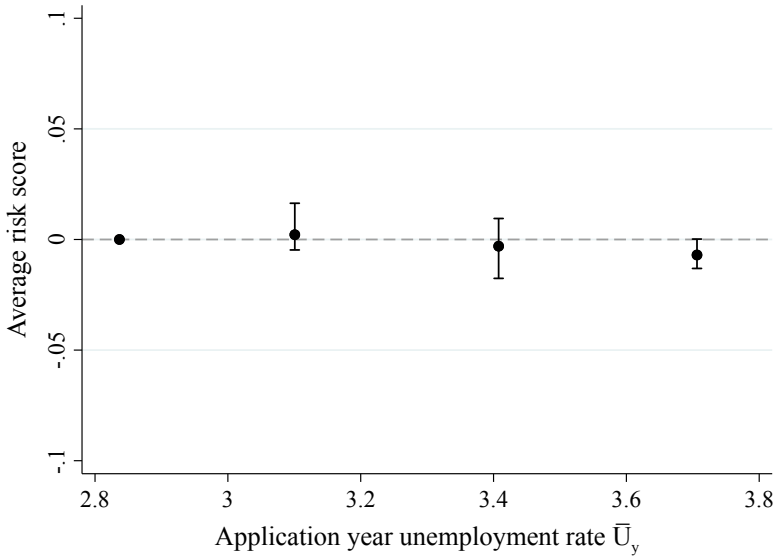
(b) Average practice size



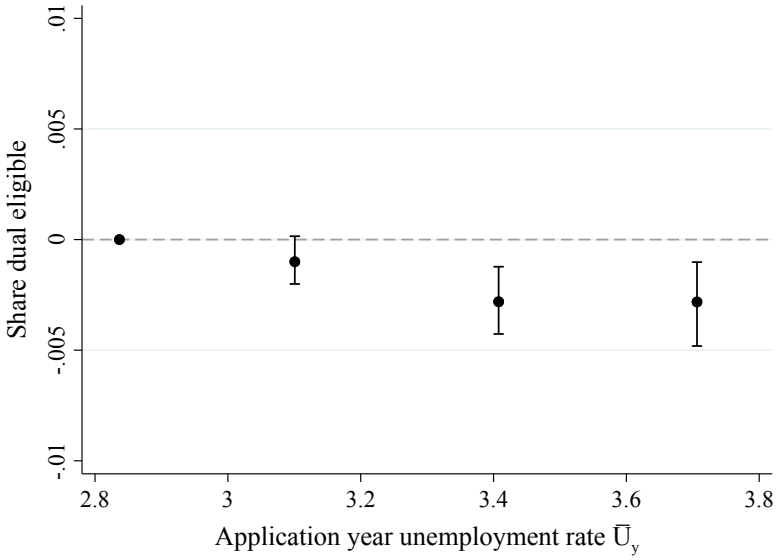
Notes: The above figures present results from estimation of equation (3) using annual total billing per Medicare beneficiary (subfigure (a)) and average practice size (subfigure (b)) as outcomes. Confidence intervals are calculated using a wild cluster bootstrap clustered by cohort (Cameron et al., 2008).The 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; standard errors are clustered at the graduation cohort level. The sample is restricted to physicians who completed their initial medical education in the United States, applied to medical school between 1989 and 2007, and have at least seven years of experience in a given outcome year. See Section II for details on the construction of $\bar{U}_y$. Data on spending per beneficiary come from the public-use Part B Medicare files from 2013–2019, data on practice size come from the public-use Medicare Physician Compare files from 2014–2019, and data on physician characteristics come from the AMA Masterfile.

Figure 5: Patient characteristics versus relevant unemployment

(a) Average risk score among Medicare beneficiaries



(b) Share Medicare beneficiaries dual eligible for Medicaid



Notes: The above figures present results from estimation of equation (3) using average risk score among Medicare beneficiaries (subfigure (a)) and share Medicare beneficiaries that are dually eligible for Medicaid (subfigure (b)) as outcomes. Confidence intervals are calculated using a wild cluster bootstrap clustered by 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; standard errors are clustered at the graduation cohort level. The sample is restricted to physicians who completed their initial medical education in the United States, applied to medical school between 1989 and 2007, 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 come from the public-use Part B Medicare files from 2013–2019, and 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 $\bar{U}_{sy}$	0.67***	0.40**	0.16***	0.10
	(0.11)	(0.18)	(0.05)	(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	5.0	3.0	2.8	1.7
b. Applicants by major group	Pre-medical applicants per 100,000		Other applicants per 100,000	
	(1)	(2)	(3)	(4)
Unemployment rate $\bar{U}_{sy}$	0.23***	0.21*	0.21***	0.13**
	(0.07)	(0.13)	(0.03)	(0.07)
R^2	0.68	0.84	0.65	0.81
Mean dependent variable	8.3	8.3	3.6	3.6
Percent of mean	2.8	2.5	5.8	3.6
c. Applicants by sex	Male applicants per spot		Female applicants per spot	
	(1)	(2)	(3)	(4)
Unemployment rate $\bar{U}_{sy}$	0.44***	0.23**	0.23***	0.17**
	(0.07)	(0.11)	(0.05)	(0.08)
R^2	0.63	0.86	0.66	0.86
Mean dependent variable	7.1	7.1	6.3	6.3
Percent of mean	6.2	3.2	3.7	2.7
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: Potential mechanisms: physician billing and practice size

a. Spending per beneficiary	(1)	(2)	(3)	(4)
Unemployment rate $\bar{U}_y$	12.34***			
	(2.07)			
	[<0.001]			
Percent non-traditional		3.89***		2.45**
		(0.52)		(0.73)
		[<0.001]		[0.03]
Acceptance rate			-4.30***	-2.28
			(0.90)	(1.19)
			[0.004]	[0.19]
Observations	1,382,410	1,382,410	1,382,410	1,382,410
R^2	0.12	0.12	0.12	0.12
Mean dependent variable	296.4	296.4	296.4	296.4
b. Practice size	(1)	(2)	(3)	(4)
Unemployment rate $\bar{U}_y$	-13.65***			
	(3.50)			
	[<0.001]			
Percent non-traditional		-4.19**		-3.71
		(1.40)		(2.13)
		[0.014]		[0.14]
Acceptance rate			3.84***	0.80
			(0.97)	(1.65)
			[0.004]	[0.64]
Observations	1,081,353	1,081,353	1,081,353	1,081,353
R^2	0.02	0.02	0.02	0.02
Mean dependent variable	488.8	488.8	488.8	488.8
Specialty fixed effects	✓	✓	✓	✓
Experience fixed effects	✓	✓	✓	✓
Data year fixed effects	✓	✓	✓	✓

Notes: The above table shows output from estimation of analogs of equation (2) using data at the physician-year level 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. See Section II for details on the construction of $\bar{U}_y$. Data on applicants and matriculants are from the AAMC, and data on billing and practice size are from public-use Medicare files.

Online Appendix

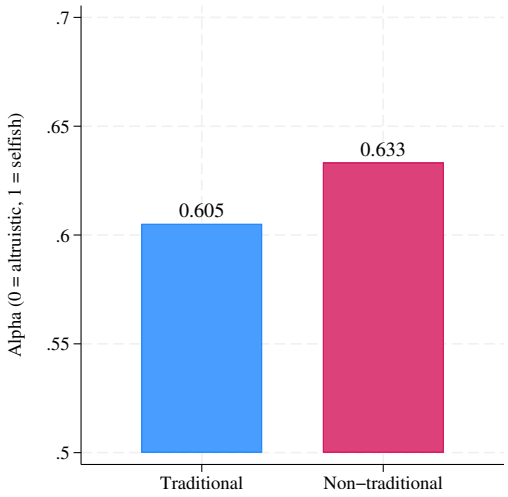
Selection into Medicine

Alexander and Schnell (2025)

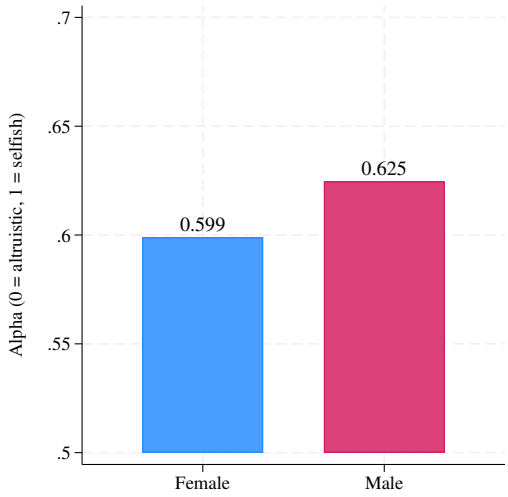
A Supplementary figures

Figure A1: Social preferences by undergraduate major and sex

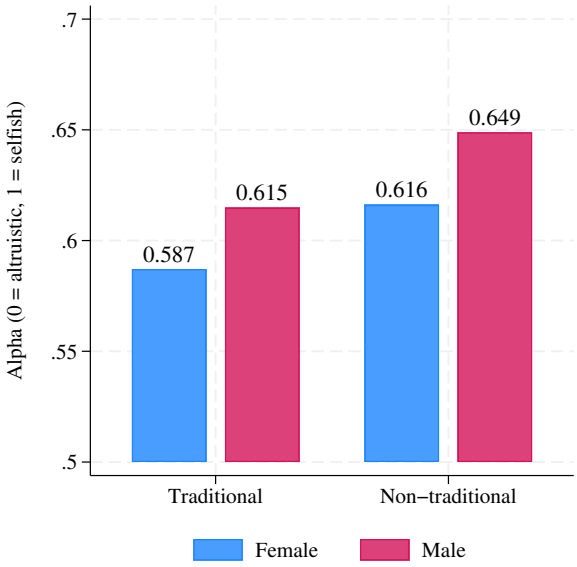
(a) By undergraduate major category



(b) By sex



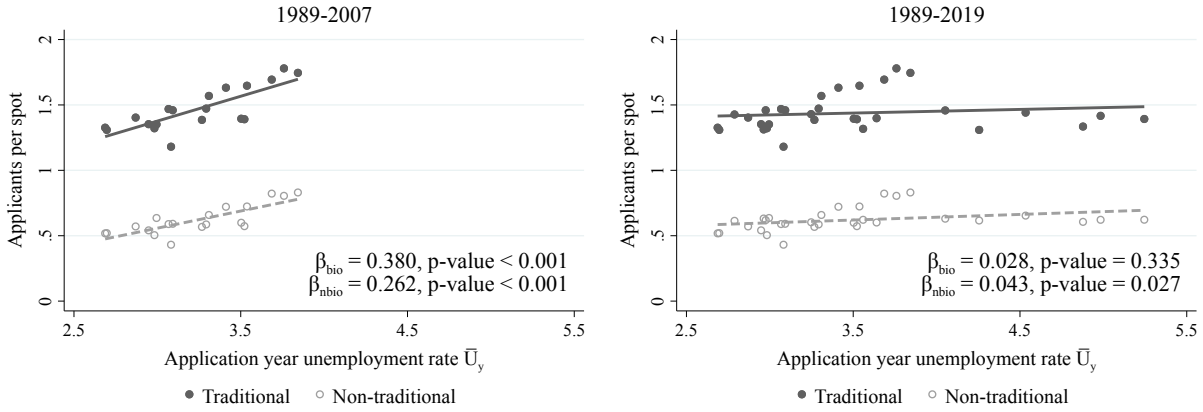
(c) By undergraduate major category and sex



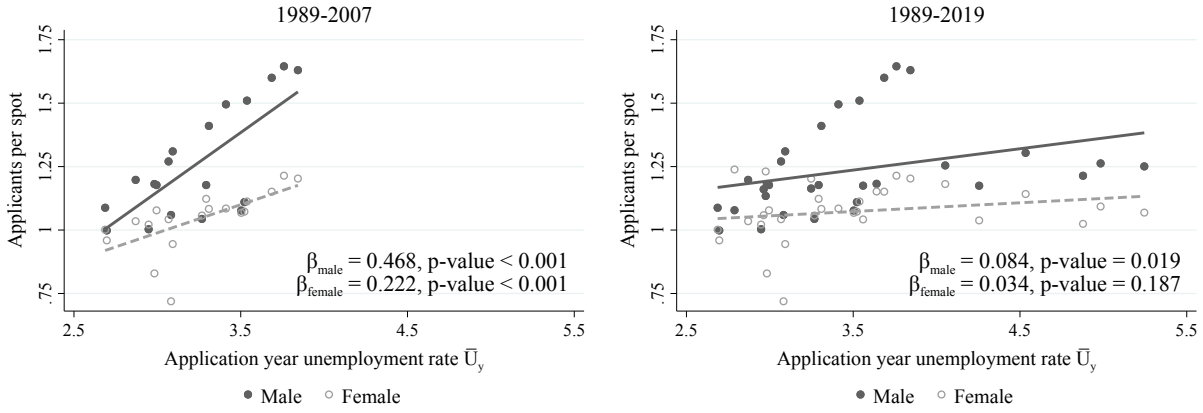
Notes: The above figures plot average measures of social preferences across undergraduate major groupings (subfigure (a)), sex (subfigure (b)), and both undergraduate major grouping and sex (subfigure (c)). Social preferences come from Li et al. (2022) and are measured using an incentivized choice experiment 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 A2: Medical school applicants per spot over time by type

(a) By undergraduate major grouping



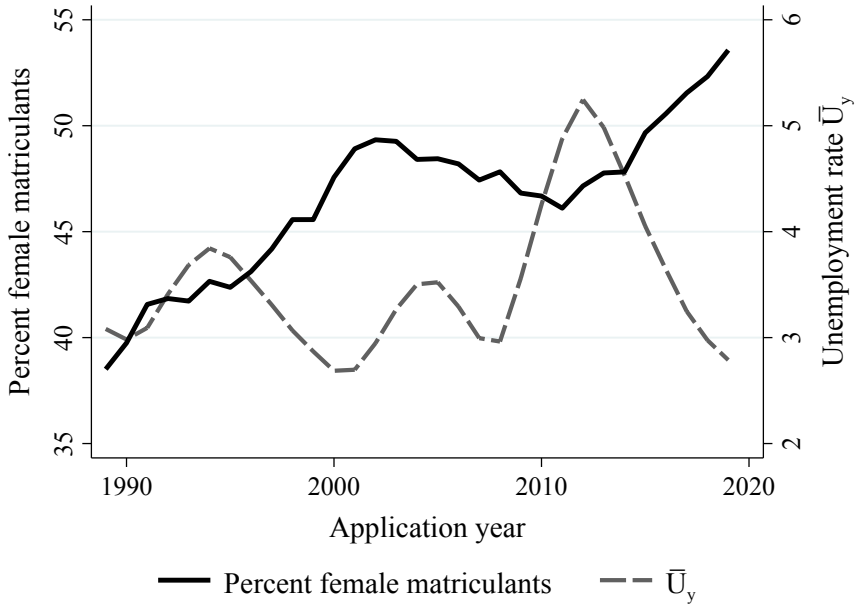
(b) By sex



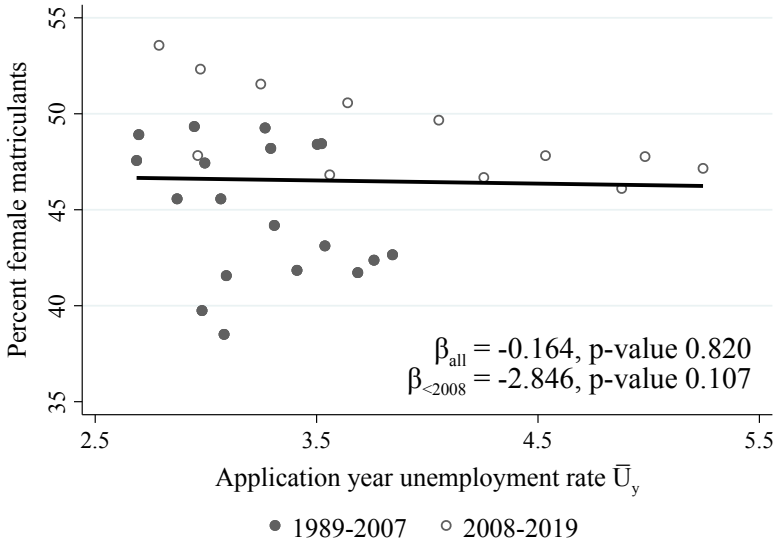
Notes: The above figures show how the annual number of applicants to medical school, divided by the number of matriculants ("spots"), covaries with the medical-school-applicant-relevant business cycle ($\bar{U}_t$) from 1989 to 2007 (left panels) and from 1989 to 2019 (right panels). Subfigure (a) separates 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 A3: Percent female matriculants over time

(a) Percent female matriculants and unemployment over time



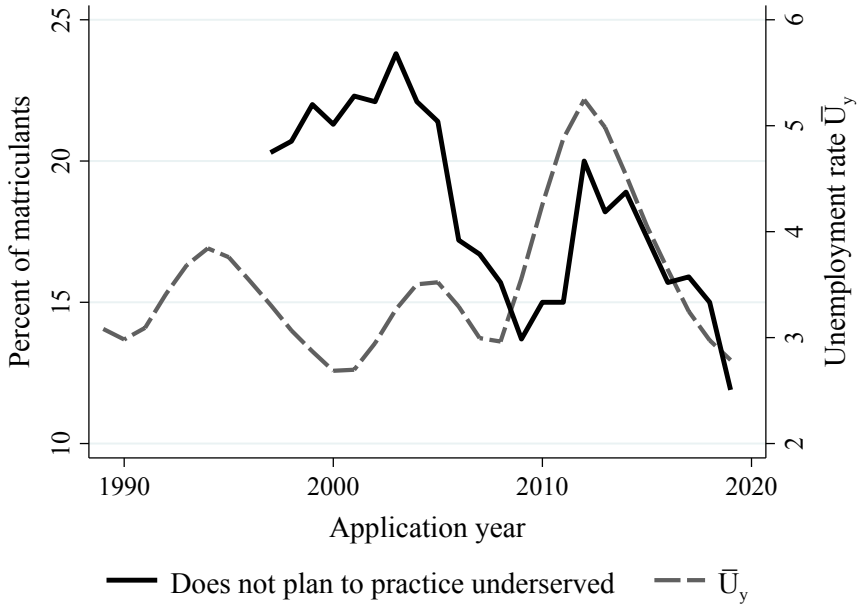
(b) Percent female matriculants versus relevant unemployment



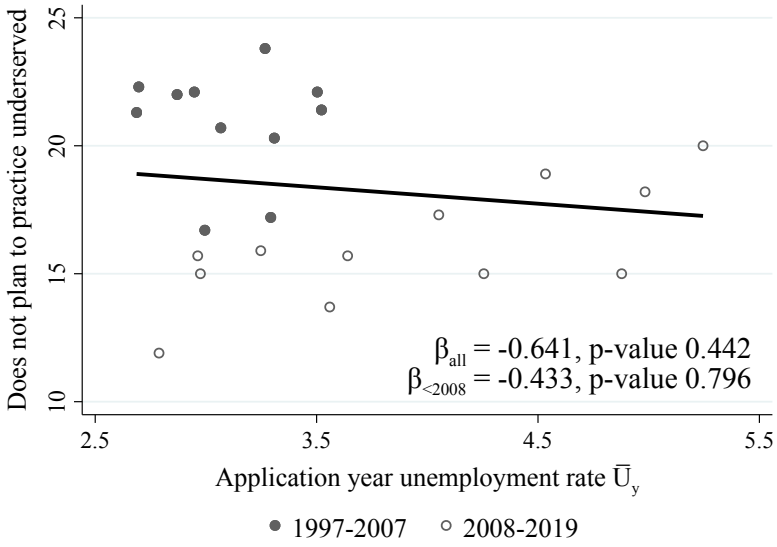
Notes: The above figures show how the annual percent of medical school matriculants who identify as female covaries with the medical-school-applicant-relevant business cycle ($\bar{U}_t$) from 1989 to 2019. Subfigure (a) presents the raw time series of these variables, while subfigure (b) shows a scatterplot 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 the percent of female matriculants on $\bar{U}_t$ with robust standard errors. See Section 2 for details on the construction of $\bar{U}_t$. Data on matriculants are from the AAMC.

Figure A4: Percent of matriculants not planning to practice in underserved area

(a) Percent of matriculants and unemployment over time



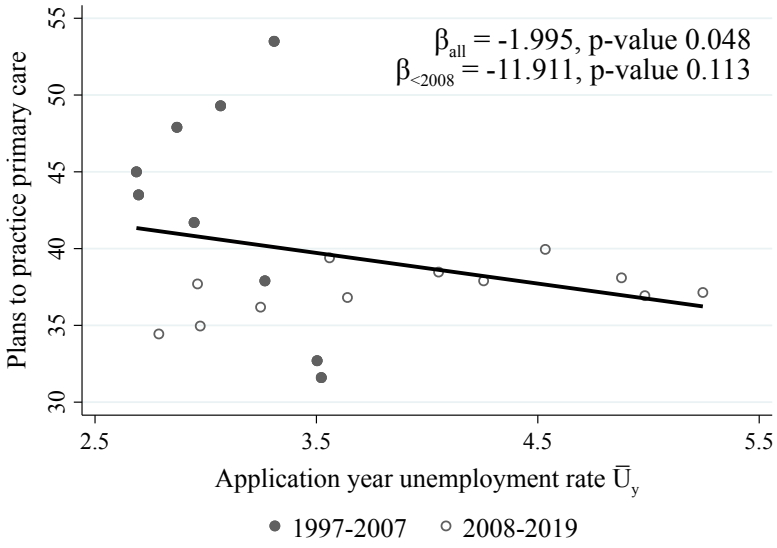
(b) Percent of matriculants versus relevant unemployment



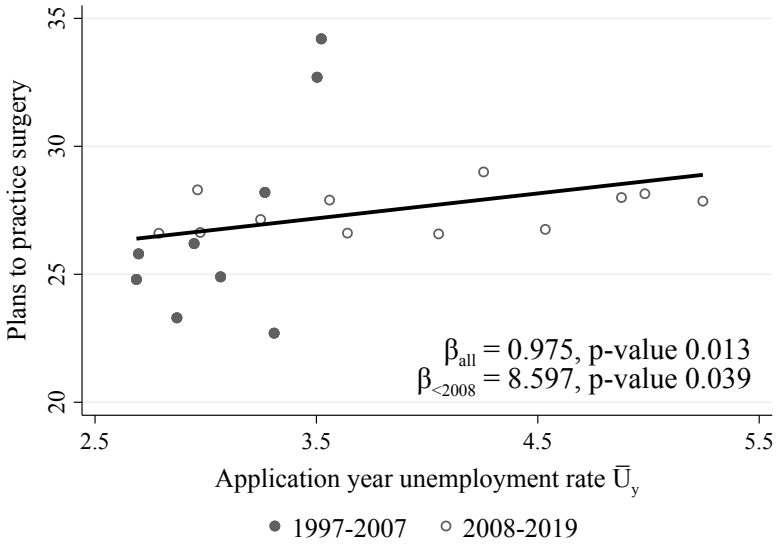
Notes: The above figures show how the annual percent of medical school matriculants responding "No" to the question "Do you plan to locate your practice in an underserved area?" covaries with the medical-school-applicant-relevant business cycle ($\bar{U}_t$) from 1997 to 2019. Subfigure (a) presents 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 (1997–2007; solid circles) and the period after (2008–2019; hollow circles). The betas and p-values reported in subfigure (b) come from bivariate regressions of the percent of matriculants not planning to practice in an underserved area on $\bar{U}_t$ with robust standard errors. See Section 2 for details on the construction of $\bar{U}_t$. Data on matriculants come from the AAMC's Matriculating Student Questionnaire.

Figure A5: Percent of matriculants planning to enter primary care, surgical specialties

(a) Primary care



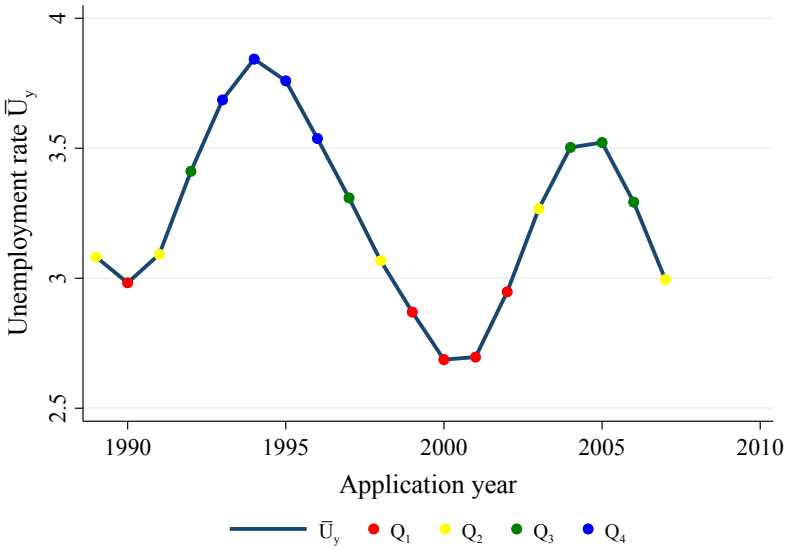
(b) Surgical specialties



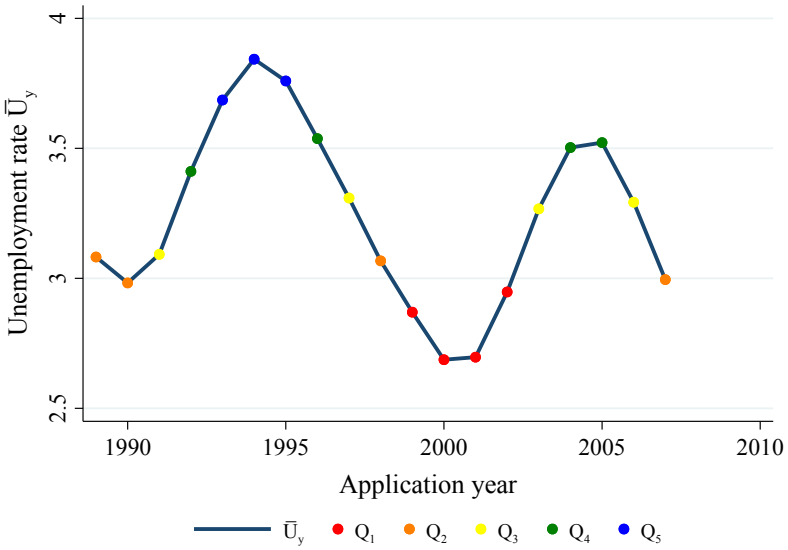
Notes: The above figures show how the annual percent of medical school matriculants reporting that they are planning to become certified in either primary care or a surgical specialty covaries with the medical-school-applicant-relevant business cycle ($\bar{U}_t$) from 1997 to 2019. "Primary care" includes family practice, pediatrics, and internal medicine; "Surgical specialties" includes ..... In both subfigures, the relationship is shown separately for the period before the Great Recession (1997–2007; solid circles) and the period after (2008–2019; hollow circles). The betas and p-values come from bivariate regressions of the percent of matriculants not planning to enter each specialty grouping on $\bar{U}_t$ with robust standard errors. See Section 2 for details on the construction of $\bar{U}_t$. Data on matriculants come from the AAMC's Matriculating Student Questionnaire.

Figure A6: Medical-school-applicant-relevant unemployment rate groupings

(a) Quartiles

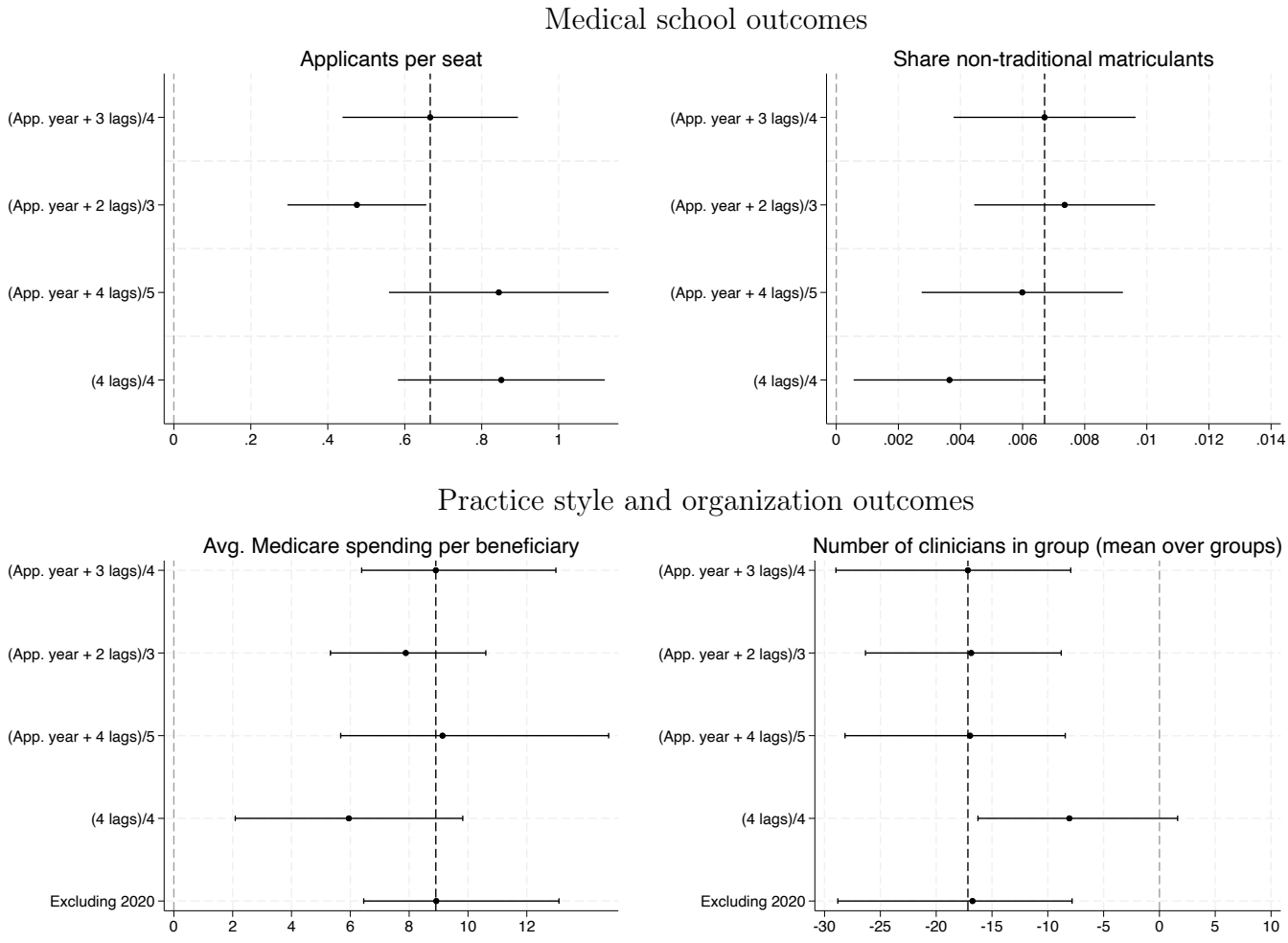


(b) Quintiles



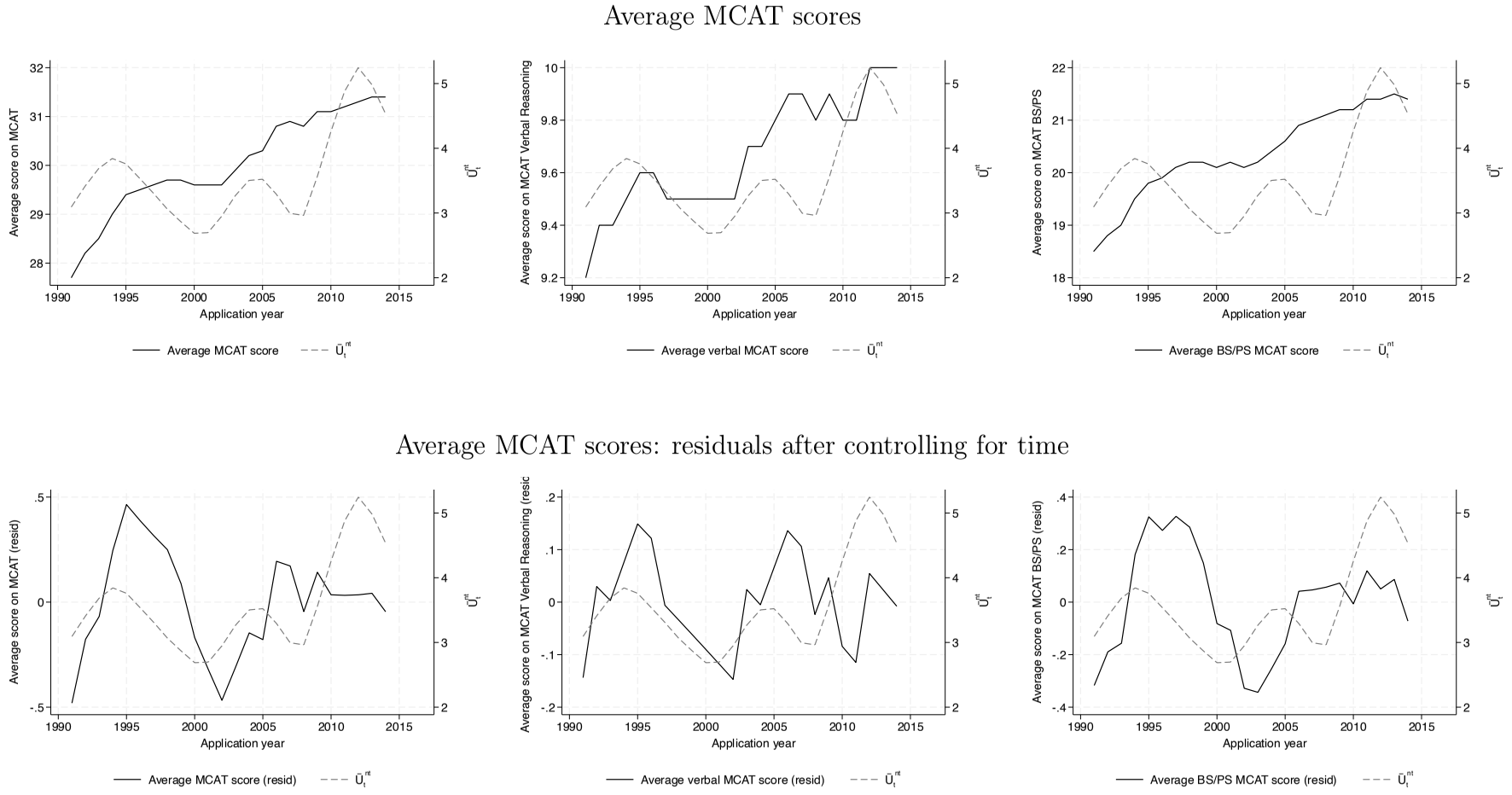
Notes: The above figures show how the medical-school-applicant-relevant business cycle ($\bar{U}_t$) from 1989 to 2007 is divided into quartiles (subfigure (a)) and quintiles (subfigure (b)). These groupings are subsequently used for analyses relying on estimation of equation (3). See Section 2 for details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

Figure A7: Robustness to timing of unemployment shock



Notes: first five coefficients from alternate definitions of the unemployment variable. Regressions correspond to Table 1, columns 2 and 5 (top row, left and right respectively), and column 1 of Tables 2 and **??** (bottom row, left and right respectively). For details on the specification, see notes of Tables 1, 2, and **??** The last row of coefficients in the bottom row of figures is from a regression excluding Medicare data from 2020.

Figure A8: 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
Medical Technologies Technicians	Zoology
Microbiology	
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	General Agriculture
Architecture	Geography
Atmospheric Sciences and Meteorology	Geology and Earth Science
Botany	Geosciences
Environmental Science	Miscellaneous Biology
Forestry	Oceanography
Cluster 5: Humanities	
Anthropology and Archeology	Linguistics and Comparative Language
Communications	Military Technologies
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	Nuclear, Industrial Radiology, and Biological Tech.
French, German, Latin, and Other Common Languages	Nutrition Sciences
General Social Sciences	Psychology
Humanities	Social Work
Journalism	Sociology
Liberal Arts	Treatment Therapy Professions
Library Science	
Cluster 6: Law / Business / Economics	
Accounting	Philosophy and Religious Studies
Economics	Political Science and Government
General Business	Pre-Law and Legal Studies
International Relations	
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 the first year of the five-year ACS (2005–2009). 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 $\bar{U}_y$	0.12**	0.69***	0.12***	0.03
	(0.05)	(0.12)	(0.04)	(0.04)
R^2	0.11	0.60	0.15	0.02
Mean dependent variable	2.3	2.3	1.7	1.5
Percent of mean	5.2	30.0	7.1	2.0
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 $\bar{U}_y$	0.03	0.38***	0.04**	0.26***
	(0.03)	(0.06)	(0.02)	(0.04)
R^2	0.02	0.62	0.11	0.64
Mean dependent variable	1.4	1.5	0.6	0.6
Percent of mean	2.1	25.3	6.7	43.3
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 $\bar{U}_y$	0.08**	0.47***	0.03	0.22***
	(0.03)	(0.09)	(0.03)	(0.05)
R^2	0.10	0.53	0.04	0.41
Mean dependent variable	1.2	1.3	1.1	1.0
Percent of mean	6.7	36.2	2.7	22.0
d. Matriculant composition	Percent non-pre-medical		Percent female	
	1989–2019	1989–2007	1989–2019	1989–2007
	(1)	(2)	(3)	(4)
Unemployment rate $\bar{U}_y$	1.25***	3.88***	-0.16	-2.85
	(0.38)	(0.80)	(0.72)	(1.67)
R^2	0.23	0.49	0.00	0.08
Mean dependent variable	31.2	30.8	46.5	45.0
Percent of mean	4.0	12.6	-0.3	-6.3
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: Potential mechanisms: patient characteristics

a. Average risk score (x100)	(1)	(2)	(3)	(4)
Unemployment rate $\bar{U}_y$	-0.69**			
	(0.26)			
	[0.032]			
Percent non-traditional		-0.19		0.24
		(0.11)		(0.23)
		[0.158]		[0.39]
Acceptance rate			0.48***	0.68**
			(0.07)	(0.25)
			[<0.001]	[0.03]
Observations	1,382,410	1,382,410	1,382,410	1,382,410
R^2	0.20	0.20	0.20	0.20
Mean dependent variable	173.1	173.1	173.1	173.1
b. Percent dual eligible	(1)	(2)	(3)	(4)
Unemployment rate $\bar{U}_y$	-0.30***			
	(0.06)			
	[<0.001]			
Percent non-traditional		-0.06*		0.02
		(0.03)		(0.04)
		[0.078]		[0.69]
Acceptance rate			0.11***	0.13***
			(0.03)	(0.03)
			[<0.001]	[<0.001]
Observations	1,382,410	1,382,410	1,382,410	1,382,410
R^2	0.09	0.09	0.09	0.09
Mean dependent variable	24.4	24.4	24.4	24.4
Specialty fixed effects	✓	✓	✓	✓
Experience fixed effects	✓	✓	✓	✓
Data year fixed effects	✓	✓	✓	✓

Notes: The above table shows output from estimation of analogs of equation (2) using data at the physician-year level 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. See Section II for details on the construction of $\bar{U}_y$. Data on applicants and matriculants are from the AAMC, and data on billing and practice size are from public-use Medicare files.