Selection into Medicine*

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Abstract

Who chooses to become a physician, and how does this selection process shape health care delivery? 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 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 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 an often-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 driving health care costs. 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). A growing literature documents heterogeneity in physician behavior and its implications for patient outcomes, yet the origins of these differences remain poorly understood. This paper investigates a fundamental but understudied question: how do individuals sort into the medical profession, and does this selection process have meaningful implications for health care delivery?

To examine how selection into medicine influences physician practice styles, this paper uses macroeconomic conditions at the time of medical school application as an exogenous shock to the applicant pool. Economic downturns—by limiting alternative employment opportunities—can influence the decision of high-skilled individuals to enter medicine rather than pursue careers in other highly paid, prestigious fields. If business cycle fluctuations alter the pool of medical school applicants, they may have long-run consequences for the characteristics of practicing physicians and, ultimately, for patient care.

Using historical data on medical school applications and matriculations from the Association of American Medical Colleges (AAMC) combined with occupation-specific unemployment rates from the Current Population Survey (CPS), we show that poor economic conditions in competing fields near the end of one's undergraduate education lead to an increase in medical school applications, both among students with pre-medical and non-pre-medical backgrounds (e.g., economics, engineering, and computer science). Moreover, these cohorts of physicians exhibit different practice styles and spending patterns decades later: Medicare data reveal that physicians from cohorts exposed to high unemployment rates at the time of application spend more per beneficiary and work in smaller practices. To further understand the implications of these findings, we are currently exploring how the use of low-value care and patient outcomes vary across cohorts that were subject to differential selection.

During an economic downturn in non-medical professions, two key changes occur. First,

as highlighted above, individuals who might otherwise have chosen alternative careers apply—and some are admitted—to medical school. Consistent with this, we show that matriculating classes following economic downturns have higher shares of students from non-pre-medical backgrounds. Additionally, 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. Together, this evidence suggests that economic downturns may lead more financially motivated individuals to enter the medical profession. This makes sense, as physicians in the United States are highly paid (Gottlieb et al., 2025), and medicine is often considered a "recession-proof" industry (Dillender et al., 2021).

Second, as the number of applicants to medical school increases during economic downturns, selectivity also rises. Consistent with this, we find slight increases in the average MCAT scores of cohorts applying in years with more applicants, suggesting that economic downturns might also lead more qualified individuals to enter medicine. Although most of our analyses focus on the reduced-form effect of business cycle fluctuations—which likely shift both preferences and skills within physician cohorts—we also explore and discuss the relative influence of each mechanism.

This paper links past work in labor and education economics on investments in human capital over the business cycle to literature in health economics documenting the nature and scope of variation in physician behavior. First, we use insights from work in education to generate a shock to physician type. Past work has found that individuals who experience recessions when they are young choose majors with better employment prospects, and prioritize income over deriving meaning from their job (Blom et al., 2021; Cotofan et al., 2023; Weinstein, 2022). On the other hand, employment in the health care sector has been shown to be stable over business cycle (Dillender et al., 2021), and physicians are very high earners (Gottlieb et al., 2025). Taken together, we show that when employment prospects in alternative occupations are poor, many individuals switch to medicine—an occupation at the top of the income distribution with stable employment over the business cycle.

After demonstrating that business cycle variation at the time of to medical school application generates a shock to average physician type, we then link variation in average physician

type to variation in how physicians practice medicine. We show that physician type is a potential explanation for the large variation in physician behavior, practice style, and costs which has been documented in prior work (see, for example, Skinner and Fisher, 2010 and Finkelstein et al., 2016). Differences in underlying physician preferences may also be a contributing factor to why physician responses to financial incentives have been found to vary widely across different settings (for example, the widely varying success across alternative payment models documented in Smith, 2021).

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. Finally, Section V provides a discussion and 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 the average 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 occupa-

tion codes.[1] 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, earth sciences, humanities, education, and pre-law/business/economics.[2] 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.[3]

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 biology, chemistry, and biochemistry have accounted for nearly half of all medical school applicants over the past three decades.

[1] 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.

[2] See Table A2 for a full list of the majors categorized into each cluster.

[3] 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 $0.3 * U_t^{aero} + 0.7 * U_t^{mech}$.

We define "traditional" 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 decide whether to apply to medical school. The decision happens during the undergraduate degree because applicants must have taken particular undergraduate classes in order the be eligible to apply. Since we only observe the year of application and it was fairly common during this period for students to take a gap year or two between college graduation and medical school, we account for this delay in our measure of economic conditions. To approximate economic conditions at the end of an applicant's undergraduate degree, we compute the medical-school-applicant-relevant unemployment rate as the average unemployment rate in the application year and the three preceding years. We denote this unemployment rate as $\bar{U}_t^{nt}$.

Figure 1 plots the economy-wide unemployment rate, the medical-school-applicant-relevant business cycle, and the unemployment rate for physicians nationally from 1980 to 2019. Since majors that commonly lead to medical school tend to produce graduates who enter occupations with relatively low unemployment rates, it is unsurprising that the medical-school-applicant-relevant business cycle consistently falls below the overall economy-wide business cycle. Although recessions are visible in each series, the relative severity of economic downturns differs for those considering medicine compared to the broader economy. Finally, physicians stand out among other high-earning occupations with an essentially flat unemployment rate profile over the business cycle, whereas other high-income or high-prestige occupations exhibit much more pronounced cyclicality.

III Medical school outcomes

III.A Data and aggregate trends

As outlined above, data on medical school applicants and matriculants come from the AAMC's Applicant Matriculant Data File from 1989-2019. These data are aggregated at the state-major-year level, where state is state of legal residence at the time of application and year is the year of application, and report the number of unique applicants and matriculants to U.S. MD-granting medical schools. The year of application is defined as the year before the year of hypothetical matriculation (eg. a student applying with the goal of matriculating in the fall of 1990 has an application year of 1989). Major is the detailed undergraduate major—so, for example, we know how many applicants (and matriculants) were biology majors from Pennsylvania in each year, and so on for other undergraduate majors and states. We limit the sample to applicants residing in US states and the District of Columbia.

We construct two primary measures from the AAMC data. First, to consider the effects of the business cycle on aggregate application behavior, we look at the total number of applicants. Second, to consider the effects of the business cycle on the composition of medical students, we construct the share of matriculating students that come from non-traditional majors, as defined in the previous section.

We begin by examining aggregate patterns in the national data. To do so, we first regress our outcomes (total number of applicants and the share of non-traditional matriculants) on the number of medical school slots available each year, to control for changes in the size of the market over time. We then take the residuals from these regressions and plot them over time against the medical-school-applicant-relevant unemployment rate, $\bar{U}_t^{nt}$.

The top panel of Figure 2 shows a strong countercyclical pattern in total applicants; more students apply to medical school when the outside options of marginal medical students experience poor economic conditions. These patterns mirror the findings from the education literature, that educational attainment rises when young adults are exposed to poor economic conditions, and vice versa (for example, Barr and Turner (2015) and Betts and McFarland (1995) show college enrollment to be countercyclical; Cascio and Narayan (2022) show local booms in low-skill jobs decreased high school graduation rates). There

is less work studying graduate school enrollment decisions, but the existing literature again suggests the relationship to be generally countercyclical (Bedard and Herman, 2008; Johnson, 2013).

One important difference between medical school and other types of graduate school is that medical school applications require specific undergraduate coursework, rather than exams which can be taken after graduation (eg. the LSAT for law school, or the GRE for many PhD programs). Typically, applicants must have taken pre-med courses during the undergraduate degree, including one year each of biology, general (inorganic) chemistry, organic chemistry, and physics.[4] Thus, the decision to apply for medical school (or at least to take the classes such that this is an option) is non-trivial, and must happen during the undergraduate degree.

While more people apply to medical school when outside options are doing poorly, whether or not this ultimately affects the composition of physician cohorts depends on whether or not marginal applicants from non-traditional majors are high quality applicants. The top panel of Figure 3 shows that not only do more total people apply when outside options are doing poorly, there is a strong countercyclical pattern in the share of matriculants entering medical school from non-traditional majors. The bottom panel of Figures 2 and 3 plot the number of applicants and the share of non-traditional matriculants against the medical-school-applicant-relevant unemployment rate, $\bar{U}_t^{nt}$. A one percentage point increase in $\bar{U}_t^{nt}$ is associated with a four percent increase in both the total number of applicants (1620 additional applicants on an average of 38,958 per year) and the share of the cohort coming non-traditional majors (an increase in the share non-traditional of 0.0124 on an average of 0.312).

Past work has documented strong sorting of undergraduates into majors based on heterogenous tastes and preferences, such as enjoyment of coursework, earnings potential, and non-pecuniary job outcomes (Arcidiacono, 2004; Kirkeboen et al., 2016; Wiswell and Zafar, 2015; Zafar, 2013). Thus, applicants that always intended to apply to medical school will

[4]As each program determines their own prerequisites, some classes are not required at all schools, but are required at most or some. Other classes that may be required include biochemistry, genetics, psychology or sociology, english, and statistics. For a list of premedical coursework required by school, see the AAMC's Premedical Coursework Chart: https://students-residents.aamc.org/medical-school-admission-requirements/medical-school-admission-requirements-reports-applicants-and-advisors.

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.

Suggestive evidence of differences in underlying preferences across these groups comes from the data from Li et al. (2022), who conduct a survey experiment to measure altruism among a group of 284 physicians. In the publicly posted data from this experiment, physicians who reported a traditional undergraduate major exhibit higher levels of altruism compared to those from non-traditional majors.[5] The gap in altruism between those coming from traditional and non-traditional majors is of a similar order of magnitude to the gap between women and men (Figure 4), and also exists both within men and women (Figure A1. While not statistically significant, these data provide suggestive evidence of differences in underlying preference parameters associated with type of undergraduate degree.

III.B State-level variation

In addition to examining the effect of $\bar{U}_t^{nt}$ on applicant behavior and cohort composition at the national level, we can also exploit state-time variation in economic conditions. Using deviations from the national business cycle at the state level for identification allows for the inclusion of flexible time controls, and provides additional (different) variation. In particular, the measuring the response to state-level deviations from the aggregate business cycle tests whether students in states where alternative occupations are hit especially hard by a recession respond more than students coming from places where these occupations are not as affected.

In the state-level analysis, we using the following regression:

$$Outcome_{st} = \beta_0 + \beta_1 \bar{U}_{st}^{nt} + \lambda_s + \lambda_t + \epsilon_{st} \tag{1}$$

where $Outcome_{st}$ is the number of applicants per capita or the share of matriculants from non-traditional majors from state s in year t, $\bar{U}_{st}^{nt}$ is the medical-school-relevant unem-

[5]Here we define traditional majors as biochemistry, biology, chemistry, molecular and cellular biology, neurobiology, and nursing; the major categories published in these data are more coarse than we are able to use in our main analysis.

ployment rate constructed at the state level, and λ_s and λ_t are state and year fixed effects, respectively. Standard errors are clustered at the state level. Figure 5 shows the variation in $\bar{U}_{st}^{nt}$ at the state level, where each grey line is a state, and the black line is the national unemployment rate, $\bar{U}_{t}^{nt}$. As shown in Figure 5, there is considerable state-level variation in $\bar{U}_{st}^{nt}$. However, there is also the potential for considerable noise to enter into the measure $\bar{U}_{st}^{nt}$, which will be less well measured in smaller states, with correspondingly small samples in the ACS. Thus, in Table 1, we show the outcomes of equation 1 both unweighted, and weighted by state-year-level population.

Applicants respond to state-level deviations in economic conditions in addition to the aggregate business cycle, though with a magnitude of around 50–60 percent of that found in the national analysis. Columns 1 and 2 of Table 1 show increases in the number of applicants per capita of 2 to 3 percent associated with a one percentage point increase in $\bar{U}_{st}^{nt}$, which is statistically significant when the regression is population weighted (column 2). Columns 3 and 4 show a parallel analysis of the share of matriculants from non-traditional majors, which follows a similar pattern to the national analysis in column 3, but disappears in column 4. We note that while applicant behavior will likely respond primarily to local economic shocks, students apply to what is essentially a national market for medical school, and so the characteristics of who gets in (columns 3 and 4) will likely depend not just on $\bar{U}_{st}^{nt}$, but also on the economic conditions in other states.

IV Practice style outcomes

IV.A Data

Medicare spending per beneficiary

Data on Medicare spending per beneficiary comes from the Medicare provider-level utilization public use files. These files are available at the provider-year level from 2013–2022, and give aggregated statistics about payments made to each physician by Medicare for care provided over the course of the year, the number of beneficiaries treated per year, the average risk score of beneficiaries, as well as physician identifiers. We define the year of application to

medical school as the year of medical school graduation minus five (four years for medical school and one additional year to get the application year and not the matriculation year).

Our measure of spending is total Medicare spending per beneficiary, which is defined using the total medicare standardized amount for the year, divided by the number of beneficiaries treated in the year. The standardized payments are constructed by CMS to be free of geographic adjustments and special program payments not directly related to resource use, and thus allow comparisons between providers to reveal differences in spending that result only from care decisions and resource use.

Practice size

Recent work examining the income of physicians in administrative tax data has uncovered a strong relationship between physician income and firm size. In Gottlieb et al. (2025), average annual earnings for physicians increases with firm size to a peak of around $470,000 for firms of eight to ten clinicians, and then decreases. This relationship may be driven by the additional business income beyond wages derived from physician ownership in smaller group practices.

Data on physician practice size comes from Medicare's physician compare public use files. These files are periodically updated by Medicare, and archived snapshots are available at an annual level from 2014-2022.[6] For each physician, the physician compare files give the count of clinicians at the organizations the physicians are associated with in the Medicare claims data. The number of clinicians in the Physician Compare files is defined as the total number of individual clinicians affiliated with the group based on the Group Practice PAC ID.[7] Each physician can be associated with more than one organization. Our primary measure of practice size is the average practice size across all unique organizations the physician is affiliated with in that year. Results showing alternative measures (eg. median practice size, minimum practice size, maximum practice size) are shown in the appendix.

[6]We use snapshots taken in December of each year for all years except for 2015. For 2015, a December snapshot was not archived, and we use a November snapshot instead.

[7]A PAC ID is a 10-digit unique numeric identifier that is assigned to each individual or organization in CMS's Provider Enrollment, Chain, and Ownership System (PECOS). Medicare determines the number of providers in each practice using the Medicare Data on Provider Practice and Specialty (MD-PPAS) file, which assigns providers to practices based on their National Provider Identifier (NPI) and Tax Identification Number (TIN).

The physician sample

When considering physician-level outcomes we restrict the sample to physicians trained in the US, who are the most exposed to our US business cycle shock. The sample is further limited to physicians we observe treating Medicare patients during the period we have Medicare data (2013-2022), and who applied to medical school during our medical school application data period (1989-2019). Finally, we limit the sample to physician-year observations where at least 10 years have elapsed after their medical school graduation. We make this final sample restriction due to the strong life cycle effects experienced by physicians. This restriction ensures we see physicians after they have completed their residency and fellowship, and during a stable period of their practice (Altonji and Zhu, 2025). These restrictions leave us with a final sample of physicians who applied to medical school between 1989 and 2007, were trained in the US, are actively practicing ten years after graduating medical school, and who treat Medicare patients.

Empirical specification

When looking at variation in physician-level practice outcomes, we want to control for a physician's job experience (measured as the number of years post-medical school graduation) to control for life cycle effects, as well as data-year fixed effects, to control for changes over time in Medicare spending. Conceptually, we would want to include in our main regression indicators for physician experience, data-year fixed effects, and also application-year fixed effects, and then we could plot the application-year fixed effects over time against $\bar{U}_t^{nt}$. The equation could be written as

$$Outcome_{it} = \beta_0 + \lambda_{cohort} + \lambda_t + \lambda_{experience} + \epsilon_{it} \tag{2}$$

where λ_t is fixed effects for data year to control for changes in Medicare spending over time, $\lambda_{experience}$ is fixed effects for years of experience post medical school graduation to control for life cycle effects, and λ_{cohort} is fixed effects for the year of application to medical school. However, including these three sets of fixed effects runs up against the well known age-period-cohort (APC) estimation problem, where these three sets of variables cannot be

simultaneously estimated due to the linear relationship between the variables.[8]

As was pointed out in Heckman and Robb (1985), the variables on the right hand side of equation 2 are proxies of underlying unobserved variables that are not themselves linearly dependent, but the problem arises because "the approximation is so crude that it creates a problem of its own". We follow this line of reasoning to break the identification problem with better information—we can replace the cohort fixed effects with the medical-school-applicant-relevant unemployment rate, $\bar{U}^{nt}_{c(i)}$, which directly measures the state of the national labor market at the time of application, and is not a linear transformation of the other variables (Heckman and Robb, 1985). While we cannot estimate individual year effects, $\bar{U}^{nt}_{c(i)}$ can be included non-parametrically (for example, in quartiles), as the quartiles will include multiple application-years grouped together from non-consecutive points in the time period.[9,10] These equation are written below,

$$Outcome_{it} = \beta_0 + \sum_{q=1}^{4} \beta_q \bar{U}(q) + \lambda_{specialty} + \lambda_t + \lambda_{experience} + \epsilon_{it} \tag{3}$$

$$Outcome_{it} = \beta_0 + \beta \bar{U}^{nt}_{c(i)} + \lambda_{specialty} + \lambda_t + \lambda_{experience} + \epsilon_{it} \tag{4}$$

where $Outcome_{it}$ is a measure of the practice style of physician i in data year t (average spending per beneficiary and practice size), $\bar{U}^{nt}_{c(i)}$ is the unemployment rate for cohort c's application to medical school (included as quartiles in equation 3, and linearly in equation 4), and λ_t and $\lambda_{experience}$ are fixed effects for data-year and years of experience after medical school graduation as defined above. We also add fixed effects for physician specialty, $\lambda_{specialty}$.

While Medicare spending per beneficiary is a useful measure of resource intensity, in our setting patients are not randomly assigned to providers. Thus, a physician could look like

[8] In our setting, the experience variable (defined as the number of years post medical school graduation) functions like age, our data-time variable like period, and our application cohort variable (defined as 5 years before medical school graduation) like birth cohort in the most typical formulation of the APC problem.

[9] Another way to estimate equation 2 is by bringing in additional outside information that would allow you to make an additional restriction, such as an equality between two of the coefficients. However, this method can lead to misspecified models with misleading results, and is often sensitive to the particular normalization which is made (eg. assuming the effect of 25 years of experience is the same as 26 years of experience give qualitatively different results than assuming the effect of 26 years of experience is the same as 27 years of experience).

[10] Figure A3 shows which years contribute to the quartiles of unemployment rates.

a physician whose practice style is high intensity, but the relationship could be driven by the fact that their patients are sicker, and not because they practice medicine differently. However, the Medicare data also report average beneficiary risk score, which we can put on the left hand side of equations 3 and 4, to show that physicians with high spending per beneficiary do not have sicker patients, at least on average. We also include average risk score as an additional control in equations 3 and 4, and show that our results are unaffected.

Results: Medicare spending per beneficiary

Average Medicare spending per beneficiary increases as the level of unemployment experienced at the time of a physician's application to medical school increases ($\bar{U}^{nt}_{c(i)}$). Figure 6 plots the coefficients on quartiles of $\bar{U}^{nt}_{c(i)}$ from equation 3, and shows a strong relationship between economic conditions in competing occupations during undergraduate years and average Medicare spending per beneficiary decades later.[11] Column 1 of Table 2 shows the coefficient on β from equation 4 when $\bar{U}^{nt}_{c(i)}$ is included linearly. From Column 1 of Table 2, a one percentage point increase in $\bar{U}^{nt}_{c(i)}$ is associated with an increase in average Medicare spending per beneficiary of approximately 3.5 percent.

It does not appear that higher average resource use for those that entered during downturns can be explained by patient selection. Theoretically, physicians that applied during downturns could be higher quality physicians, and thus see sicker patients on average—leading to higher spending per beneficiary. However, Figure 7 puts average patient risk score on the left hand side in equation 3, and finds no relationship between average risk score and $\bar{U}^{nt}_{c(i)}$.[12] Similarly, appendix table A1 looks at the effect of $\bar{U}^{nt}_{c(i)}$ on spending per beneficiary controlling for the average patient risk score, and finds very similar results to those in Table 2.

Results: Practice size

Physicians who applied for medical school during periods of high unemployment (high $\bar{U}^{nt}_{c(i)}$) also practice in smaller practices, on average. Figure 8 plots the coefficients on quartiles of

[11] Results are similar if quintiles of $\bar{U}^{nt}_{c(i)}$ are used instead of quartiles (see Figure A4)

[12] Results are similar if quintiles of $\bar{U}^{nt}_{c(i)}$ are used instead of quartiles (see Figure A5)

$\bar{U}^{nt}_{c(i)}$ from equation 3, and shows a pattern of decreasing practice size as $\bar{U}^{nt}_{c(i)}$ increases.[13]

Evidence on mechanisms

During times of high $\bar{U}^{nt}_{t}$, two things happen: the type of students accepted to medical school shifts to include a higher share of non-traditional students, and applying to medical school also becomes more competitive: more applications are received for a fixed number of slots.When schools receive more applications, they are able to be more selective in who they accept; Figure A7 shows suggestive evidence of small increases in the average MCAT scores of matriculating students who applied during periods of poor economic conditions. Thus, changes in practice style associated with poor economic conditions prior to medical school could be the result of more financially motivated people becoming physicians, or stem from the ability of medical schools to choose higher quality applicants, if these higher quality applicants end up in smaller firms, practicing more intensive medicine.

In columns 2 through 4 of Tables 2 and 3, 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 $\bar{U}^{nt}_{c(i)}$. 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.

An outstanding question is whether the style of medicine that results in higher Medicare spending per beneficiary that is associated with cohorts that applied to medical school during periods of high $\bar{U}^{nt}_{t}$ is good or bad for patients. In other words, is the higher spending coming from health care services with high or low returns for patients? Is this pattern a sign of high or low quality physicians being selected into the profession? While we cannot answer these question with the public use Medicare data, we plan to investigate these questions directly using the confidential Medicare claims data in the next iteration of this paper. In particular, we plan to investigate spending separately on high versus low value services.

[13]Results are similar if quintiles of $\bar{U}^{nt}_{c(i)}$ are used instead of quartiles (see Figure A6)

V 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 $\bar{U}_t^{nt}$ 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, on average. 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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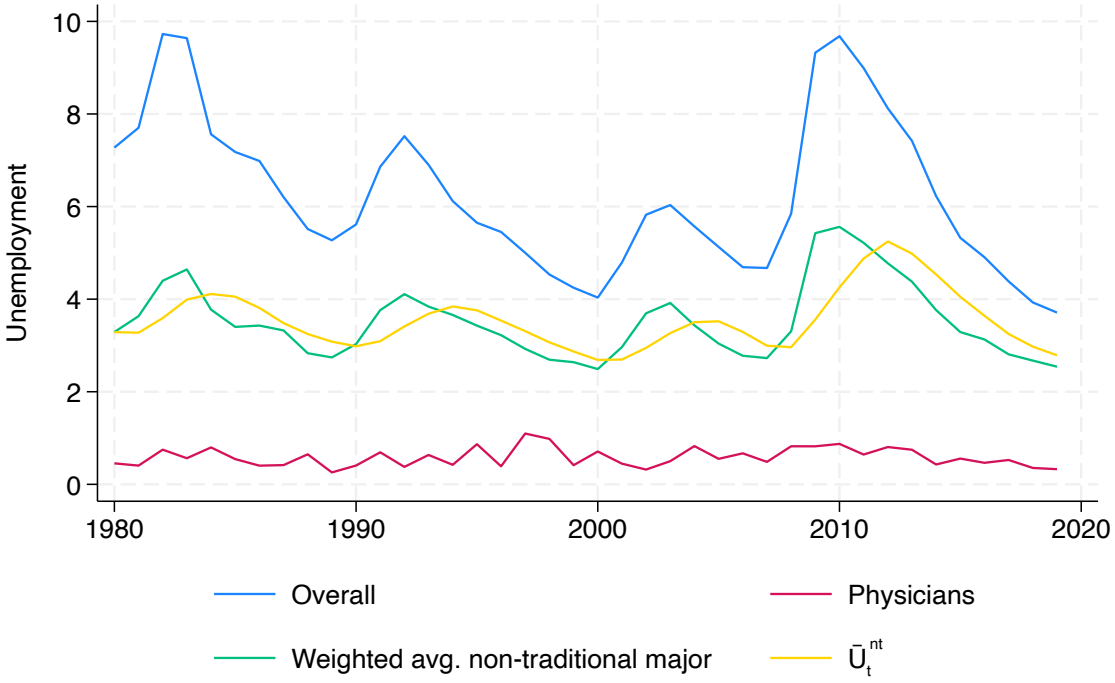
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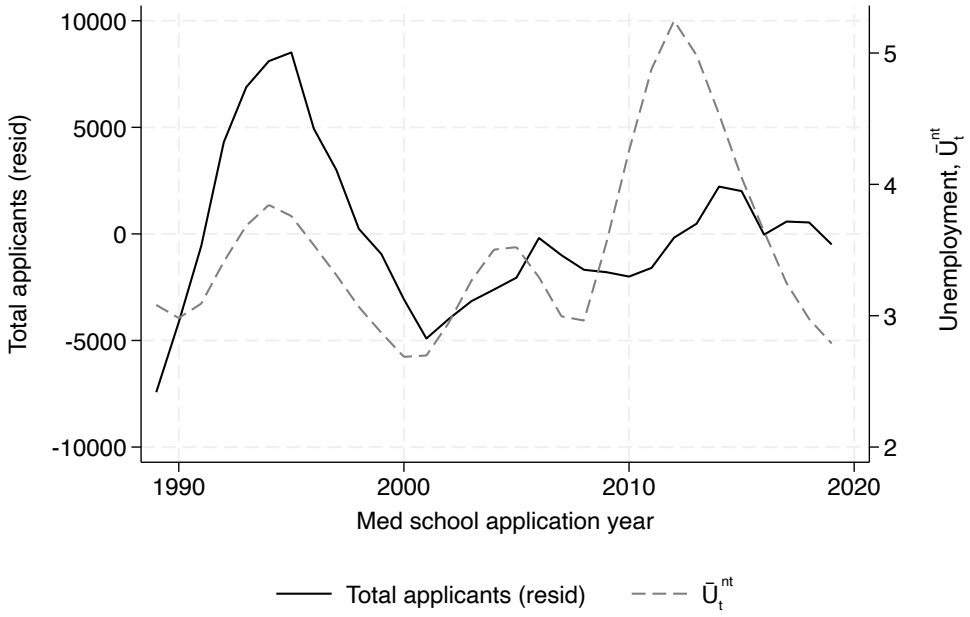
VI Figures

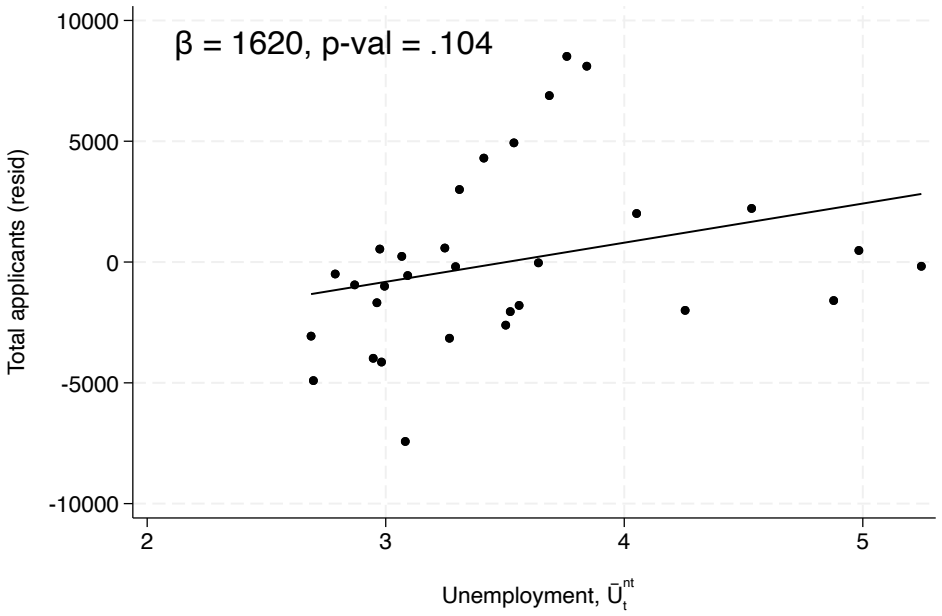
Figure 1: Unemployment rates over tine



Notes: Unemployment rates come from the CPS.

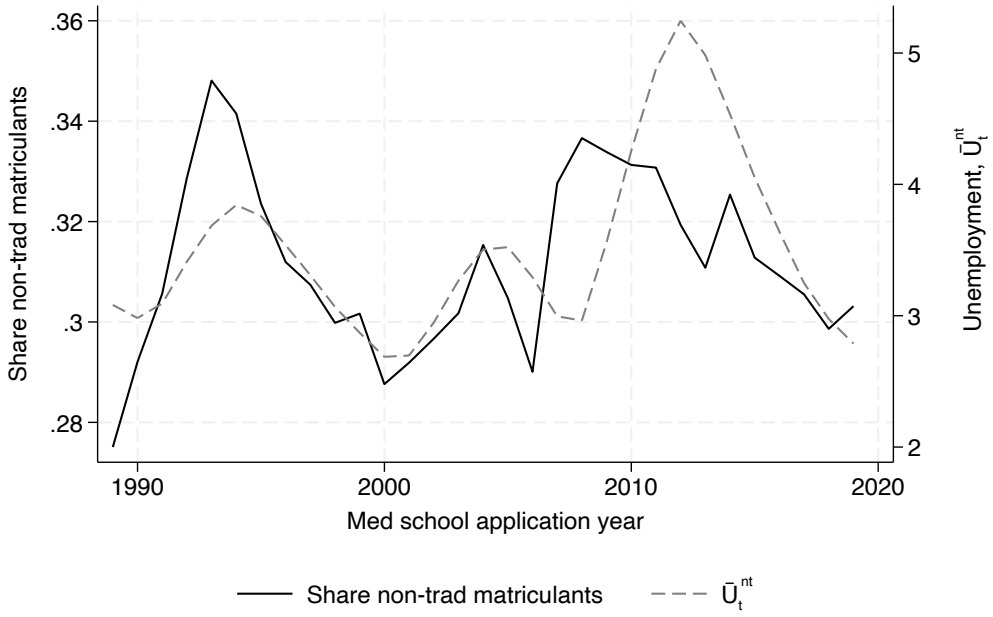
Figure 2: Total applicants over time

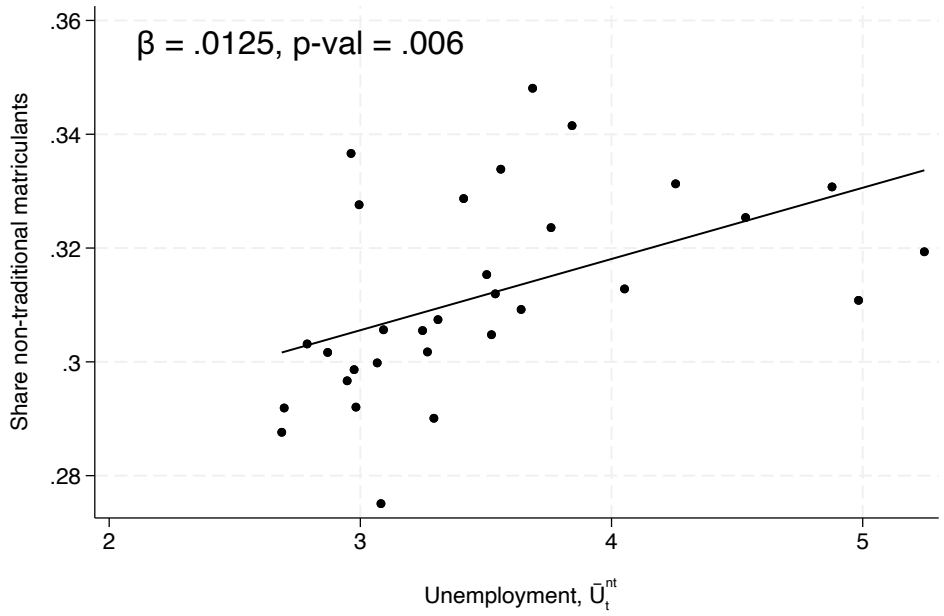




Notes: Residuals after controlling for the total number of matriculants. Beta and p-value from a bivariate regression of the residuals on $\bar{U}_t^{nt}$, with robust standard errors.

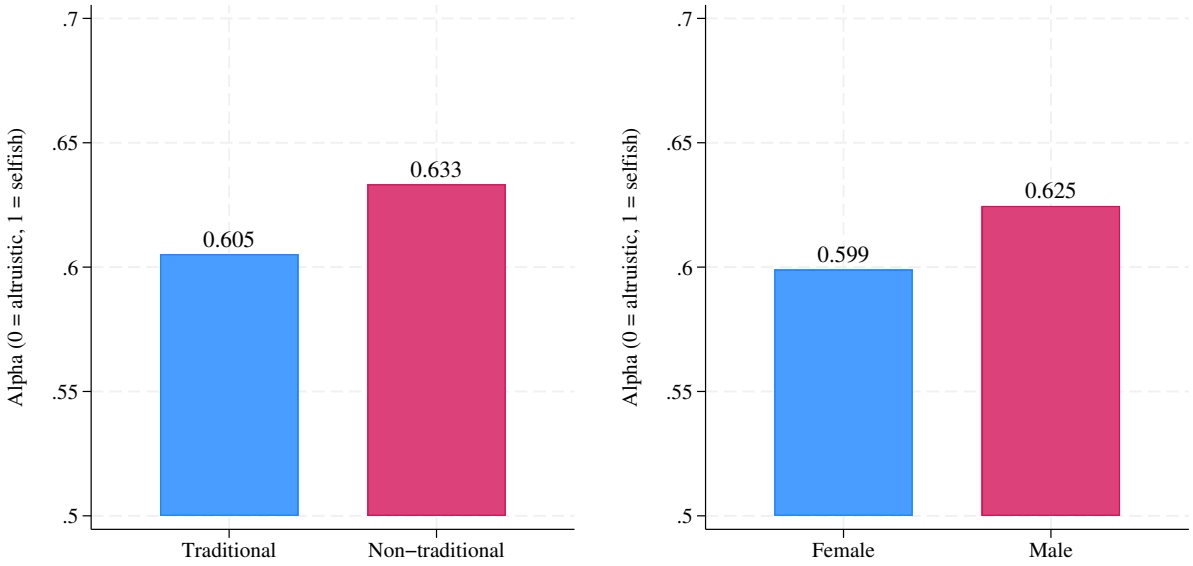
Figure 3: Share non-traditional applicants over time





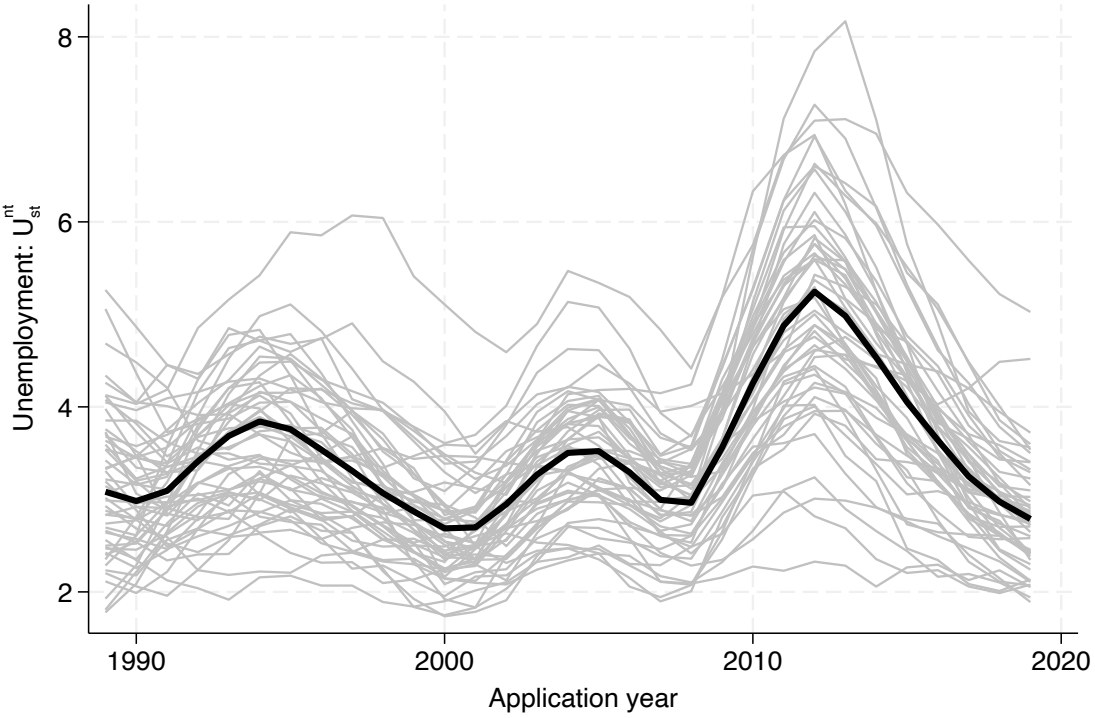
Notes: Residuals after controlling for the total number of matriculants. Beta and p-value from a bivariate regression of the residuals on $\bar{U}_t^{nt}$, with robust standard errors.

Figure 4: Undergraduate major as a proxy for underlying type.



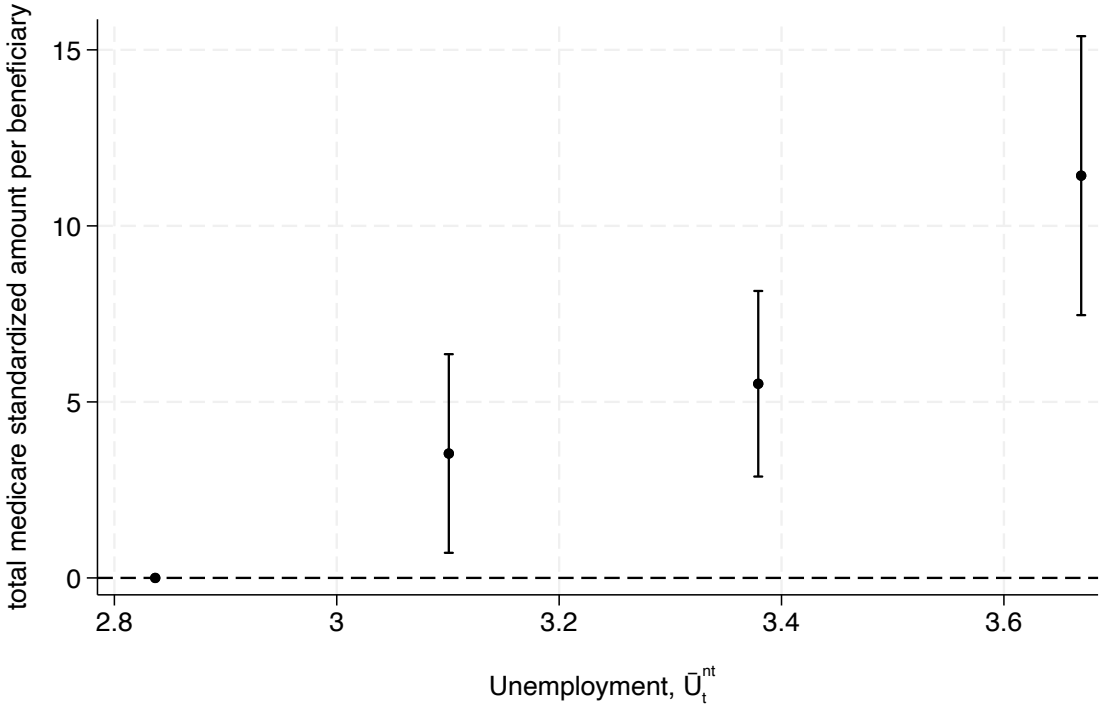
Notes: Underlying data on altruism come from Li et al. (2022).

Figure 5: State-level variation in unemployment: $\bar{U}_{st}^{nt}$



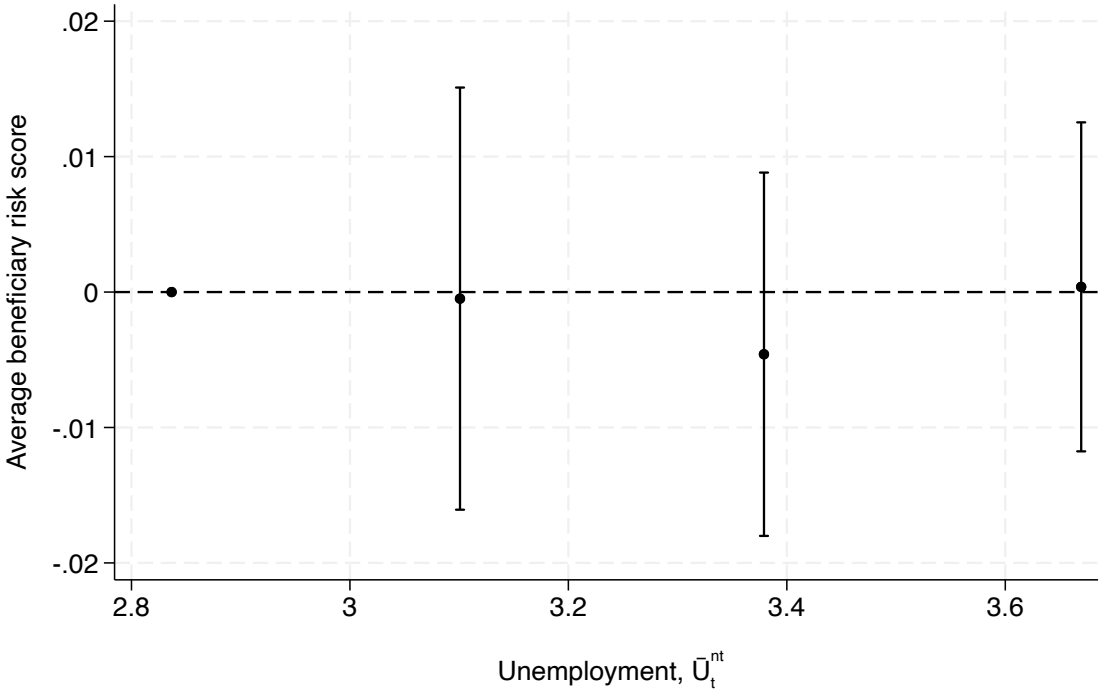
Notes: Each grey line is a state-specific measure of unemployment, the bold black line is the national measure.

Figure 6: Medicare spending per beneficiary



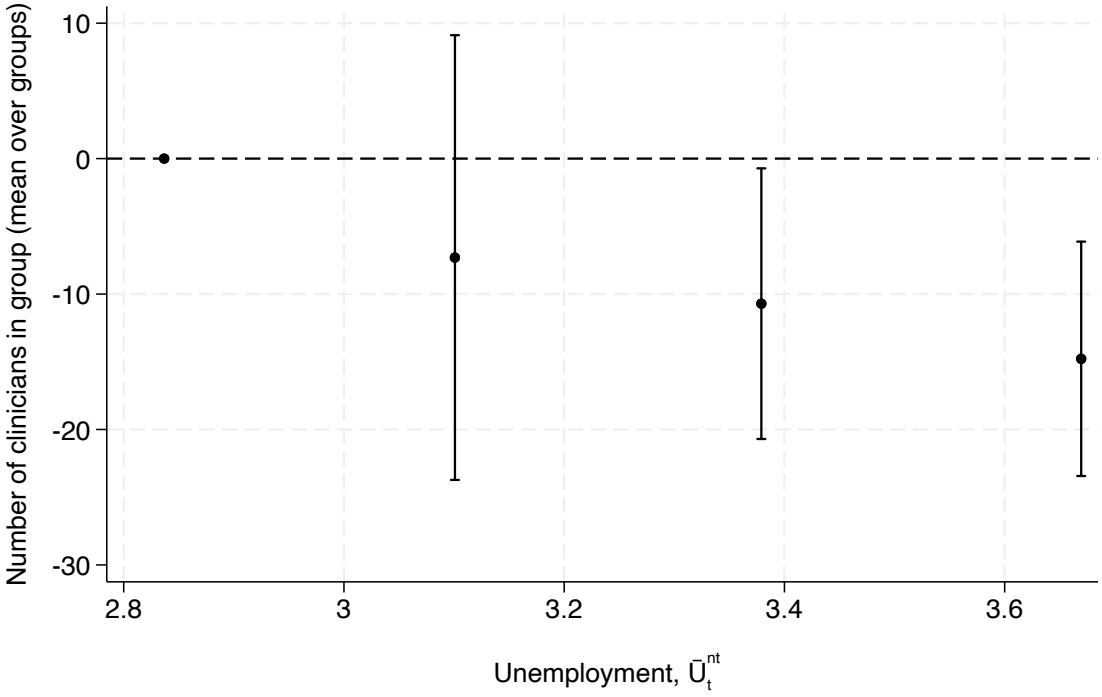
Notes: Data at the physician-year level. Sample is physicians trained in the US, who applied to medical school between 1989 and 2019, and who appear in the Medicare physician-level utilization files from 2013-2022, and who are at least 10 years past their medical school graduation year. Standard errors clustered at the cohort level.

Figure 7: Average risk score



Notes: Data at the physician-year level. Sample is physicians trained in the US, who applied to medical school between 1989 and 2019, and who appear in the Medicare physician-level utilization files from 2013-2022, and who are at least 10 years past their medical school graduation year. Standard errors clustered at the cohort level.

Figure 8: Average practice size



Notes: Data at the physician-year level. Sample is physicians trained in the US, who applied to medical school between 1989 and 2019, and who appear in the Medicare physician compare files from 2014-2022, and who are at least 10 years past their medical school graduation year. Standard errors clustered at the cohort level.

VII Tables

Table 1: State-level analyses

	Total applicants per capita (100k)		Share matriculants non-traditional (*100)	
	(1)	(2)	(3)	(4)
$\bar{U}_{st}^{nt}$	0.242	0.402**	0.464	-0.110
	(0.225)	(0.179)	(0.357)	(0.344)
State FEs	✓	✓	✓	✓
Year FEs	✓	✓	✓	✓
Population weighted		✓		✓
Obs.	1,530	1,530	1,530	1,530
R^2	0.82	0.86	0.50	0.63
Mean	13.21	13.21	26.85	26.85
Pct of mean	1.8	3.0	1.7	-0.4
Clusters	51	51	51	51

Notes: standard errors clustered at the state level.

Table 2: Medicare spending per beneficiary

	(1)	(2)	(3)	(4)
$\bar{U}_t^{nt}$	12.17***			
	(2.24)			
Share non-trad		2.07***		1.59***
		(0.46)		(0.43)
Acc. rate			-0.59***	-0.22
			(0.20)	(0.17)
Experience FEs	✓	✓	✓	✓
Data year FEs	✓	✓	✓	✓
Specialty FEs	✓	✓	✓	✓
Observations	1,632,533	1,632,533	1,632,533	1,632,533
R^2	0.16	0.16	0.16	0.16
Mean dep. var.	316.90	316.90	316.90	316.90
Cohorts	19	19	19	19

Notes: Physicians with at least 10 years of experience post medical school graduation. Data at the physician - year level. Time period from medical school application year 1989-2007. Standard errors clustered at the cohort level. Share non-traditional is share*100; acceptance rate is acceptance rate*100.

Table 3: Practice size

	(1)	(2)	(3)	(4)
$\bar{U}_t^{nt}$	-17.76***			
	(5.31)			
Share non-trad		-3.59***		-3.83***
		(0.96)		(1.31)
Acc. rate			0.80***	-0.11
			(0.24)	(0.41)
Experience FEs	✓	✓	✓	✓
Data year FEs	✓	✓	✓	✓
Specialty FEs	✓	✓	✓	✓
Observations	1,362,792	1,362,792	1,362,792	1,362,792
R^2	0.05	0.05	0.05	0.05
Mean dep. var.	519.62	519.62	519.62	519.62
Cohorts	19	19	19	19

Notes: Physicians with at least 10 years of experience post medical school graduation. Data at the physician - year level. Time period from medical school application year 1989-2007. Standard errors clustered at the cohort level. Share non-traditional is share*100; acceptance rate is acceptance rate*100.

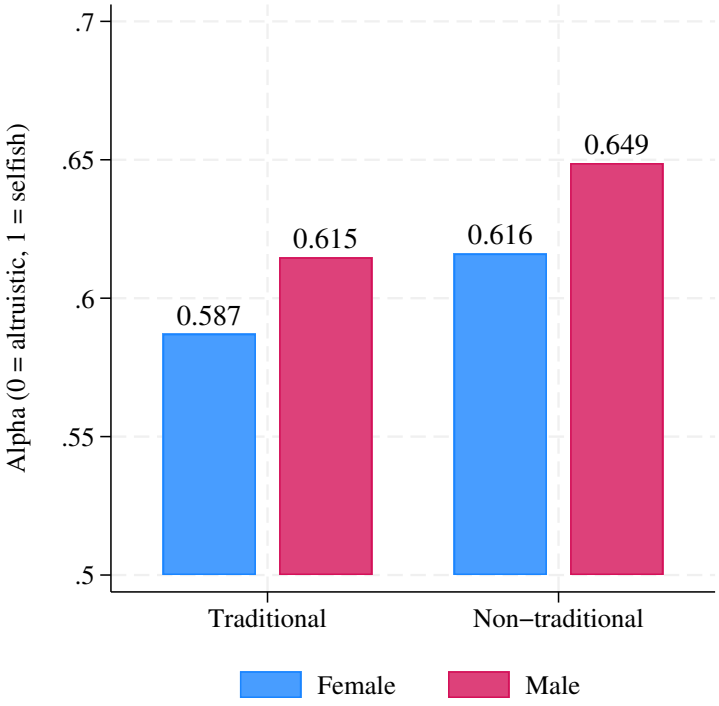
Online Appendix

Selection into Medicine

Alexander and Schnell (2025)

A Appendix figures

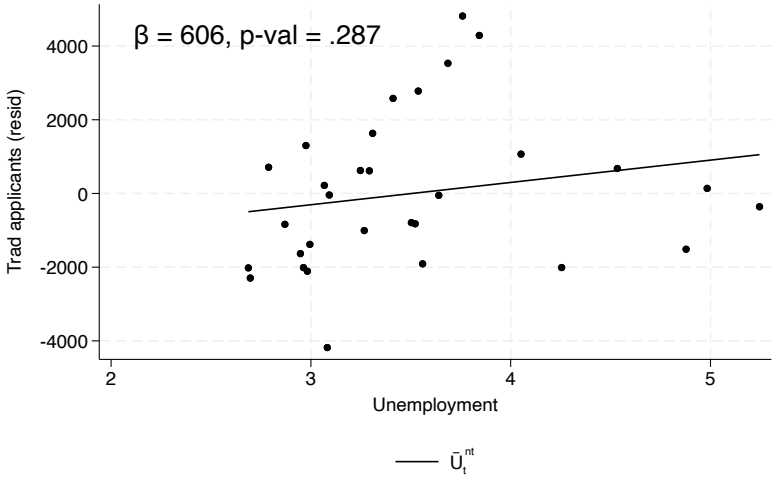
Figure A1: Undergraduate major as a proxy for underlying type.



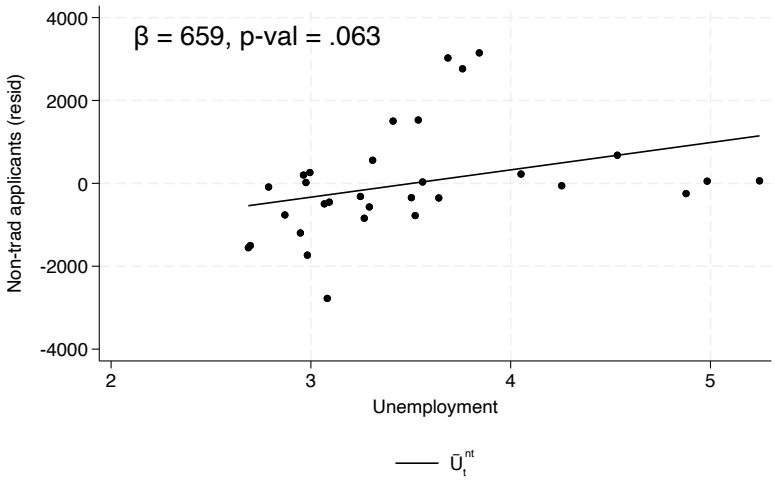
Notes: measure of altruism from Li et al. (2022).

Figure A2: Applicants over time by type

Number of traditional applicants and $\bar{U}_t^{nt}$

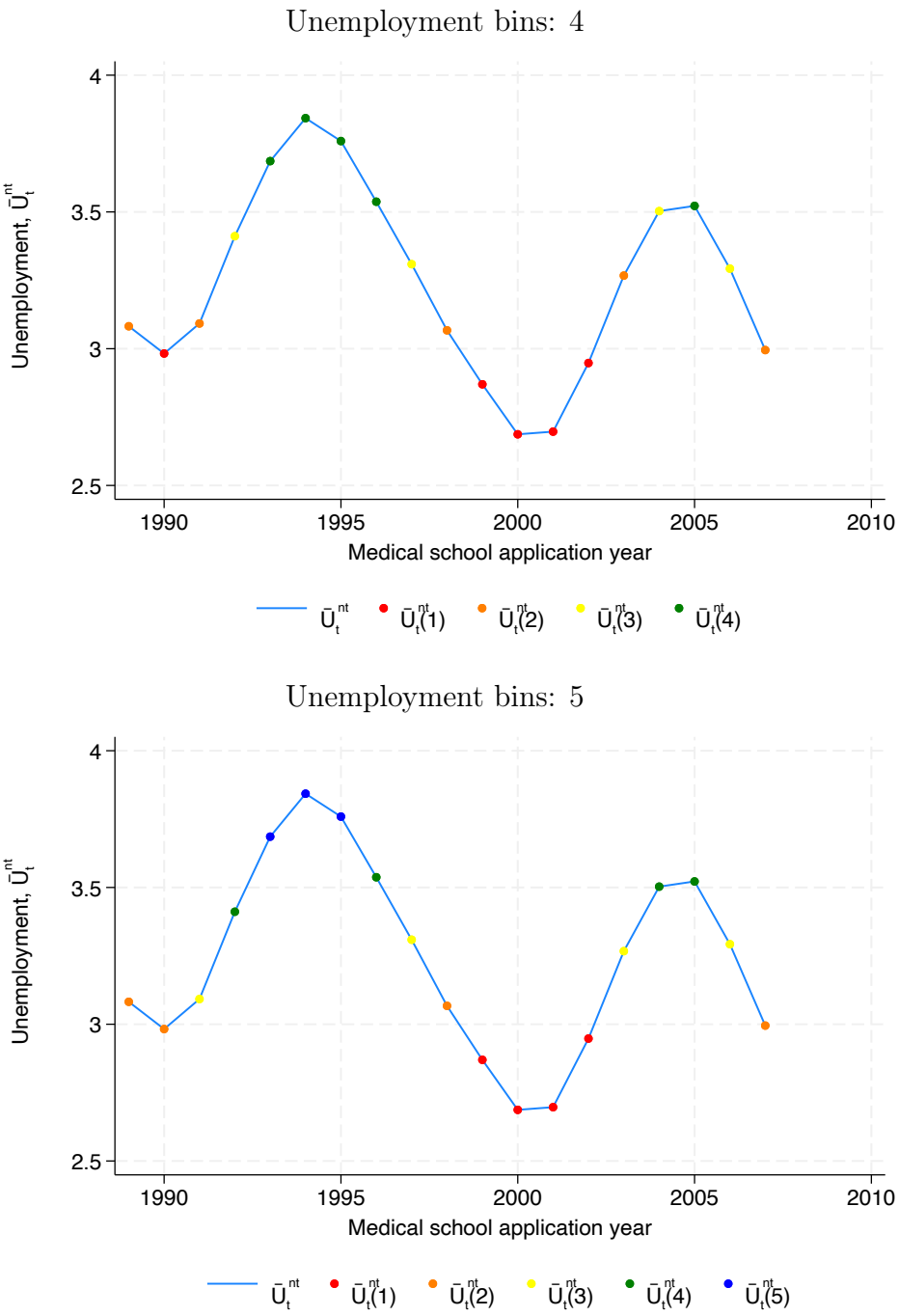


Number of non-traditional applicants and $\bar{U}_t^{nt}$



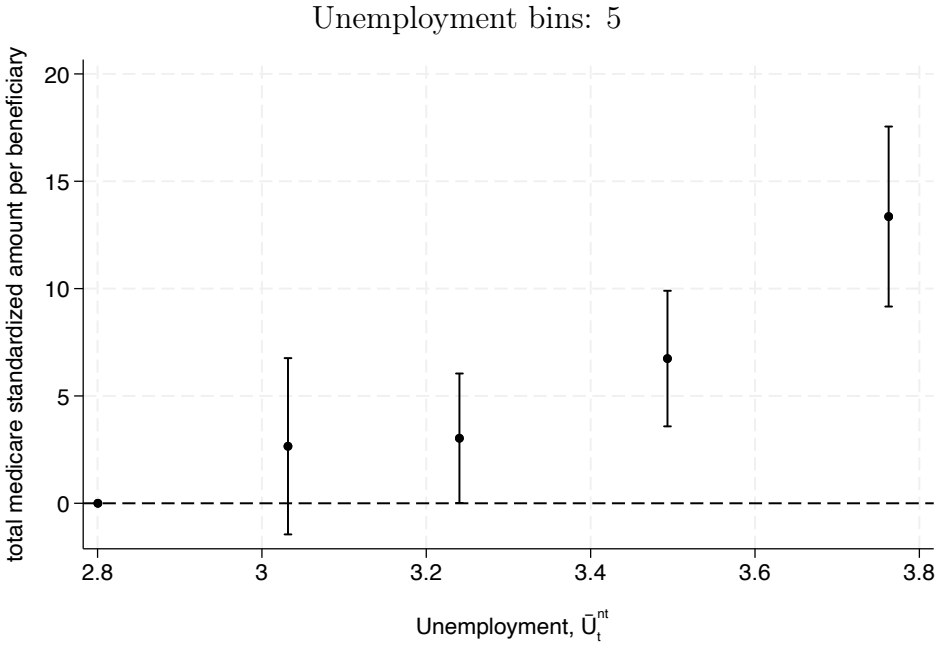
Notes: residuals after controlling for the total number of matriculants.

Figure A3: Med-school-relevant unemployment rate: quartiles and quintiles



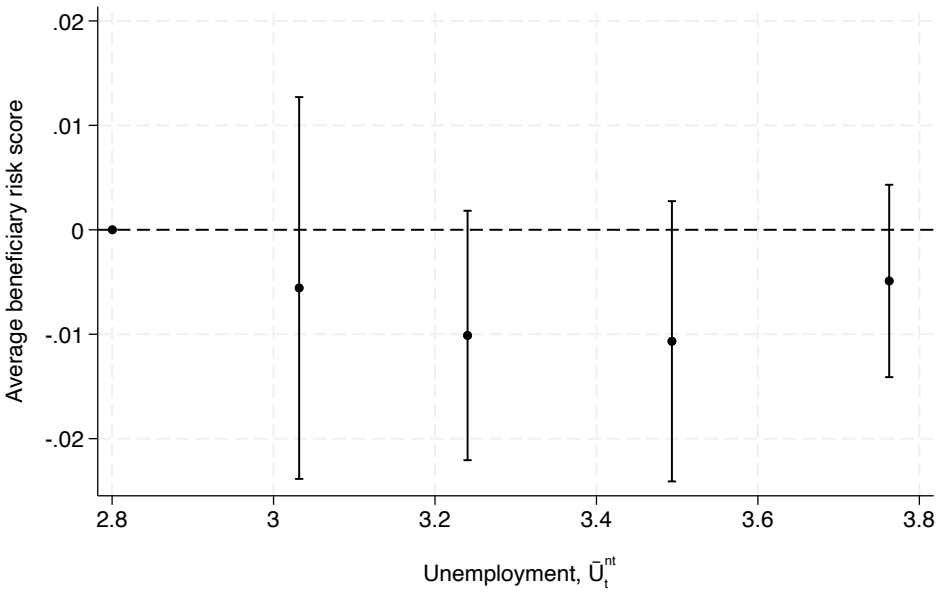
Notes: Unemployment rates come from the CPS.

Figure A4: Medicare spending per beneficiary



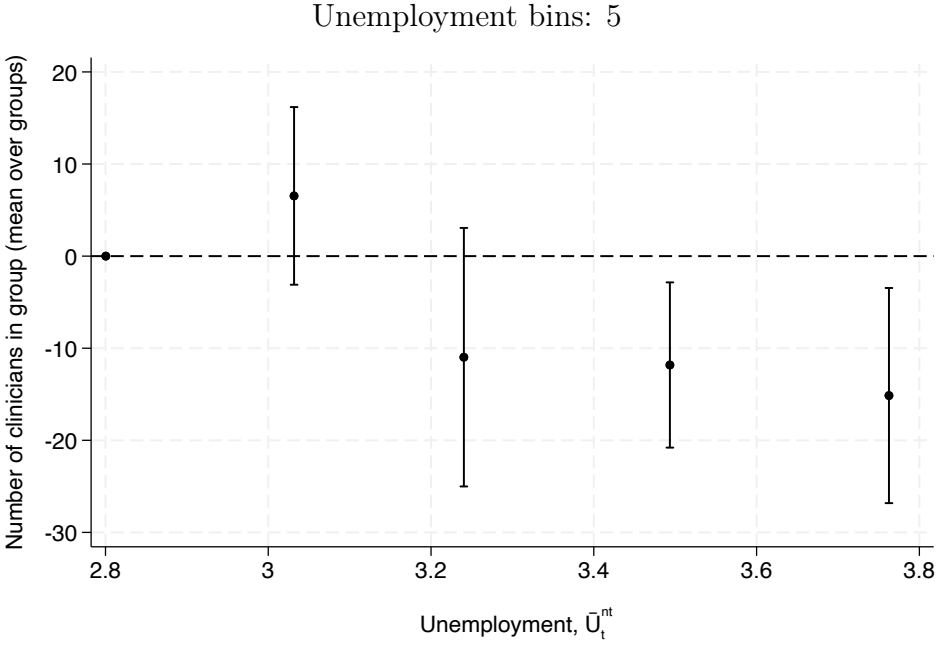
Notes: Data at the physician-year level. Sample is physicians trained in the US, who applied to medical school between 1989 and 2019, and who appear in the Medicare physician-level utilization files from 2013-2022, and who are at least 10 years past their medical school graduation year. Standard errors clustered at the cohort level.

Figure A5: Average risk score



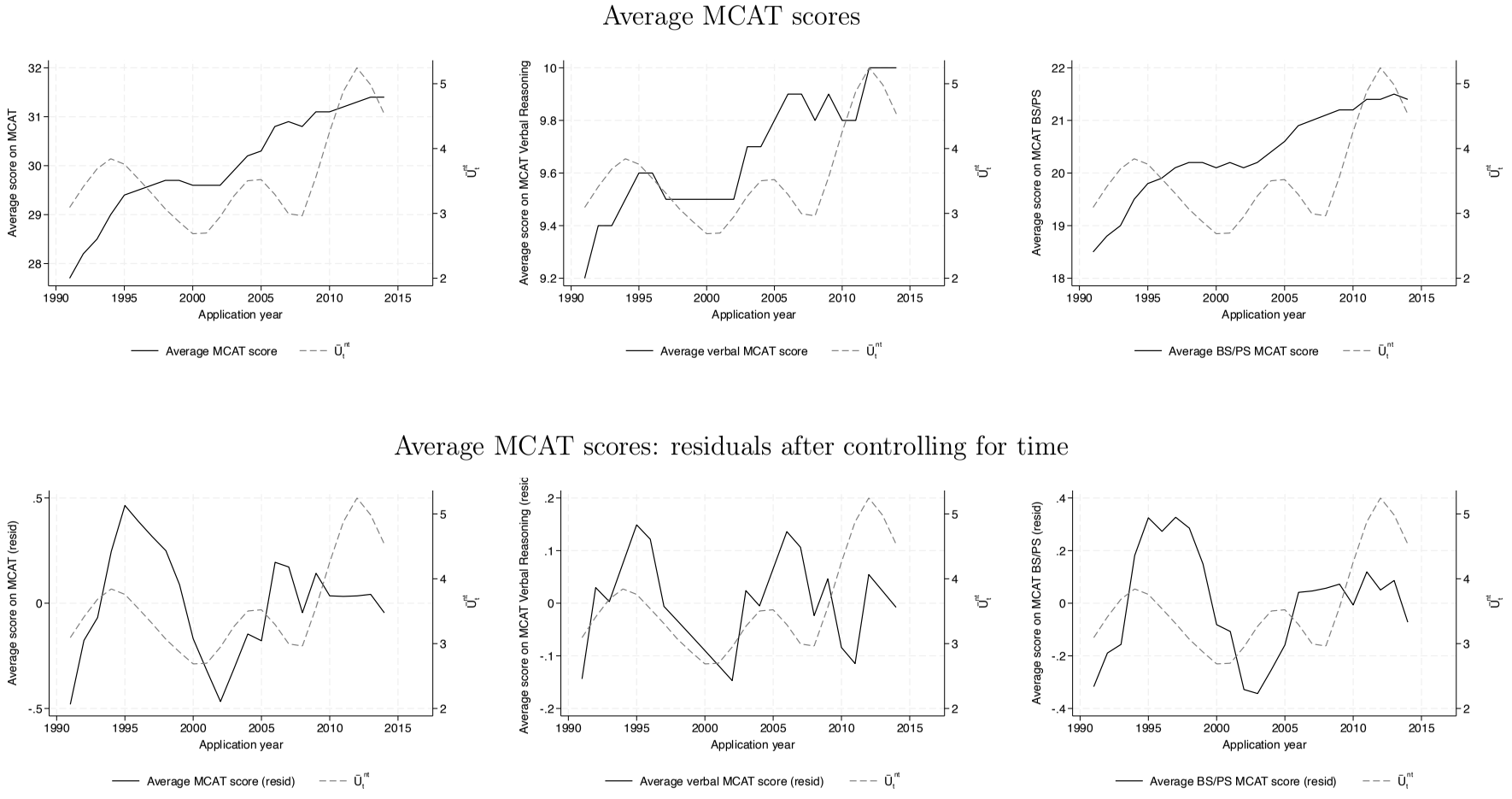
Notes: Data at the physician-year level. Sample is physicians trained in the US, who applied to medical school between 1989 and 2019, and who appear in the Medicare physician-level utilization files from 2013-2022, and who are at least 10 years past their medical school graduation year. Standard errors clustered at the cohort level.

Figure A6: Average practice size



Notes: Data at the physician-year level. Sample is physicians trained in the US, who applied to medical school between 1989 and 2019, and who appear in the Medicare physician compare files from 2014-2022, and who are at least 10 years past their medical school graduation year. Standard errors clustered at the cohort level.

Figure A7: 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 Appendix Tables

Table A1: Medicare spending per beneficiary: controlling for risk scores

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\bar{U}_t^{nt}$	12.170***	12.286***						
	(2.242)	(2.175)						
Share non-trad			2.073***	2.113***			1.590***	1.705***
			(0.459)	(0.442)			(0.425)	(0.409)
Acc. rate					-0.595***	-0.589***	-0.216	-0.182
					(0.197)	(0.190)	(0.174)	(0.167)
Experience FEs	✓	✓	✓	✓	✓	✓	✓	✓
Data year FEs	✓	✓	✓	✓	✓	✓	✓	✓
Specialty FEs	✓	✓	✓	✓	✓	✓	✓	✓
Avg. risk score		✓		✓		✓		✓
Observations	1,632,533	1,632,533	1,632,533	1,632,533	1,632,533	1,632,533	1,632,533	1,632,533
R^2	0.161	0.162	0.161	0.162	0.161	0.162	0.161	0.162
Mean dep. var.	316.904	316.904	316.904	316.904	316.904	316.904	316.904	316.904
Cohorts	19	19	19	19	19	19	19	19

Notes: Physicians with at least 10 years of experience post medical school graduation. Data at the physician - year level. Time period from medical school application year 1989-2007. Standard errors clustered at the cohort level. Share non-traditional is share*100; acceptance rate is acceptance rate*100.

Table A2: Major clusters

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

Notes: undergraduate majors grouped via K-means clustering, according to the similarity in the distribution across occupations in ACS (5 year, 2005-2009).