University of Toronto
Department of Economics

Working Paper 681

Dynamic Decision Making Under Rolling Admissions: Evidence from U.S. Law School Applications

By Yao Luo and Yu Wang

December 03, 2020

Dynamic Decision Making Under Rolling Admissions: Evidence from U.S. Law School Applications

By Yao Luo and Yu Wang*

Abstract

Admission processes in many higher education markets are inherently dynamic. We study timing of student application and school admission under rolling admissions using a unique U.S. law school market dataset. Our results show that law schools employ non-stationary admission standards within application cycles: applications submitted earlier enjoy a considerable admission advantage relative to later applications. We rationalize such strategies in a simple yield management model and provide evidence for three types of frictions that constrain applicants from applying earlier.

Keywords: *Matching; Decentralized; Timing; Frictions; Higher Education.*

JEL: *I23, I28.*

* Luo: Department of Economics, University of Toronto, Toronto, ON M5S 3G7, Canada. Email: yao.luo@ utoronto.ca. Wang: Department of Economics, Ryerson University, Toronto, ON M5B 2K3, Canada. Telephone: 1-215-919-1358. Email: wangyu5@ryerson.ca. We are grateful for the financial support from the Social Sciences and Humanities Research Council of Canada and the Faculty of Arts at Ryerson University. We benefit from discussions with Victor Aguirregabiria, Garaub Aryal, Andrew Ching, Holger Sieg and Aloysius Siow. We thank Ashley Brown, Lara Demerji, Melinda Kroone, Mariana Kouzela, Nathan Locke and Jiaqi Zou for excellent research assistance. All usual disclaimers apply.

I. Introduction

Rolling admissions are commonplace in higher education markets, employed by all law schools and medical schools as well as many business schools, graduate schools, and colleges in the United States. While they are inherently dynamic decisions, with both applicants and schools exhibiting strategical timing within application cycles, the previous empirical literature usually assumes a static setup. Furthermore, there is limited evidence regarding the various tradeoffs in such dynamic admission processes. To the best of our knowledge, this paper is the first to address this gap in the literature by empirically investigating the dynamics in rolling admissions.

Rolling admissions are dynamic by nature. Under rolling admissions, applicants may submit applications to schools at any point within a usually very large time window, and schools can make offers at any time for applications that have already been received, instead of having to wait until a submission deadline by which all applications are received. Correspondingly, offer recipients may also accept or reject the offers as these offers are extended to them. Given the limited capacity of each program, schools need to decide whether to make early offers and thus fill up seats possibly sooner, or postpone offer-making until a later time where an updated pool of applications are realized. As these factors of consideration take on different values over the application cycle, admission standards may fluctuate over the cycle as well.

In this paper, we present evidence that applications submitted at later points in the application cycle suffer a large penalty in the form of decreased likelihood of admission relative to comparable applications submitted earlier under rolling admissions. We rationalize why schools favor earlier applicants using a yield management model. Finally, we provide evidence for three types of frictions that constrain applicants from applying earlier.

We focus on admissions to the J.D. programs of U.S. law schools via *Regular Decision* programs, where rolling admissions are universally adopted by all schools. We assemble a large, unique dataset on applicants' list of schools, application timing, and corresponding admissions results, which allows us to isolate intertemporal changes in school admission thresholds from applicant selection in application timing.

To guide our empirical analysis, we start by proposing a simple, generic model of rolling admissions to show that schools may strategically raise admissions thresholds for later applications relative to earlier ones in this market. Our model captures two important elements of school admissions processes highlighted in Che and Koh (2016) and incorporates them in a dynamic model: first, schools have capacity constraints and both over- and under-enrollment are costly,[1] and second, schools face enrollment uncertainty as an applicant may receive multiple offers but can only accept one offer, with her preferences over these offers being *a priori* unknown to schools. Our model also captures an interesting feature of J.D. admissions: schools are strongly discouraged from requesting any kind of commitment from *Regular Decision* offer recipients before April 1,[2] although application cycles start as early as September of the previous year. As such, exploding or short-fuse offers are rare for the vast majority of the application cycle, although applicants may accept their favorite offer or reject their dominated offers long before this response deadline.[3]

[1]Law schools are reportedly concerned about both under- and over-enrollment. Under-enrollment can be financially costly to schools and may lead to layoffs or even buyouts of tenured professors (Scheiber (2016)). Over-enrollment may make it tough for schools to place the students when they graduate (Stetz (2018) and Ward (2018)), thereby pulling down the school's ranking. To avoid under-enrollment, some schools may even lower tuition (Johnson-Elie (2015)) or admit low credential students likely to have trouble graduating or passing the bar (Rivard (2015)). On the other hand, to avoid over-enrollment, some schools may even offer scholarships to admitted students willing to defer entry (Froomkin (2009)).

[2]The Law School Admission Council (2017).

[3]In fact, anecdotal evidence suggests that it is common for applicants to commit to schools significantly in advance of the response deadline instead of waiting until the last minute. See,

In our dynamic setup, making offers in one go after all applications are received, as typically assumed in the literature studying higher education markets, turns out to be a dominated strategy for schools. Instead, schools are better off making offers in multiple rounds, learning the preference of earlier offer-recipients through their responses of acceptances, rejections, or offer holding, and hedging enrollment risks by adjusting subsequent admissions decisions based on these responses. This information revelation channel creates additional benefits of admitting earlier applicants relative to later applicants for schools to control the yield. Consequently, large costs of missing enrollment targets may result in an admissions advantage for earlier applicants.

Motivated by the model implications, we test for the escalation of admissions thresholds using the data from the U.S. legal education market. We assemble a large, unique dataset containing 87,389 applications submitted to J.D. programs at 193 law schools by 9,323 applicants. Our data is captured from *Law School Numbers*, a popular website among law school applicants, which was founded in 2003 as a free, publicly accessible online database for the purpose of encouraging information sharing regarding admission results.

The key novelty point of our data is the presence of rich micro information at the application level, including not only which schools each applicant applies to and which applicants each school admits, but also the timestamps regarding when each applicant submits each application, and when each school makes each offer. Our data also contains a large variety of measures of applicant characteristics.

Proceeding to empirical analysis, we first document that the timing of both

among others, Vault Law Editors (2009) and The Career Center at the University of California at Berkeley (2020) for descriptions about how law school seats are filled "throughout" the admissions season. Some schools may fill the entire class early and start to extend offers of deferred admissions to applications submitted as early as January (Kowarski (2018)).

applications and admissions is highly dispersed. On average, an application is submitted 94 days from the initial opening of school application systems, with a standard deviation of 45 days, while an offer is made 144 days from the initial opening date, with a standard deviation of 47 days. Schools often move even earlier than applicants: on average, applicants submit their first application 81 days from the initial opening, while schools make their first offer only 67 days from the opening.

We then present evidence that delays in submission - taking more days to submit since opening - lower the applicant's chances of admission. The main threat to identification is that application timing is not random, such that early and late applications may differ in unobserved ways which also affect admission probability. First, the mix of applicants who apply early may differ from the mix of applicants who apply late. For instance, an earlier application may demonstrate stronger planning and organizational skills on the part of the applicant, which are characteristics that are valued by law schools in the evaluation of prospective students. Second, applicants may have private information on their match quality with schools and apply earlier to schools that are more likely to give them offers.

To resolve the concern of selection in unobserved applicant heterogeneity, we first exploit the rich measures in the dataset and control for a large variety of applicant characteristics, including LSAT scores, undergraduate GPA, gender, race, college types, college majors, years out of school, location, and detailed descriptions of extracurricular activities. We then exploit the longitudinal structure of the dataset and control for applicant fixed effects using the subsample of over 90% of applicants who applied to multiple schools.

To test for the importance of selection in unobserved match quality, we rely on an institutional feature that creates discontinuities in submission timing that are perceived by schools but not by applicants. Specifically, schools generally accumulate applications until a sufficiently large pool is formed and then evaluate these applications together, with the time cutoffs of such evaluation rounds unknown to applicants. We propose a novel test: if the admission advantage of early applications is driven by schools raising admissions thresholds over time, then this advantage should disappear if we restrict to applications within the same evaluation rounds. If this advantage is driven by applicants applying earlier to better-matched schools, the advantage should remain intact even for applications in the same rounds.

Our empirical result that schools impose significantly higher admissions thresholds for later applicants withstands these two identification challenges. Overall, an application delay of 100 days is associated with a drop in admission probability of around 8 percentage points - a disadvantage comparable to lowering the applicant's undergraduate GPA by 0.26 or LSAT scores by 2.1 points. Rephrased from a different perspective, if an application in the second evaluation round were submitted early enough to be reviewed in the first round - even if "earlier" means as little as one day in advance - the application would be 2.75 percentage points more likely to be accepted. Moving forward from an even later evaluation round to the first round could produce even greater advantages in admission probability.

Going one step further, we construct a measure of the degree of competition faced by each school using the quality of its applicants' alternative offers. We document that schools facing stronger competition and correspondingly greater enrollment variation are indeed more biased towards earlier applicants.

After establishing these results, we explore further why many applicants still apply late despite the associated large penalty in admission probabilities. In fact, 69.3 percent of applications are submitted after the cutoff of the first evaluation round. We proceed to identify three types of frictions that prevent applicants from applying early: (1) applying to schools is time-consuming, and thus applicants with tighter daily time budgets have to progress more slowly, thereby elongating their application processes; (2) applicants take the LSAT exam in October or December of the application season and must wait for their scores to be released; and (3) each application is costly in both time and financial terms, with admission outcomes *a priori* uncertain, and thus applicants may strategically sequentialize applications so they can re-evaluate their portfolio's school composition based on information they learn throughout the application process, such as the admission results of their earlier applications.

We document empirical evidence for the existence of all three types of frictions. In particular, we classify the applicants who only apply on weekends as being highly time constrained. As predicted by our classifications, these applicants start submissions late and also apply to fewer schools. Additionally, our results show that 9.5% of applicants are partially constrained by late release of LSAT scores for at least one submission, and 2.2% of applicants are fully constrained for all their submissions. Last, we show that earlier admission results have large, significant effects on the list of schools applicants apply to later on. This suggests that applicants do strategically postpone applications to incorporate new information of earlier admission results into later portfolio decisions.

Our findings thus have important policy implications. A growing variety of measures have been advocated by the literature to reduce the various application frictions in higher education markets, with the purpose of promoting equal education opportunities. Most of these measures, such as free counseling guidance, are designed to encourage the constrained applicants to apply to more schools or to more selective schools. Yet we show that, even holding application choices constant, access to education is still not equal, as some applicants are constrained from taking advantage of the inherently nonstationary admission standards within application cycles. Our results suggest additional probable measures to level the playing field, such as switching to a centralized admissions system that eliminates school incentives to make early offers, providing more frequent LSAT test dates, and providing more information regarding one's admission probabilities at each school.

The rest of the paper is organized into seven sections. Section II provides a literature review. Section III characterizes equilibrium admission strategies in a simple model of rolling admissions. Section IV explains institutional details. Section V describes the data. Section VI presents empirical results on the existence of an admission advantage for early applications and distinguishes between various possible explanations, and Section VII investigates the contributing factors towards late submissions. Finally, Section VIII concludes. Additional details can be found in the Appendix.

II. Literature Review

Our paper builds on the literature studying frictions in the application processes of higher education markets. For instance, Chade, Lewis and Smith (2014) characterizes how application costs and admission uncertainty affect applicant strategies theoretically. Fu (2014) quantifies these effects using data on high school graduates from the 1997 National Longitudinal Survey of Youth. Pallais (2015) documents that even a $6 one-shot reduction in application fees can induce substantially different application decisions among low-income college applicants. Knight and Schiff (2019) finds that allowing students to submit a single application to multiple institutions at the *Common Application* platform reduces their time costs in applications significantly. Bettinger et al. (2012), Hoxby and Turner (2013), Hoxby and Turner (2015), Carrell and Sacerdote (2017), and Dynarski et al. (2020) find that incomplete information regarding colleges, college application strategies, or the complicated financial aid application processes reduces college matriculation, especially low-income family representation at more selective colleges. Complementary to these studies that mainly focus on how application frictions affect the size or school composition of application portfolios, we examine a new aspect where the frictions influence application decisions with respect to the timing of submissions.

Our paper is also related to the literature studying frictions within the admission processes of decentralized college admissions. One notable source of frictions is that applicant preferences are unknown to schools. Che and Koh (2016) considers the cases wherein schools feature rigid capacities, such that enrollment uncertainty resulting from the unknown applicant preferences is costly to schools. They show that the matching outcomes are theoretically unstable and inefficient in static settings. On the other hand, Avery and Levin (2010) considers the cases wherein schools value applicant preferences directly and prefer admitting students that value them more highly. They find that the co-existence of *Early Decision* and *Regular Decision* programs offers a valuable opportunity for applicants to signal their preferences to schools, as one can apply to only one school through the *Early Decision* Program and the admission outcome is binding. Consequently applications submitted in the *Early Decision* track enjoy a large admission advantage over those in the *Regular Decision* track. Complementary to these works, our paper examines the admission friction similar to the one characterized in Che and Koh (2016) in a dynamic setup, focusing only on applications submitted to *Regular Decision* tracks.

III. A Motivating Model

We propose a simple, stylized model of rolling admissions to show that schools may strategically raise admission thresholds for later applications relative to earlier applications. We borrow the enrollment uncertainty story in Che and

Koh (2016) and consider its implication in a dynamic setup. Che and Koh (2016) show that, to control yield, schools may strategically admit students likely to be overlooked by competitors; consequently, highly ranked students may receive fewer admissions or have a higher chance of receiving no admissions than lower ranked ones. Our model yields similar implications from a different perspective: under rolling admissions, to control yield, schools may forego more favorable applicants arriving later in favor of less favorable applicants arriving earlier.

To set up the model, consider an application cycle of two periods, $t = 1, 2$. At the beginning of each period, N applicants arrive exogenously, labelled as "early" and "late" applicants, respectively. There are two schools, $s = A, B$, both featuring capacity $\kappa < N$. Each applicant is of type (e_A, e_B), where e_s is the quality of the applicant's profile as perceived and observed specifically by school s. The probability that an applicant prefers school s to the other school is p_s, with $p_A + p_B = 1$. The realization of each applicant's preference is her private information. As our emphasis is on preference uncertainty, we only consider a "snapshot" of the game with applicant quality e_s realized in the very beginning: throughout the game, school s perfectly forecasts the realization of e_s for both early and late applicants.

We now describe the timeline of actions. In each period, newly arriving applicants make the first move by applying to both schools,[4] followed by the schools making offers, ending with the offer-recipients responding to their offers. In period 1, there are three possible responses of offer-recipients. Those who receive an acceptance offer from their more preferred school accept the offer. If they also receive an offer from their less preferred school, they also reject this dominated offer. Those who only receive an offer from their less preferred school

[4]Since we focus on analyzing school strategies, we abstract away from modelling the applicant's strategic choices regarding timing and portfolio composition.

can hold the offer and wait.[5] In period 2, schools may select from an applicant pool composed of newly arrived late applicants and the remaining early applicants. After the schools make their second round offers, all applicants who have not made commitments in period 1 accept their best offer at hand; applicants who do not receive any offers remain unmatched. Notably, the number of offer recipients accepting, rejecting, and holding offers in period 1 is the private information of each school.

We proceed to describe the objective function of schools. School s obtains payoff $U(e_s)$ from matriculation of an applicant of type e_s and incurs a constant per-student cost λ for either unfilled seats or enrollment exceeding λ. More specifically, the ex-post payoff that school s receives at the end of the game is

$$\pi_s = \sum_{i=1}^{2N} A_{s,i} U(e_{s,i}) - \lambda \left| \sum_{i=1}^{2N} A_{s,i} - \kappa \right| \tag{1}$$

where subscript i is an index for applicants, $A_{s,i}$ is a dummy variable that takes on a value of 1 if applicant i receives and accepts an offer from school s, and $\sum_{i=1}^{2N} A_{s,i}$ represents the total size of enrollment. Conditional on receiving an offer from school s, the applicant accepts the offer either if school s is her preferred school or if she prefers the opponent school but does not receive the opponent school's offer. The first part of π_s represents the aggregate utility of student enrollment, while the second part represents the capacity cost of missing an enrollment target.

There are two interpretations of the capacity cost of missing the enrollment target. The first interpretation is that schools may find it challenging to accommodate a large student body in the case of over-enrollment, and suffer from insufficient tuition revenue in the case of under-enrollment. The second interpre-

[5]Our model can be extended to cases where applicants postpone offer acceptances and rejections, as long as the probability of postponing is known by schools and is not too high.

tation is that schools highly value the diversity of its student body,[6] and either over- or under-enrollment of a subgroup of applicants may break the balance of class composition. Therefore, our model can also be interpreted as schools making admissions decisions on a sub-group of applicants.

The optimization problem of school s is thus about whom to make offers to in the first period and, observing the responses of offer recipients by the end of the first period, whom to make offers to in the second period. We focus on symmetric pure strategy equilibrium under the assumption that schools are Bayesian maximizers of their expected payoff.

The key feature of the model is an information revelation channel. In particular, through the responses of offer recipients in period 1, school s obtains information on both factors that determine the enrollment decision of an applicant: which school she prefers, and whether she also receives an offer from the opponent school.

First, school s learns the preferences of all offer-recipients in period 1 based on their responses. The preferences of those who accept or reject offers are revealed trivially. Those who hold offers must prefer the opponent school; otherwise, they would have accepted the offer from school s instead of holding onto it.

Second, school s narrows down the set of decision nodes the opponent school can possibly reach in period 2: by the end of period 1, the number of acceptances the opponent school receives is no less than the number of rejections school s receives, while the number of rejections the opponent school receives is no more than the number of acceptances school s receives, because only those who have received both offers will reject one and accept the other. School s thus has a

[6]For instance, The Law School Admission Council (2018) states that "Law schools will select candidates who fall somewhere on a flexible continuum of the school's academic parameters and who contribute to a diverse class. Each applicant may offer something distinctive to a class-diversity is one factor among many in a holistic file review."

more accurate belief about the possible admission standards the opponent school may adopt in period 2 and, correspondingly, the probability of an applicant receiving one of these offers.

Third, school s narrows down the early applicants who have received offers from the opponent school back in the beginning of period 1: those rejecting school s must have received the opponent school's offer while those putting school s on hold must not have. The remaining opponent offers must be shared between those accepting offers from school s and those not receiving offers from school s. School s thus has an updated belief about the probability of each early applicant receiving an opponent offer back at the beginning of period 1.

We will then show how this information revelation channel encourages schools to favor earlier applicants in admissions, by constructing a numerical example. Before moving onto the details, we make a few assumptions so that the numerical model solution is tractable. First, we assume that $U(e_s)$ is strictly increasing in e_s, and schools have heterogeneous tastes such that e_A and e_B are independent.[7] An immediate result is that schools would take monotonic admission strategies, by finding a threshold in each period t for new and remaining applicants, respectively, and admit all available applicants in the market with e_s above it.[8] Second, we refine the equilibria based on the type of strategies schools may take, as the original large set of deviating strategies may entail a large set of equilibria. More specifically, we restrict to the equilibria where school s consistently plays the same period 2 strategy following the same period 1 strategy

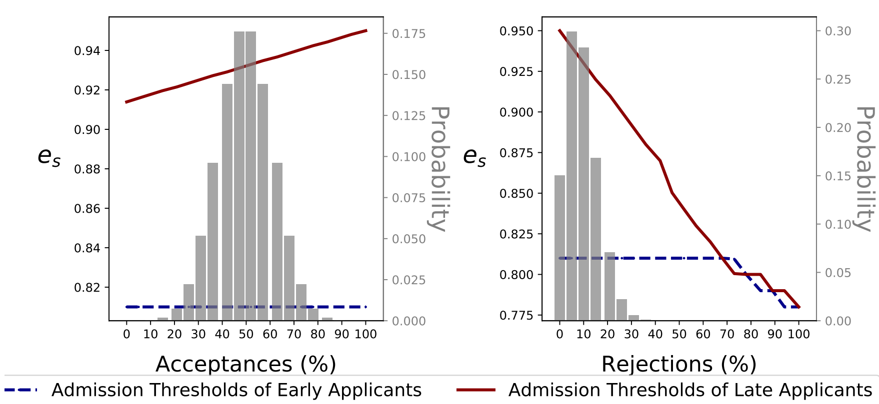
[7]We make the independence assumption to guarantee that the equilibrium features a monotonic admission strategy as will be explained later. Allowing for correlation between e_A and e_B may induce a non-monotonic solution as characterized in Che and Koh (2016), which is less intuitive in explaining the key driving forces in our model.

[8]This is because enrollment uncertainty is the same across applicants, yet applicants with higher realizations of e_s are more desirable to school s. To see the first point, recall that all applicants share the same preference parameters p_s; and from school s' perspective, they are equally likely to receive an offer from the opponent school. Therefore, schools just rank applicants by their realizations of e_s and make offers moving down the list.

it plays, regardless of the opponent school's period 1 strategy. Intuitively, this refinement means that, even if the opponent school deviates in period 1, school s plays in both periods as if the opponent school did not deviate. Our numerical example is constructed accordingly.

Figure 1 illustrates that offer-recipients' responses in period 1 substantially affect school admission strategies in period 2. In other words, the information learned through these early offer-recipient responses are important to schools in the admissions process. More specifically, we examine how admission strategies are adjusted according to the fraction of acceptances in the left panel and the fraction of rejections in the right panel. In both panels, the dashed curves represent the admission thresholds for early applicants, accounting for both period 1 and period 2 admissions, the solid curves represent the admission thresholds for late applicants, and the grey bars represent the probability of school s receiving each fraction of acceptances or rejections by the end of period 1.

FIGURE 1. ADMISSION THRESHOLDS BY FRACTIONS OF ACCEPTANCES/REJECTIONS OF PERIOD 1 OFFERS



Note: $U(e_s) = e_s$, $N = 100$, $\kappa = 24$, $\lambda = 3.0$, $p_A = p_B = 0.5$, and e_s are drawn from $Uniform(0, 1)$. There exists a unique equilibrium under this parametric specification. At equilibrium, the admission rates for early applicants are higher than those for late applicants by an average of 12.19 percentage points.

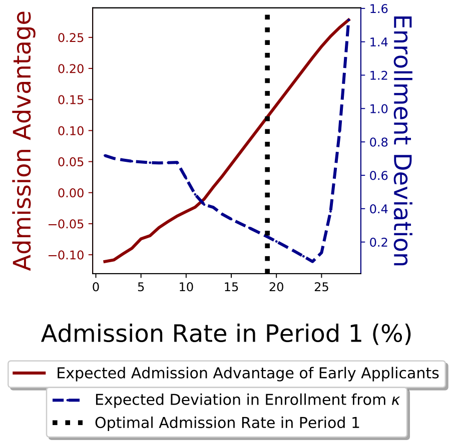
Schools adjust their period 2 admission strategies mainly through adjusting their admission threshold for late applicants. As shown in Figure 1, the admission thresholds for late applicants vary greatly depending on the responses of early-offer recipients. As school s receives more acceptances, it hedges for increasing over-enrollment risks by raising its admissions threshold to reduce the number of offers it makes to late applicants; similarly, when school s receives more rejections, it hedges for increasing under-enrollment risks by lowering its admission threshold to increase the number of offers to late applicants.

On the other hand, the schools' admissions threshold for remaining early applicants in period 2 is not very responsive to early acceptances and rejections received by schools and correspondingly remains flat for the most part. This is because the marginal late applicant is of much higher quality e_s than the marginal early applicant, and thus school s will not make additional offers to early applicants in period 2. In the cases where a very large fraction of offers are rejected in period 1 and a lot of offers are made to late applicants, as shown towards the right end of the right panel, the quality threshold for the marginal late applicant drops to a level similar to that for the marginal early applicant, and school s will make additional offers to the remaining early applicants as well.[9]

As the information learned in period 1 is valuable to schools when hedging for enrollment risks, schools have incentive to reveal more such information by making a greater number of offers in period 1, which leads to an admission advantage for earlier applicants. As shown in Figure 2, a greater number of period 1 offers lower expected enrollment deviations up to a turning point.

[9]Which group of applicants enjoy an admission advantage is then indefinite, depending on which group is less likely to receive an offer from the opponent school either in period 2 or back in period 1, and correspondingly, involves less uncertainty in accepting the round 2 offers from school s.

FIGURE 2. EARLY-APPLICANT ADVANTAGE AND ENROLLMENT RISKS BY ADMISSION RATES IN PERIOD 1



Note: $U(e_s) = e_s$, $N = 100$, $\kappa = 24$, $\lambda = 3.0$, $p_A = p_B = 0.5$, and e_s are drawn from $Uniform(0,1)$. There exists a unique equilibrium under this parametric specification. At equilibrium, the admission rates for early applicants are higher than those for late applicants by an average of 12.19 percentage points.

More specifically, we vary school s' admission threshold in period 1 and optimize its strategies in period 2 accordingly while holding the opponent school's equilibrium strategy constant. The horizontal axis represents the admission rate in period 1. The solid curve represents the admission advantage of early applicants, calculated as the difference in admission thresholds between late and early applicants, and the dashed curve represents deviation in enrollment from κ, $E\left|\sum_{i=1}^{2N} A_{s,i} - \kappa\right|$.

The early-application advantage rises with admissions rates in period 1, while average enrollment deviation from κ decreases initially and then increases later. The turning point is where "too many" period 1 offers are made, thus over-enrollment risks grow dramatically and can no longer be hedged through period 2 strategies.[10] Therefore, before schools reach the turning point, their period

[10]It is also interesting to see that the initial part of the early-applicant advantage curve is negative or, in fact, an "admission disadvantage". This is caused by an information externality in the equilibrium: as only those with two offers will make one rejection, and as school s makes

1 offer decisions need to take into account the tradeoffs between lowering enrollment risks versus crowding-out a greater number of strong late applicants. The dotted vertical line denotes the optimal period 1 strategy balancing this tradeoff.

We now turn to the legal education market to explore if schools do favor earlier applicants over their later-arriving peers.

IV. Institutional Background

The legal education market is large and dense. There are around two hundred U.S. law schools offering J.D. programs accredited by the American Bar Association (ABA), with each J.D. program enrolling roughly 200 new students on average every year.[11] We describe the programs, applicants, as well as application and admission practices of law schools in more detail below.

First, J.D. programs are highly standardized across law schools as schools must adhere to strict instructions outlined by the ABA, as well as with information disclosure policies as outlined by the Law School Admission Council (LSAC). Consequently, curriculums are structured very similarly across schools. In addition, schools annually disclose a common set of statistics to gauge program performance, covering selectivity, educational resources, and job placements.

Despite the standardization of both program structure and data disclosure, as well as the fact that placements are concentrated in the legal profession, prestigious judicial clerkships and large law firm positions (i.e. *Big Law*) have always

very few offers in period 1, the opponent school receives very few rejections in period 1 and thus makes very few offers in period 2; consequently, the probability of a late applicant accepting an offer from school s upon receiving the offer is close to one, as that is likely her only offer. Because of this, school s is better off making its period 2 offers to late applicants instead of the remaining early applicants, whose enrollment decisions involve much higher uncertainty.

[11] Take the 2013-2014 application cycle for example: according to the official statistics released by the American Bar Association, a total of 202 law schools received 386,285 applications, made 170,089 offers, and enrolled 39,675 freshmen.

been secured disproportionally by graduates of top-ranking law schools. As a result, law school rankings play a significant role in prospective law students' application decisions. The most influential ranking for law schools is the U.S. News and World Report (USN), [12] which publishes the ranking of every law school accredited by the ABA. Specifically, it reports the numerical ranking for each of the top 100 law schools and classifies the remaining schools as either third-tier or fourth-tier. Prospective law students routinely consult USN law school rankings before making application and acceptance decisions, administrators monitor the same rankings closely, and many schools have adopted policies intended to influence or respond to their respective ranking.

To be eligible to apply to J.D. programs, one has to have LSAT scores and a bachelor's degree by time of entry. The LSAT exams are administered four times a year: once in each of February, June, October, and December. Test scores are released around three weeks following the exam. Although all past scores are displayed on the LSAT results report, it is widely believed that schools focus heavily on the highest score in admissions decisions, which follows the USN using each entering class' highest LSAT scores to rank schools since 2005. This incentivizes applicants to take the test repeatedly.

Lastly, we describe the application and admission processes of the legal education market. As regulated strictly by the LSAC, application and admission practices feature a high degree of homogeneity. In this paper, we focus on applications submitted through the *Regular Decision* track. Most schools begin to accept applications on September 1 and continue accepting applications until August of the following year.[13] In general, there are no hard deadlines for

[12]According to Sauder and Espeland (2007), "USN rankings dominate legal education. While other law school rankings are published and disseminated, none of these rankings have had the impact of USN. The law school administrators interviewed for this study all agreed that the USN rankings were by far the most consequential."

[13]In our sample, 51.3% of schools set their opening date for application submissions to

applications, although some schools may set a priority deadline in early March and only guarantee that applications submitted before that deadline will be reviewed. In addition to *Regular Decision* track, some schools offer *Early-Decision* (ED) or *Early-Action* (EA) tracks, though an applicant may only apply to one ED or EA program at a time.

A complete application package usually consists of undergraduate studies transcripts, postgraduate studies transcripts, LSAT scores, letters of recommendation, a resume, and the personal statement. According to *the Official Guide to ABA-Approved Law Schools* published annually by the LSAC, there are two factors among these materials that can be evaluated objectively across all candidates and are the strongest predictors of success in law school, thus making them fundamental tools for admission committee decision making: undergraduate GPA and LSAT score. We thus refer to GPA and LSAT scores as "Hard" factors. In contrast, other components of an applicant's package are termed "Soft" factors.

Law school applications are made through the Credential Assembly Service (hereby CAS) website, operated by the LSAC. Applicants need to first register for an account on the CAS platform and then upload transcripts and letters of recommendation. The platform will compile transcripts, letters of recommendation and LSAT scores into a joint report and transmit the report to each law school the applicant wishes to apply to. Remaining materials such as the resume and personal statement can either be submitted by the applicant to each law school individually or through the CAS platform.

Applying to law school is financially costly. To take the LSAT once costs around \$200, and registration on CAS costs another \$200. Law schools charge an application fee of roughly \$60 and it costs \$45 to transmit a copy of an

September 1 and 34.7% set their opening date between September 2 and September 15.

application package to each school. After the initial application, applicants are allowed to update CAS reports (i.e. LSAT results, transcripts, or letters of recommendation) with law schools at no additional cost.

After receiving an application package, law school admissions committees usually make decisions in several evaluation rounds. As described in The Law School Admission Council (2018), qualifications far exceeding a school's admission standards usually result in an offer in the first round of decisions, though below-par qualifications will likely be rejected. At the vast majority of law schools, however, most applicants are neither distinctly above nor below par, and as such, offers or rejections cannot be made without more in-depth consideration of other factors by the admissions committee. The length of time required for this consideration process varies by law school.

A notable feature of the market is its regulation on exploding offers, which refer to offers that will be retracted if not accepted within a short period of time, such as one or two weeks, potentially complicating the matching process as applicants may need to commit to a school before hearing back from others. As the LSAC states that law schools should not request any commitments from applicants before April 1, exploding offers do not exist for the most part in this market. To a large extent, applicants can wait until all offers are made to make any commitments.[14]This feature simplifies the structure of the empirical environment.

V. Data

A. Data Source

Our empirical analysis is mainly based on large-scale data from a popular website among law school applicants, the Law School Numbers – founded in 2003 as a publicly accessible online database, the website allows for free account reg-

[14]In our data, 99.5% of applications and 92.3% of offers are made before April 1.

istration with the purpose of encouraging information sharing. A registered user has a profile page and an application page. A user's profile page contains a wide range of self-reported personal characteristics including LSAT scores, undergraduate GPA, gender, race, college name or type, college major, years out of college, state, and a description of extracurricular activities, while the application page contains a list of self-reported applications. For each application, the user reports the names of the law schools to which they have applied, the application track (i.e. *Regular Decision* or *Early Decision*), the date(s) of submission, the admission results, and the date(s) of admission results. Finally, the user may disclose which school's offer he or she accepts.

Out of the captured data, we construct a baseline sample containing non-missing values for the key variables in our analysis. Our baseline sample consists of 87,389 applications submitted by 9,323 applicants. We discuss the sample selection process in detail below.

In the initial step, we filter our data based on key applicant characteristics. First, we restrict the data time frame to the seven application cycles, 2006 to 2013, during which the popularity of *Law School Numbers* peaked. Second, we keep only applicants who report both LSAT scores and undergraduate GPA. As explained in the previous section, these two measures are the most important determinants of admissions decisions. Third, we restrict our sample to applicants who disclose admission results for at least one application among their portfolios. Finally, we drop international applicants to the best of our abilities, as schools may have a quota for international applicants that is separate from their quota for domestic U.S. applicants.[15] We approximate international applicants as those describing their undergraduate institutes as foreign.

[15] According to the Applicant and Application Counts released by the American Bar Association for 2009-2012, international applicants account for only 3.7%.

In the second step, we proceed to filter our sample data based on key application characteristics. We first restrict our sample to applications submitted through the *Regular Decision* track. We then drop applications with unreported dates of submission. Last, for repeat applicants who report applications in multiple application cycles, we keep only applications submitted in the last cycle. This is necessary because *Law School Numbers* allows a school to be reported at most once by each applicant, thus application data in earlier years may be overwritten in later years.

One concern is whether the data from *Law School Numbers* may be considered representative of the population data. We now offer evidence that along the two most critical admission determinants, LSAT scores and GPA, our sample distributions of applications and offers closely resemble those of the population distribution.

To begin, we exploit a unique data advantage of the legal education market: law school disclosure of their number of applications and offers by fine grids of LSAT and GPA, as encouraged by the LSAC. Of the 193 member law schools, 77 disclose such information for at least one year in our sample period. The majority of these schools report the statistics by intervals of 0.25 for GPA and intervals of 5 points for LSAT scores. Given that the feasible range for GPA is from 0.00 to 4.00 and for LSAT scores is from 120 to 180, the grid statistics provide a detailed portrait of application and admission patterns. See Figure A1 for an example of such disclosure.

We then compute the corresponding distributions of applications and offers in our data and compare them to that in the official LSAC data. In particular, for each year of a school's official data disclosure, we count the number of applications and offers observed in our data in the same year and of the same school. Next, we pool these counts from all available years and compute density distributions along LSAT scores and GPA for each school. We find that our sample distributions match population distributions quite well per school. To present results more succinctly instead of on a school-by-school basis, we further pool counts from all schools, weight schools so that their number of observations in the sample are comparable to that of the official data,[16] re-compute the density functions for this weighted pooled sample, and show the comparisons in Figure A2.

Overall, our sampling distribution matches the population distribution quite well. A small discrepancy occurs at the comparison of application distributions, with the sample distribution of applications slightly leaning towards the higher end of LSAT scores. However, our sample distribution of offers matches the population distribution quite closely. A plausible explanation for the coexistence of a close match of offer distributions and a discrepancy in match of application distributions is that we under-sample those of both poor credentials and few offers. As applications in this subsample are generally below the admission thresholds of their applied schools, they do not directly contribute to shaping the matching equilibrium. Generally speaking, we are confident that our data have captured the behaviors of the important players in this market.

B. *Summary Statistics*

We first document the dispersion in the timing of application submission. As shown in Table 1, an applicant submits 9.37 applications on average. The point at which the application is submitted varies greatly both across applicants and applications made by individual applicants. As shown in Table 2, pooling all applications together, an application is submitted 96 days since September 1 on average, and 94 days since initial opening of applications at each school, with a

[16]The weight of observations from each school is the ratio of official LSAC number of applications to the total sample number of applications.

standard deviation of 45 days. On the other hand, the span between the first and last application per applicant averages 29 days. It is worth noting that the distribution of submission timing is not uniform. It takes an applicant only 8 days on average to submit the first half of their applications, while it takes 21 days to submit the second half. This difference suggests strategic timing of submissions as applicants may selectively delay applications to certain schools.

Table 1—Summary Statistics of Applicants

	Mean	SD	Median
GPA	3.47	0.39	3.55
LSAT	163.18	7.86	164.00
# Applications Per Applicant	9.37	6.28	9.00
# Offers Per Applicant	4.67	3.66	4.00
# Rejections Per Applicant	1.99	2.96	1.00
# Waitlists Per Applicant	1.63	1.88	1.00
# Pending Per Applicant	1.08	2.17	0.00
# Applicants: 9323, # Applications: 87389			

Source: Computed by authors using *Law School Numbers*.

Next, we show that it is common for schools to make early and dispersed offers. As shown in Table 1, 50% of applications in our sample yield offers, 39% yield either direct rejections or waitlists, and the remaining 11% have undisclosed results. For 83.4% of the offers, we also observe the dates on which the offers are made. As shown in Table 2, schools on average start making offers 67.6 days after their opening date, which is even earlier than the average date applicants start applying. It takes schools roughly 78 days to finish making the first half of their offers, and a much longer 142 days to make the second half of offers. Pooled together, offers are, on average, sent out 143 days from the initial opening date with a standard deviation of 47 days.

Lastly, our sample also contains a number of additional measures regarding applicants and application characteristics.[17] For instance, 67.0% of applicants

[17]See Appendix A2 for details on how we quantify these measures.

report the state in which they reside, 66.4% of applicants report gender and race, 22.7% of applicants report a full set of "soft" characteristics ("Soft" factors), including college name or type, undergraduate major, years out of undergraduate program, and a description of extracurricular activities.

Table 2—Summary Statistics: Timing of Application Submissions and Offers

	Mean	SD
At Applicant Level (Obs = 9323.0)		
Date of First App: # Days since Initial Opening	81.27	46.08
Span of Dates of First Half of Apps	7.64	13.79
Span of Dates of Last Half of Apps	21.14	28.50
At Application Level (Obs = 87389.0)		
Submission Delay: # Days since Initial Opening	93.86	45.17

	Mean	SD
At School Level (Obs = 193.0)		
Date of First Offer: # Days since Initial Opening	67.60	26.50
Span of Dates of First Half Offers	79.47	25.64
Span of Dates of Second Half Offers	142.77	42.62
At Offer Level (Obs = 36321.0)		
Offer Dates: # Days since Initial Opening	143.51	46.68

Source: Computed by authors using *Law School Numbers*.

VI. Admission Advantage of Early Applications

In this section, we investigate whether schools do raise admission thresholds for later applications relative to earlier applications. We first present a baseline regression result documenting a large negative correlation between submission delay and receiving an offer. Next, we isolate two alternative explanations that may also result in this negative correlation: (1) there exists applicant heterogeneity, with earlier applications more likely to be submitted by higher-quality applicants; and (2) there exists heterogeneity in match quality, with applicants selectively applying earlier to schools that are more likely to give them offers. We conclude the section by arguing that schools do apply a time-dependent admission threshold and treat early applications much more favorably. Additionally, in Appendix A3, we document that schools facing more intense competition focus even more on earlier applicants. In Appendix A4, we conduct a number of robustness checks.

A. *Baseline Results*

Equation (2) shows our baseline regression specifications.

$$y_{is} = \beta_0 + \theta\Delta_{is} + \sum_{j=1}^{J} \beta_j X_{is}^j + \epsilon_{is}, \tag{2}$$

where y_{is} is a binary variable taking value 1 if applicant i receives an offer from school s by the end of the application cycle and 0 otherwise, Δ_{is} measures the *Submission Delay*, calculated as the difference between the date of submission and the date of initial opening at school s, and X^j represents control variables, including year fixed effects, school fixed effects, LSAT scores, and undergraduate GPA. The effect of submission delay on admission likelihood, θ, is our parameter of interest. Column (1) in Table 3 shows the results: an application delay of 100 days is associated with a drop in probability of admission of 8.3 percentage points. As a back-of-the-envelope calculation, this is equivalent to a reduction in GPA of 0.27 points (≈0.7 standard deviations) or a reduction in LSAT scores of 2.2 points (≈0.28 standard deviations).

B. *Isolating Alternative Explanations*

We proceed by controlling for applicant heterogeneity. We first include an exhaustive set of measures of applicant characteristics, including gender, race, years out of college, college type, college major(s), and a wide range of extracurricular activities (i.e. "soft" factors). Columns (2) and (3) in Table 3 display

Table 3—The Effect of Application Timing on Admission Chance

	(1) Admitted	(2) Admitted	(3) Admitted	(4) Admitted	(5) Admitted
Submission Delay	-0.0839	-0.0820	-0.0781	-0.0821	-0.0766
	(0.00515)	(0.00614)	(0.0106)	(0.00918)	(0.00918)
GPA	0.318	0.310	0.307		
	(0.00669)	(0.00790)	(0.0142)		
LSAT	0.0374	0.0394	0.0365		
	(0.000502)	(0.000585)	(0.00103)		
Observations	87389	59191	21407	86513	86513
FE_Year	Yes	Yes	Yes	Yes	Yes
FE_School	Yes	Yes	Yes	Yes	Yes
GPA_LSAT	Yes	Yes	Yes		
Gender_Race		Yes	Yes		
Softs			Yes		
FE_i				Yes	Yes
In_State					Yes

Standard errors in parentheses

Note: Admitted is a binary variable that takes value 1 if the applicant is admitted and 0 otherwise. *Submission Delays* are measured in hundreds of days. Standard errors are clustered at the applicant level.

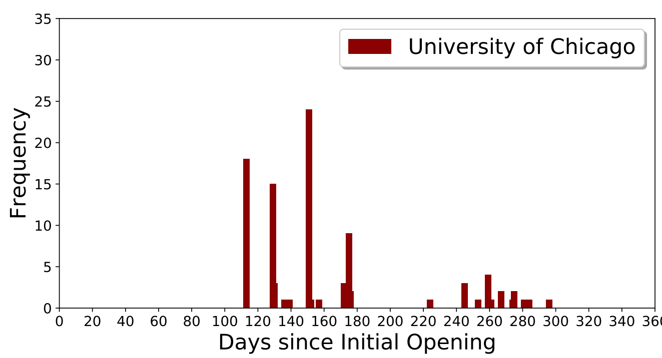
the results.[18] Next, we exploit the longitudinal structure of the dataset and control for individual fixed effects using the subsample of applicants who submitted multiple applications. Column (4) in Table 3 displays the results. One important variable that affects match quality is home bias, as applicants may prefer schools located in the same state, and schools may likewise prefer applicants residing in the same state. Exploiting our measure of the geographical location of applicants, we include a variable indicating if an applicant is in the same state as the school in the regression and report its results in column (5). Our coefficient on submission delay remains statistically significant and large throughout all these specifications.

[18]As described in section V.B, our dataset contains the additional measures of characteristics only for a subset of applicants, and thus the number of observations differ substantially across regression specifications in Table 3. Despite this, all tested specifications yield statistically significant and quantitatively similar estimates for our coefficient of interest.

We then move on to test for the importance of the second alternative explanation. We exploit an institutional feature that creates discontinuities in application timing that are perceived by law schools but not by applicants. In practice, many law schools evaluate applications and make offers in rounds. In other words, they accumulate a pool of applications up to a certain cutoff date, make offer decisions for this pool, and continue to accumulate applications arriving in subsequent pools while holding off evaluations until the end of each round.

Figure 3 illustrates the existence of evaluation rounds using admission decisions data to capture the total number of offers sent on each day over time from 2008 to 2009, using the University of Chicago Law School as an example. The distribution exhibits several sharp discontinuities, corresponding to potential evidence of application accumulation for evaluation in rounds by the admission committee.

Figure 3. Number of Offers Granted on Each Day: Application Season 2008-2009



Source: Computed by authors using *Law School Numbers*.

As schools do not announce the culmination of each round to applicants, the evaluation round of an application can be viewed as an exogenous outcome to applicants. If the admission advantage of early application is mainly driven by unobserved match quality, we should still observe an admission advantage for applications submitted earlier rather than later **within** the same evaluation round. On the other hand, if the admission advantage of early applications is mainly driven by schools raising the admissions threshold over time, this advantage should only exist **across** but not **within** evaluation rounds.

To evaluate these scenarios in practice, the first step is to determine the opening and cutoff dates for each evaluation round at each law school. We focus on the first round of the evaluation process. Although schools may or may not evaluate applications in strictly separate rounds throughout the entire application season, our data suggests that very few of them make offers immediately in the early stages of the decision-making process. Almost all of them hold off on sending out offers until accumulating a sufficiently large pool of applications. Administratively, schools may also be occupied with promotional activities during this time in September and October.

We proxy the cutoff date of the first round, or equivalently, the opening date of the second round, as the date of the first offer observed in the data. Table 2 shows the statistics regarding Round 1 cutoff dates.

Although it would be ideal to include the cutoff dates in all subsequent evaluation rounds, it is difficult to identify these cutoffs in practice. This is because schools may save some applications that fall near the quality cutoff for subsequent evaluation rounds and eventually decide to make an offer. In the data, we cannot tell from an offer how many evaluation rounds the underlying application has undergone, and correspondingly, whether all offers made during this period are evaluated in one big round or in multiple separate rounds.

We formalize this empirical strategy in equation (3):

$$(3) \qquad y_{is} = \beta_0 + \theta_1 \Delta^I_{is}(1 - D_{is}) + \theta_2 \Delta^L_{is} D_{is} + \gamma D_{is} + \sum_{j=1}^{J} \beta_j X^j_{is} + \epsilon_{is},$$

where y_{is} is a binary variable that takes value 1 if applicant i receives an offer from school s and 0 otherwise; Δ^I_{is} measures application i's submission delay from school s' initial opening date; Δ^L_{is} measures the submission delay from school s' round 2 opening date, the latter of which we interpret from the data as the date of school s' first offer; D_{is} is a binary variable taking value 0 if application i is submitted in school s' first evaluation round and 1 otherwise.

Additionally, γ measures the admission disadvantage of applications submitted in a later evaluation round relative to those in the first evaluation round; θ_1 measures the admission disadvantage of later applications relative to earlier ones within the same first evaluation round; θ_2 measures the admission disadvantage of later applications among applications in all later rounds.

As discussed above, differentiating between the story of non-stationary admission thresholds and the story of applicants applying earlier to better-matched schools can be formulated as performing a hypothesis test on the value of θ_1. If the admission advantage is driven by time-dependent admissions thresholds, we should expect this advantage to exist across but not within evaluation rounds, i.e. $\theta_1 = 0$. On the other hand, if the admission advantage is driven by unobserved match quality, we should expect this advantage to exist throughout the whole sample, i.e. $\theta_1 < 0$.

As for the remaining two parameters, γ and θ_2, although they do not contribute to distinguishing between the two stories, they do help confirm the existence of admission advantages of early applications. Therefore, we would expect both $\gamma < 0$ and $\theta_2 < 0$.

Results are shown in Table 4. Columns (1)-(3) apply different sets of control variables of applicant characteristics, and column (4) controls for applicant fixed effects. Column (5), our preferred specification, also controls for whether an applicant resides in the same state as a school on top of applicant fixed effects. Both γ and θ_2 are significantly negative, confirming the existence of later-application admission disadvantage. Our test statistic, the coefficient estimate $\hat{\theta}_1$ for submission delay within the first evaluation round, is not statistically different from zero. Therefore, we cannot reject our null hypothesis that the admission advantage of early applications is driven by time-dependent admissions thresholds, rather than by unobserved match quality.

TABLE 4—THE EFFECT OF SUBMISSION TIMING ON ADMISSION CHANCE: DISCONTINUITY SPECIFICATIONS

	(1) Admitted	(2) Admitted	(3) Admitted	(4) Admitted	(5) Admitted
Delay from Initial Opening× In Rd1	-0.0172	-0.0215	0.0189	-0.0257	-0.0220
	(0.0159)	(0.0189)	(0.0310)	(0.0172)	(0.0172)
In Later Evaluation Rds	-0.0270	-0.0301	-0.0101	-0.0308	-0.0275
	(0.00996)	(0.0118)	(0.0195)	(0.0114)	(0.0114)
Delay from Rd2 Opening× In Later Rds	-0.0941	-0.0896	-0.0905	-0.0932	-0.0889
	(0.00669)	(0.00807)	(0.0142)	(0.00950)	(0.00950)
Observations	87375	59181	21401	86499	86499
FE_Year	Yes	Yes	Yes	Yes	Yes
FE_School	Yes	Yes	Yes	Yes	Yes
GPA_LSAT	Yes	Yes	Yes		
Gender_Race		Yes	Yes		
Softs			Yes		
FE_i				Yes	Yes
In_State					Yes

Standard errors in parentheses

Note: Admitted is a binary variable that takes value 1 if the applicant is admitted and 0 otherwise. *Submission Delay* is measured in hundreds of days. Standard errors are clustered at the applicant level.

Continuing on, we revisit the implications of our results in light of the evaluation rounds of schools. Since admissions thresholds increase at defined points over time instead of continuously, it is important to submit an application for evaluation in earlier rounds. However, in our data, 69.3% of applications are submitted after the first evaluation round. Our results show that submitting an application in the second evaluation round earlier such that it is reviewed in the first evaluation round could give the application a greater likelihood of admission of 2.75 percentage points - even if "earlier" means as little as a single day in advance. A jump from even later evaluation rounds to the first evaluation round could produce even greater admission premiums.

Last, we compare our results to the admissions advantage of applying through *Early Action* or *Early Decision* tracks instead of *Regular Decision* tracks in the college education market. Both EA and ED tracks feature much earlier deadlines than regular decision tracks. Different from early applications in our environment though, an applicant can only submit a single EA or ED application at a time. ED also requires enrollment commitment from applicants once they receive offers. Therefore, EA and ED also serve as tools for an applicant to signal to a school that it is his or her top choice. As documented in Avery and Levin (2010), among the 28 elite colleges, an EA (ED) application is associated with a 17 to 20 percentage point (31 to 37 percent) increase in admissions probability.

Our results can be viewed as the isolated effects of early-submission admission probabilities, excluding the effects of signaling preferences to schools. Roughly speaking, the admission premium of applying during the first evaluation round relative to the second is a hefty one sixth of the total early-application premium of EA.

Following our story, one would predict that schools facing greater competition intensity, reflected in the data as a lower acceptance probability of their admission offers, should render schools even more lenient towards early applicants. This is because the less likely an offer is accepted, the greater the number of offers the school needs to send out in order to achieve an enrollment close to its target. As the variation in the number of acceptances increases with the volume of offers, schools facing more intense competition would have stronger incentives to target early applicants to control the yield. In Appendix A3, we construct a measure of competition intensity faced by each school using the quality of applicants' alternative offers and confirm this prediction.

Lastly, we conduct robustness checks to ensure that the admission advantage of applying early is not driven by two plausible measurement errors in the data. First, the options to update LSAT scores and transcripts throughout the application process renders these scores positively correlated with submission timing, while we only observe one set of GPA and LSAT scores in the data. We exploit the fact that these updates are only likely to occur at the end of the semester or after LSAT results release dates, and show that our results are stable when restricting to a subsample of applicants who are unlikely to update their application package. We also argue that since applicants only have incentive to update these results if the new scores are better than the earlier ones, this would, if anything, bias our estimates of the early application advantage downwards, not upwards. Second, admissions results of a subset of applications are not disclosed. In the robustness check, we repeat our empirical exercises excluding these applications and find similar results. More details can be found in Appendix A4.

VII. Why Do Some Still Apply Late?

A puzzle that naturally arises is why applicants still apply late in spite of the substantial admission advantage associated with early applications. In this section, we provide suggestive evidence for three types of frictions that constrain applicants from applying earlier: (1) applicants may have tight time constraints, (2) applicants who take the LSAT exam in October or December of the application season must wait for their scores to be released, and (3) since each application is costly in both time and financial terms and associated with *a priori* uncertain admission outcomes, applicants may strategically postpone applications to accommodate new information on their admissions results.

A. Time Constraints

The most straightforward explanation is that preparing an application is time-costly, thus applicants with tighter daily time constraints have to progress more slowly and elongate their applications process. Applicants incur two types of time costs. First, applicants incur an "entry" time cost to prepare the common part of application materials. Second, although law schools require very similar application materials, applicants may still incur a marginal time cost to tailor each additional application after the initial submission. Moreover, law school applicants have diverse backgrounds, with a substantial 67% already out of college in our sample and presumably working full-time. Although intuitively straightforward, it is challenging to quantify the importance of this explanation, as direct measures of time constraints are difficult to obtain. To circumvent this obstacle, we take a novel approach by classifying "busy" applicants as those who submit all applications on weekends. For our sample, this constitutes 5% of applicants.

We next document how busy applicants differ in submission patterns from their peers. As shown in Table 5, busy applicants tend to, on average, start submitting applications 10 days later than their peers and submit 3 fewer applications overall. These differences result from the interaction of entry time cost and marginal time cost with tight time budget constraints.

Our results imply that time costs for applications are high. This is consistent with Fu (2014), which estimates that, in the college market, when accounting for all types of applicant-side barriers - such as the cost to collect information and prepare application materials, the stress to meet the application deadlines, and the anxiety felt while waiting for admissions results - the cost of the first application totals as much as $1,900. The estimated cost for subsequent applications, while lower, may still cost as much as $900 for the second, $330 for the

Table 5—The First Day and Total Number of Applications by Applicants of Different Time Constraints

	(1) # Apps	(2) # Apps	(3) # Apps	(4) Delay	(5) Delay	(6) Delay
Only at Weekends=1	-3.315	-3.227	-4.160	10.83	7.986	12.02
	(0.247)	(0.310)	(0.519)	(2.089)	(2.567)	(5.006)
Observations	9323	6193	2123	9323	6193	2123
GPA_LSAT	Yes	Yes	Yes	Yes	Yes	Yes
Gender_Race		Yes	Yes		Yes	Yes
Softs			Yes			Yes

Standard errors in parentheses

Note: Delay is measured in days.

third, and $270 for later applications.

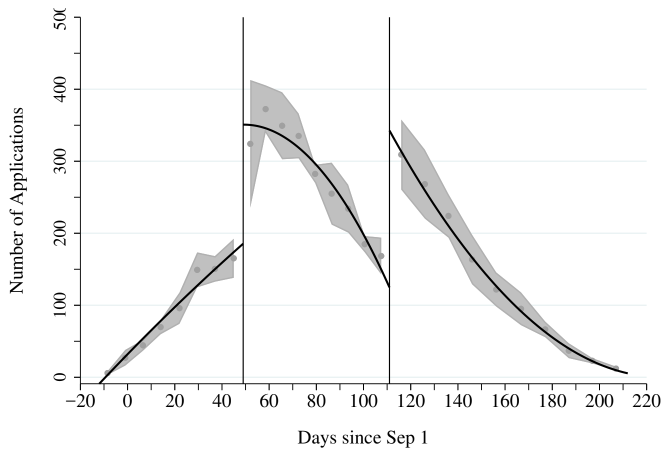
B. Late LSAT Exam Taking

Some applicants may also be constrained by the release date of their LSAT results. Applicants who take their LSAT in October or December of the application season may have to postpone their submissions until such time as their test scores are released. To quantify the size of applicants constrained by the release of exam results, we exploit the discontinuity in the number of submissions before and after result release dates.

We illustrate the idea in Figure 4. The two vertical lines mark LSAT results release dates for the October and December exams, respectively. The fitted curves correspond to the polynomial estimates of the number of application submissions over time, with the length of bins being one week. As shown, there are two substantial jumps in application volume immediately following each test score release date.

We then provide back-of-the-envelope calculations to measure the size of applicants constrained by these results release dates. In particular, we compare the number of applicants who apply within one week after release dates to those who do so one week before. The difference is our proxy for the size of constrained

FIGURE 4. NUMBER OF APPLICATIONS SENT AROUND LSAT SCORE RELEASE IN OCT AND DEC



Source: Computed by authors using *Law School Numbers*.

applicants. We construct this measure out of two considerations. First, we focus on applications submitted almost immediately after the release of LSAT results, as these applications are likely well-prepared apart from their LSAT results, and thus constrained only by the release of the latter. Second, we difference out the number of submissions completed just before the results release. Intuitively, we assume such applicants are unconstrained by the release date of LSAT results and simply happen to submit around this time, thus we can assume that the total number of such applicants remains similar immediately before and after each release date.

Following this idea, we provide an upper and lower bound estimate for the size of constrained applicants. The upper bound is the size of those who are partially constrained for any number of applications and who submit any applications just after the results release, while the lower bound is the size for those who are fully constrained for all applications and only those who submit all their applications just after the results release. It follows that our estimates are 888 and 207 applicants at the upper bound and lower bound, respectively, or 9.5% and 2.2% of all applicants. Why would applicants take these exams in the second half of the year instead of earlier is beyond the scope of this paper. However, it is worth nothing that such behaviors are commonplace. According to the statistics released by the LSAC for our sample period, 35% and 29% of all exam takers in a calendar year take the test in October and December, respectively. One implication of our results is that more frequent test offerings may substantially level the playing field for applicants.

C. Strategic Delay for New Information

A third reason is that applicants may strategically postpone submissions in order to accommodate new information available over time in the application process. Applicants have incentive to do so because each application is costly and the admission outcome is uncertain. More specifically, we document evidence that applicants may update the school composition of their portfolio in response to earlier admission results.

First, we delineate schools by their rankings so that we can compare applicant portfolio composition. As explained earlier, although schools differ in many other aspects, USN school rankings are a highly influential factor in the application/decision process. School rankings also provide a concise way to measure and compare school quality. In light of this, we formulate our question more specifically as measuring the effect that receiving the admissions results of earlier applications has on the ranking of schools an applicant applies to later on.

We proceed by defining the time interval of gathering "updates." In an adhoc manner, we define it as the time interval between every two application rounds for each applicant. Each round is a unique date on which an applicant submits at least one application. Thus, *Offer Updates* refers to offers arriving between an applicant's two application rounds, while *Rejection Updates* refers to rejections arriving in such intervals. It is worth noting that our definition starts from the second application round, when "updates" are likely to occur. Correspondingly, in our regression sample, we keep only applications submitted after the first application round.

We regress the ranking of the schools each applicant applies to using the updates she receives since the previous round of application. Each observation corresponds to one application submitted by applicant i to school s in round r. One challenge is that the effect of new offers and rejections on later application portfolios can be nonlinear, influenced by both school rankings and applicant credentials. For instance, an offer from a top school may be more important than an offer from a lower-ranking school, while the same offer from a given school may have a different effect on a high-caliber applicant versus a low-caliber one. To capture this nonlinearity, we include not only indicator variables for if one has offer/rejection updates, but also the school ranking of the best new offers and new rejections. In addition, we include various sets of measures of applicant characteristics. Lastly, we include applicant fixed effects in two regressions to also account for heterogeneous preferences.

Table 6 displays the results. We document strong encouraging effects from new offers and discouraging effects from new rejections in all specifications. In our preferred specifications, controlling for individual fixed effects in columns (4) and (5), the arrival of a new offer encourages an applicant to target schools ranking 2.2 places higher. Meanwhile, the arrival of a new rejection leads to a more conservative target ranking of over 8 places lower. Columns (1)-(3) suggest the encouraging/discouraging effects are differential along school rankings. Accounting for "Rank of the Best new Offer" and "Rank of the Best New Rejection" averaging 43 and 33, respectively, columns (1)-(3) deliver similar average effects as columns (4)-(5).

Table 6—The Effect of Applicant Admission Results on Subsequent Application Choices

	(1) Ranking	(2) Ranking	(3) Ranking	(4) Ranking	(5) Ranking
With Offer Updates	-9.011	-9.742	-11.52	-2.224	-2.209
	(0.787)	(1.037)	(1.813)	(0.883)	(0.877)
With Offer Updates× Ranking of the Best New Offer	0.127	0.136	0.134	-0.0310	-0.0313
	(0.0191)	(0.0235)	(0.0362)	(0.0200)	(0.0198)
With Rejection Updates	-2.271	-1.531	-0.354	8.561	8.326
	(2.030)	(2.593)	(4.027)	(2.453)	(2.462)
With Rejection Updates× Ranking of the Best New Rej	0.152	0.159	0.0926	0.00796	0.0127
	(0.0602)	(0.0794)	(0.0993)	(0.0681)	(0.0692)
Observations	29591	19738	7441	29591	29591
FE_Year	Yes	Yes	Yes	Yes	Yes
FE_Month	Yes	Yes	Yes	Yes	Yes
GPA_LSAT	Yes	Yes	Yes		
Gender_Race		Yes	Yes		
Softs			Yes		
FE_i				Yes	Yes
In_State					Yes

Standard errors in parentheses

Note: Ranking refers to school ranking as listed in the *U.S. News and World Reports*, where the school with ranking 1 has the highest possible ranking. Standard errors are clustered at the applicant level.

Applicants may adjust the school composition of their portfolio later on given earlier admissions results for two reasons. First, the marginal value of an additional application changes depending on earlier admission results. For instance, an applicant may not find it worthwhile to apply to a less-selective school if she has already applied to a number of other schools and expects to get some offers out of them. This additional application, however, may turn out to be worthwhile if the applicant keeps receiving rejections later on. Second, applicants may adjust their belief about the competitiveness of their application package based on earlier admissions results. This explains why applicants apply to the higher ranking and usually more selective schools after receiving offers, and conversely, apply downwards after receiving rejections.

VIII. Conclusion

Many higher education markets use decentralized admissions mechanisms and feature various frictions in the application and admission processes. Understanding these frictions and their effects on applications and admissions have paramount fairness and welfare implications. In this paper, we focus on an under-studied yet important dimension of application decisions influenced by these frictions: the timing of application submissions. We find that later applications suffer a substantial drop in admission probability relative to earlier applications. Despite this disadvantage, many applicants still apply late because of tight time budgets, taking the LSAT in the midst of an ongoing application cycle, and applications being both costly and having *a priori* uncertain admission outcomes. To quantify the applicants' dynamic tradeoffs over the application cycle, we need to build and estimate a structural model that accounts for these frictions and the admission uncertainty under rolling admissions. We leave this for future research.

REFERENCES

Avery, Christopher, and Jonathan Levin. 2010. "Early Admissions at Selective Colleges." *The American Economic Review*, 100(5): 2125–2156.

Bettinger, Eric P., Bridget Terry Long, Philip Oreopoulos, and Lisa Sanbonmatsu. 2012. "The Role of Application Assistance and Information in College Decisions: Results from the H&R Block FAFSA Experiment." *The Quarterly Journal of Economics*, 127(3): 1205–1242.

Carrell, Scott, and Bruce Sacerdote. 2017. "Why Do College-Going Interventions Work?" *American Economic Journal: Applied Economics*, 9(3): 124–51.

Chade, Hector, Gregory Lewis, and Lones Smith. 2014. "Student Portfolios and the College Admissions Problem." *The Review of Economic Studies*, 81(3): 971–1002.

Che, Yeon-Koo, and Youngwoo Koh. 2016. "Decentralized College Admissions." *Journal of Political Economy*, 124(5): 1295–1338.

Dynarski, Susan, C.J. Libassi, Katherine Michelmore, and Stephanie Owen. 2020. "Closing the Gap: The Effect of a Targeted, Tuition-Free Promise on College Choices of High-Achieving, Low-Income Students." *Working Paper*.

Froomkin, Michael. 2009. "Miami Law to Offer Students $5K Public Interest Scholarship to Defer." *Discourse.net*.

Fu, Chao. 2014. "Equilibrium Tuition, Applications, Admissions and Enrollment in the College Market." *Journal of Political Economy*, 122(2): 225–281.

Hoxby, Caroline M., and Sarah Turner. 2013. "Expanding College Opportunities for High-Achieving, Low Income Students." *SIEPR Working Paper 12-014*.

Hoxby, Caroline M., and Sarah Turner. 2015. "What High-Achieving Low-Income Students Know about College." *American Economic Review (P&P)*, 105(5): 514–17.

Johnson-Elie, Tannette. 2015. "Law Schools Adjust to Increasingly Lower Enrollment." *Insight Into Diversity.*

Knight, Brian, and Nathan Schiff. 2019. "Reducing Frictions in College Admissions: Evidence from the Common Application." *NBER Working Paper No. 26151.*

Kowarski, Ilana. 2018. "How Applying to Law School Early Could Pay Off." *The U.S. News and World Reports.*

Pallais, Amanda. 2015. "Small Differences that Matter: Mistakes in Applying to College." *Journal of Labor Economics*, 33(2): 493–520.

Rivard, Ry. 2015. "Lowering the Bar." *Inside Higher Ed.*

Sauder, Michael, and Wendy Espeland. 2007. "Fear of Falling: The Effects of U.S. News and World Reports Rankings on U.S. Law Schools." *Law School Admission Council Research Report Series 07-02.*

Scheiber, Noam. 2016. "An Expensive Law Degree, and No Place to Use It." *New York Times.*

Stetz, Mike. 2018. "Enrollment Up at Some Schools, But Is That Good or Bad?" *National Jurist.*

The Career Center at the University of California at Berkeley. 2020. "Law School - Timeline." *Division of Student Affairs.*

The Law School Admission Council. 2017. "LSAC Statement of Good Admission and Financial Aid Practices."

The Law School Admission Council. 2018. "How Law Schools Determine Whom to Admit."

Vault Law Editors. 2009. "The Application Timeline: Will Applying to Law School Later." *The Vault.*

Ward, Stephanie Francis. 2018. "While Number of Lawyer Jobs Have Been Decreasing, Law School Applications Are Up More Than 8%." *The ABA Journal.*

APPENDIX

A1. Comparisons between the Sample Data and the Official Data

Figure A1. An Example of Official Disclosure on Number of Applications and Offers by LSAT Scores and GPA

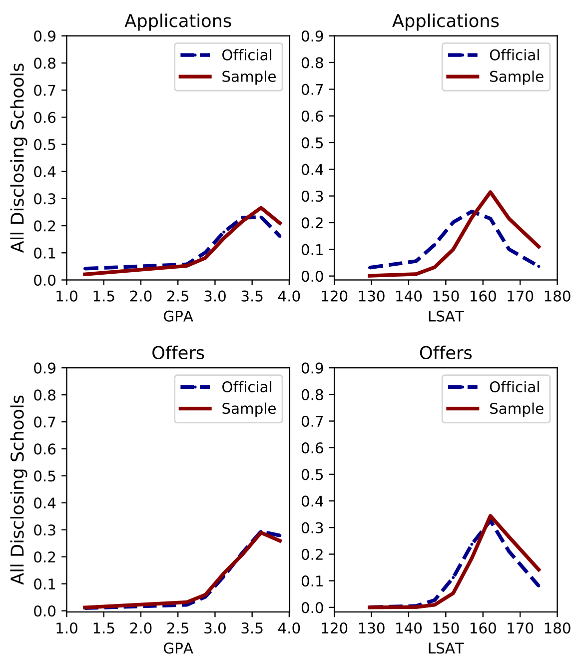
Vanderbilt University Law School
This grid includes only applicants who earned 120-180 LSAT scores under standard administrations.

LSAT	GPA: 3.75 +		3.50 - 3.74		3.25 - 3.49		3.00 - 3.24		2.75 - 2.99		2.50 - 2.74		2.25 - 2.49		2.00 - 2.24		Below 2.00		No GPA		Total	
Score	Apps	Adm	Apps	Adm	Apps	Adm	Apps	Adm	Apps	Adm	Apps	Adm	Apps	Adm	Apps	Adm	Apps	Adm	Apps	Adm	Apps	Adm
175-180	5	5	2	2	4	4	4	0	1	0	0	0	0	0	1	0	0	0	0	0	17	11
170-174	24	24	18	18	28	18	12	2	3	0	5	0	0	0	1	0	0	0	2	2	93	64
165-169	154	153	193	177	135	43	69	8	33	0	9	0	3	0	1	0	1	0	5	5	603	386
160-164	311	90	425	91	286	32	145	13	69	0	16	0	5	0	1	0	1	0	12	4	1271	230
155-159	215	5	272	9	184	7	109	7	55	1	21	0	5	0	1	0	0	0	10	0	872	29
150-154	76	5	112	8	104	13	87	10	37	0	24	0	10	0	6	0	1	0	8	0	465	36
145-149	34	0	52	1	48	0	40	0	35	0	14	0	8	0	2	0	1	0	6	0	240	1
140-144	11	0	17	0	21	0	16	0	15	0	9	0	9	0	6	0	0	0	5	0	109	0
135-139	4	0	3	0	9	0	11	0	7	0	7	0	2	0	3	0	1	0	2	0	49	0
130-134	0	0	1	0	2	0	1	0	2	0	3	0	1	0	2	0	1	0	1	0	14	0
125-129	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	1	0
120-124	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	0
Total	834	282	1095	306	821	117	494	40	257	1	109	0	43	0	24	0	6	0	52	11	3735	757

Apps = Number of Applicants Adm = Number Admitted Reflects 99% of the total applicant pool.

Source: The Official Guide to Law Schools.

Figure A2. Sample v.s. Official Probability Distributions: All Disclosing Schools



Source: Law School Numbers and the Official Guide to Law Schools.

A2. Additional Measures of Applicant and Application Characteristics

We classify race into {White, Asian, Hispanic, African, Mexican, Puerto Rican, Native American or Alaskan}, with the latter four granted admission advantage by the LSAC as the Underrepresented Minority. We classify college majors into {Social Sciences, Arts and Humanities, Business and Management, Natural Sciences, Engineering, Health Professionals, and Other}. For double majors, we check both categories. For college name or type, we first try to recover school names. Then, based on reported names and descriptions, we classify a subset of values into {Nationally Ranked, Regionally Ranked} according to the U.S. News and World Reports College Rankings to obtain numerical rankings. Any remaining descriptions are ambiguous and thus cannot be mapped to the USN. We classify these into {Described Positively, Described Negatively, Described Neutrally} based on tones of descriptions. Lastly, we breakdown extracurricular activities into a set of binary variables, {Athletic achievements, Community service or volunteer experience, Greek society, Non-Greek campus activities, Military experience, Legal internship, Non-legal internship, Legal work experience, Non-legal work experience, Overseas experience, Strong recommendation letter, Leadership}, and assign each binary variable a value of 1 if an applicant reports having a related experience.

A3. Heterogenous Admission Advantages of Early Applicants across Schools

Following our story, one would predict that schools with more intense competition, reflected as lower acceptance probability of their offers, should focus even more on early applicants. The reason is intuitive: the less likely an offer is accepted, the greater the number of offers the school needs to send out in order to achieve an enrollment close to its target. As the variation in number of acceptances to a higher volume of offers is greater than that to a lower volume, schools with more intense competition would have stronger incentives to target early applicants to control the yield.

More specifically, as a back-of-the-envelope calculation, given capacity κ and acceptance probability τ, a school needs to make $Q = \frac{\kappa}{\tau}$ offers to ultimately achieve an expected enrollment of κ. If all offers are made in one round, the variance of acceptances to these offers, applying the variance formula for the Binomial distribution, is $Variance = Q\tau(1-\tau) = \frac{\kappa}{\tau} \times \tau \times (1-\tau) = \kappa(1-\tau)$. Therefore, the lower the τ, the higher the variation in responses, and consequently, the greater the benefits from filling some seats early in the admission process.

To test this prediction empirically, we first construct measures for the competition faced by each school as the quality of alternative offers received by applicants of the school. Recall that although applicant preferences towards schools are heterogenous, USN school rankings play an important role in these preferences, as applicants are more likely to prefer a higher ranking school to a lower ranking one. We thus propose two proxies for characterizing the quality of applicant outside offers: the number of offers from (weakly) higher-ranking schools, and the gain in rankings from the school in question to the highest-ranking school that actually makes the applicant an offer.[19] The key advantage of these two proxies is that they can be constructed for every applicant to the school in question no matter if the applicant has received its offer in reality; therefore, unlike observed yield rates, they are immune from the endogenous selective targeting of school admission strategies. A limitation of these two proxies, however, is that not all schools are numerically ranked; lower ranking schools are usually coarsely classified as "Tier 3" or "Tier 4" every year. Therefore, we construct these proxies only for applicants to the schools that received numerical rankings over our entire sampling period. After these two proxies are computed for each applicant-school pair, we aggregate them at the school level, by calculating the mean of the first proxy as well as the median of the second proxy for the entire pool of applicants to each school.

Table A1 displays the outside offer statistics of applicants that apply to schools consistently ranked above 75th over our sampling period. We divide these schools further into two groups, Top 14 schools and Top 15-75 schools. Top 14 schools refer to the 14 prestigious law schools that historically occupy the top 14 places in the USN Rankings. Although their rankings may change across the years amongst themselves, they always rank higher than the remaining schools. Applicants to top 14 schools hold an average of 1.1 offers from higher-ranking schools, with their most competitive outside admission offer ranking approximately the same as the school in question. In other words, a typical applicant to a top 14 school usually holds an offer from another top 14 school. Applicants to a top 15-75 school hold an average of 2.1 offers from higher-ranking schools, with their most competitive outside offers from schools ranking approximately 5 places higher than the school in question. Overall, lower ranking schools face almost double the competition from other schools.

Next, we modify our regression specifications by adding an interaction term between ap-

[19]In computing these measures, we also include the outside offers applicants receive from Early Decision programs.

Table A1—Summary Statistics: Competing Offers Held by Applicants to Each School

	Mean	SD
Mean, # Higher Ranking Offers per Applicant		
Top 14 Schools	1.13	0.68
Top 15-75 Schools	2.08	0.35
Median, Largest Gain in Ranks through Outside Offers per Applicant		
Top 14 Schools	-0.04	2.38
Top 15-75 Schools	5.08	5.78

Note: Computed by authors using *Law School Numbers*.

plication submission delay and measures of competition faced by each school: the number of offers from higher ranking schools, and the largest gain in ranking through an outside offer, aggregated at the school level. Regression results are shown in Table A2. The coefficients of both interaction terms are negative and significant. These results suggest that the greater the competition intensity faced by a school, as reflected by better outside offers received by its applicants, the greater its admissi on advantage for earlier applicants.

Table A2—Admission Advantage of Early Applicants across Schools

	(1) Admitted	(2) Admitted
Submission Delay	-0.00911	-0.0874
	(0.0181)	(0.0124)
Delay× Number of Higher Ranking Offers	-0.0517	
	(0.00835)	
Delay× Gain in Rankings from Outside Offers		-0.00309
		(0.00101)
Observations	61210	61210
FE_Year	Yes	Yes
FE_School	Yes	Yes
FE_i	Yes	Yes
In_State	Yes	Yes

Standard errors in parentheses

Note: Delay are measured in hundreds of days. *Number of Higher Ranking Offers* and *Gain in Rankings from Outside Offers* are statistics calculated at the school level. Standard errors are clustered at the applicant level.

A4. Robustness Checks

In this section, we conduct robustness checks to ensure that the admission disadvantage of late applications is not driven by two non-classical measurement errors in the data. First, applicants are able to update their LSAT scores and transcripts throughout the application process, making these scores positively correlated with submission timing, while we only observe one LSAT score and one GPA in the data. Second, admissions results of a subset of applications are not disclosed. These missing values may bias our estimated correlation between submission delay and admissions probability. We conduct robustness checks to examine if our findings can withstand these two challenges.

Updating LSAT scores and Transcripts

One concern is that applicants can update their LSAT scores and GPA throughout the application process, while we only capture them once in the data.

First, we argue intuitively that our main results, the admission advantage for earlier applications, are not driven by this discrepancy in measures of credentials. Applicants would have incentive to update their LSAT scores or transcripts only when later scores are strictly better than earlier scores. Therefore, in the case of one applicant with multiple scores in the process, the later applications must be of higher caliber than earlier applications. Thus, this measurement error can only bias our main results of early-application advantage downwards, below the true value.

Next, we repeat our empirical exercise, restricting to a subsample that is unlikely to update their LSAT scores or transcripts, by exploiting the usually long time gaps between these score updates. For instance, LSAT exams are administrated only four times a year, while transcripts can be updated only at the end of an academic term. We can thus select a subsample of applications submitted during these gaps and examine if our findings remain intact for this subsample.

We first restrict to applications submitted between the release of test scores for the October and December exams. The subsample consists of applicants using the same LSAT scores across all submitted applications. We further assume that applicants are not likely to update their GPA before the end of December and drop all applications submitted after December 18th, or one week before Christmas, which we use as a proxy for the end of the academic semester. Although academic terms differ across colleges in terms of quarters or semesters, as many as 84% of undergraduate students at a 4-year institution granting bachelor's degrees reference a semester-based academic calendar system.[20] Therefore, most students are unlikely to have updated transcripts until the end of the semester. In summary, for this subsample, each applicant would have the same LSAT scores and GPA for all applications. [21]

Regression results are shown in columns (1) and (2) in Table A3. Overall, our regression coefficients are robust. The coefficient for *In Later Evaluation Rounds* becomes insignificant, possibly because our subsample selection has left us with too few observations in the first evaluation round.

[20]Calculated by the authors using the 2003-2004 National Postsecondary Student Aid Studies. NPSAS is a large-scale, nationally representative survey conducted every four years by the U.S. Department of Education.

[21]Although applicants may obtain better test results after late December and could potentially update this subset of applications, they would have used the same documents to do so. Thus, even if the academic measures we observe in the data are still different from the actual ones, they remain the same across each applicant's applications. Our inclusion of applicant fixed effects would absorb the effect of measurement errors on the admission probabilities.

Selective Disclosure of Admission Results

Another measurement error that could potentially bias our results is selective disclosure of admission results. As we describe above, the admissions results of 11% of all applications are not disclosed and display as "Pending". Throughout the analysis, we treat these applications as not generating offers. Nonetheless, it could also be that these applications do yield offers and that the applicants choose or forget to report them. Below, we discuss why we believe our results are not driven by this selective disclosure.

We first argue that these applications are more likely to have generated rejections instead of offers. As a back-of-the-envelope calculation, we compare the rankings of law schools of these applications to that of the best offers and worst offers an applicant has reported. As high as 54% of *Pending* applications are to schools ranked strictly higher than the best offer, while only 6% rank strictly lower than the worst offer. This suggests *Pending* schools seem more likely to be stretch schools with higher odds of rejection, rather than safety schools with lower odds of rejection. Treating them as not yielding offers thus seems more reasonable than the alternative.

In the second step, we leave out applications with unclear results and repeat our main empirical analysis using only the subsample with reported admission results. As shown in columns (3) and (4) in Table A3, our coefficients remain statistically significant and large.

TABLE A3—THE EFFECT OF SUBMISSION TIMING ON ADMISSION CHANCE: ROBUSTNESS CHECKS

	(1) Admitted	(2) Admitted	(3) Admitted	(4) Admitted
Submission Delay	-0.149		-0.0419	
	(0.0331)		(0.00947)	
Delay from Initial Opening× In Rd1		-0.0448		-0.0157
		(0.0410)		(0.0173)
In Later Evaluation Rds		-0.0445		-0.0242
		(0.0295)		(0.0115)
Delay from Rd2 Opening× In Later Rds		-0.173		-0.0449
		(0.0322)		(0.00972)
Observations	37873	37869	76175	76163
FE_Year	Yes	Yes	Yes	Yes
FE_School	Yes	Yes	Yes	Yes
FE_i	Yes	Yes	Yes	Yes
In_State	Yes	Yes	Yes	Yes
Unclear_Results	Kept	Kept	Dropped	Dropped
Updated_Documents	Excluded	Excluded	Allowed	Allowed

Standard errors in parentheses

Note: Column (1) and (3) take baseline specifications controlling for applicant fixed effects, or the same as Column (5) in Table 3. Column (2) and (4) take regression discontinuity specifications controlling for applicant fixed effects, or the same as Column (5) in Table 4. *Unclear_Results* indicates whether applications not disclosing admission results are included or dropped. *Updated_Documents* takes the value *Excluded* when we use the subsample whose LSAT scores/GPA are unlikely to change, and *Allowed* otherwise. *Submission Delays* are in hundreds of days. Standard errors are clustered at the applicant level.

A5. Algorithm to Solve for Model Equilibrium

We formulate our search for symmetric pure strategy equilibrium of the admissions game in two steps, under the assumption $p_A = p_B = 0.5$ in our numerical example. First, for each possible round 1 admissions strategy (shared by both schools), we examine if the corresponding subgame has a symmetric equilibrium. If the answer is positive, we move onto the next step. In the second step, given the opponent school taking the round 1 admission strategy and the round 2 admission strategy in the associated subgame equilibrium, we deviate the round 1 strategy of our home school, compute the corresponding best round 2 strategies, and examine if this deviation is profitable. If there does not exist a profitable deviation, the strategies characterized in step 1 constitute a symmetric equilibrium.

We articulate our algorithm in more detail below. We first introduce a few notations. We use X_{1s} to denote the number of offers school s makes to early applicants in round 1, X_{2s} for the number of offers made to the remaining early applicants by school s in round 2, and X_{3s} for the number of offers made to late applicants by school s. Note that characterizing school admission strategies as the number of offers made in each round is equivalent to that of instating cutoff thresholds in applicant quality e_s.

We also classify three groups of applicants whose enrollment decisions are uncertain from the perspective of school s by the end of period 1 as "Offer Holders," "Remaining Early Applicants," and "Late Applicants." "Offer Holders" refers to early applicants who receive round 1 offers from school s and hold onto them at the end of period 1. Such behavior implies that they prefer the opponent school but have not received its offer in round 1. Offer holders will only accept the offer from school s if they do not receive an offer from the opponent school again in round 2. "Remaining Early Applicants" refers to early applicants who do not receive round 1 offers from school s. Should they receive an offer from school s, "remaining early applicants" and "late applicants" will accept the offer either when they prefer school s to the opponent school, or when they do not receive an offer from the opponent school.

1) Pick a value x from $\{0, 1, 2, ...N\}$ as the round 1 admission strategy and assign $X_{1A} = X_{1B} = x$. Next, examine if there exists a symmetric equilibrium for the subgame following this strategy in steps 2-5.

2) X_{1A} and X_{1B} are taken as given. Take a guess of $\sigma_{2B}(R_B, A_B)$ and $\sigma_{3B}(R_B, A_B)$ for each possible realization of R_B and A_B, with $R_B \in \{0, 1, 2, ..., \min(X_{1A}, X_{1B})\}$ and $A_B \in \{0, 1, 2, ..., X_{1B} - R_B\}$.

    a) We examine the information provided by realizations of R_A, A_A, and $W_A = X_{1A} - R_A - A_A$ on the decision nodes that school B can possibly reach.

    b) A rejection of school A implies that the applicant has an offer from school B and prefers school B to A, which further implies that he has accepted the offer from school B. Therefore, school B has received at least R_A acceptances.

    c) An applicant accepts school A's offer as long as he prefers school A to B. He cannot have also accepted school B's offer. He may or may not have rejected school B, depending on whether he has received an offer from school B.

    d) An applicant holds school A's offer because he did not receive school B's offer. Therefore, it must be that he neither accepted nor rejected school B's offer.

    e) The applicants who have not received school A's offer may accept or hold school B's offer and must not reject school B's offer.

    f) In summary, given $R_A = r_A$ and $A_A = a_A$, we can bound the number of acceptances A_B school B receives as $r_A \leq A_B \leq \min(X_{1B}, r_A + N - X_{1A})$.

g) Furthermore, we can bound the number of rejections R_B school B receives based on its acceptances A_B as follows: $0 \leq R_B \leq \min(X_{1B} - A_B, a_A)$.

h) Therefore, we can rewrite the conditional expectation as

$$\begin{aligned} & E(X_{2B}|R_A = r_A, A_A = a_A, W_A = w_A) \\ = \; & E(X_{2B}|R_A = r_A, A_A = a_A) \\ = \; & E\Big(\sigma_{2B}(A_B, R_B)|r_A \leq A_B \leq \min(X_{1B}, r_A + N - X_{1A}), 0 \leq R_B \leq \min(X_{1B} - A_B, a_A)\Big) \end{aligned}$$

3) For the three groups of applicants with enrollment uncertainty, calculate for each possible realization of $R_A = r_A$ and $A_A = a_A$: (1) their probability of receiving an offer from school B, and (2) their probability of eventually accepting the offer from school A conditional on receiving an offer from school A. The latter is a function of the former.

a) Those who reject school A's offer have secured r_A offers from school B. Those who hold an offer from school A have not received any offers from school B. Those who accept school A's offer may receive school B's offer.

b) Therefore, round 1's remaining $X_{1B} - r_A$ offers from school B are evenly distributed among the "Offer Acceptants" and "Remaining Early Applicants," the probability of which is characterized as $(X_{1B} - r_A)/(a_A + N - X_{1A})$.

c) The applicants who do not receive a round 1 offer from school B have equal chance of receiving a round 2 offer from school B. These applicants may come from "Offer Acceptants", "Remaining Early Applicants", and "Offer Holders" of school A, with a size of $N - r_A - (X_{1B} - r_A) = N - X_{1B}$, sharing X_{2B} offers.

d) For "Offer Holders":

i) The probability of receiving an offer from school B is $p_{1B} = E(X_{2B}|R_A = r_A, A_A = a_A)/(N - X_{1B})$. Intuitively, it is calculated as the probability of receiving a school B offer in round 2 conditional on not receiving one in round 1.

ii) The probability of accepting school A's offer is $1 - p_{1B}$, i.e. the probability they do not receive an offer from school B.

e) For "Remaining Early Applicants":

i) The probability of receiving an offer from school B is the probability of receiving one in round 1, plus the probability of not receiving one in round 1 and receiving one in round 2; i.e., $(X_{1B} - r_A)/(a_A + N - X_{1A}) + \Big(1 - (X_{1B} - r_A)/(a_A + N - X_{1A})\Big) \times E(X_{2B}|R_A = r_A, A_A = a_A)/(N - X_{1B})$.

ii) The probability of accepting school A's offer if one is received is $1 - p_{2B} + 1/2p_{2B}$, where $1 - p_{2B}$ measures the probability that remaining early applicants only receive an offer from school A, and $1/2p_{2B}$ measures the probability that they receive both offers and prefer school A to B.

f) For "Late Applicants":

i) The probability of receiving an offer from school B is $p_{3B} = E(X_{3B}|R_A = r_A, A_A = a_A)/N$.

ii) The probability of accepting school A's offer if one is received is $1 - p_{3B} + 1/2p_{3B}$, where $1 - p_{3B}$ measures the probability that remaining early applicants only receive an offer from school A, and $1/2p_{3B}$ measures the probability that they receive both offers and prefer school A to B.

4) For each realization of responses to round 1 offers $A_A = a_A$, $R_A = r_A$, taking the probabilities calculated in steps 3d-3f as given, find the pair of X_{2A} and X_{3A} that maximize school A's intermediate payoff. We can thus trace out $\sigma_{2A}(R_A, A_A)$ and $\sigma_{3A}(R_A, A_A)$ for $R_A \in \{0, 1, 2, ..., \min\{X_{1A}, X_{1B}\}\}$ and $A_A \in \{0, 1, 2, ..., X_{1A} - R_A\}$.

5) Go back to step 2, replace $\sigma_{2B}(r_B, a_B)$ with $\sigma_{2A}(r_A, a_A)$ and $\sigma_{3B}(r_B, a_B)$ with $\sigma_{3A}(r_A, a_A)$. Iterate for convergence between $\{\sigma_{2A}(r_A, a_A), \sigma_{3A}(r_A, a_A)\}$ and $\{\sigma_{2B}(r_B, a_B), \sigma_{3B}(r_B, a_B)\}$. A convergence means that we find an equilibrium for the subgame associated with round 1 strategy x. We label these equilibrium objects as $\sigma^*(R_s, A_s)$, $\sigma^*(R_s, A_s)$.

6) Calculate the ex-ante payoff for school A, $\pi_A(X_{1A} = x, X_{1B} = x)$ by integrating its intermediate payoffs at equilibrium. Note that we need to use conditional probability when integrating.

7) Now we move back to the first round of the game and examine if there exist profitable deviations of round 1 strategies. We restrict analysis to values of x that are accompanied with symmetric subgame equilibrium. More specifically, we fix $X_{1B} = x$, fix round 2 strategies of school B as $\sigma^*_{2s}, \sigma^*_{3s}$, and assign alternative values $\tilde{x} \neq x$ for X_{1A}.

8) For each realization of responses to round 1 offers $R_A = \tilde{r}_A \in \{0, 1, 2, ..., \min(\tilde{x}, x), A_A = \tilde{a}_A \in \{0, 1, 2, ..., \tilde{x} - \tilde{r}_A\}$ under round 1 strategy $X_{1A} = \tilde{x}$, find the best round 2 admission strategy $\tilde{X}_{2A}$ and $\tilde{X}_{3A}$ of school A, as well as the associated ex-post payoff, with

$$\begin{aligned} & E(X_{2B}|\tilde{r}_A, \tilde{a}_A) \\ = \quad & E\Big(\sigma^*_{2B}(R_B, A_B)|\tilde{r}_A \leq A_B \leq \min(x, \tilde{r}_A + N - \tilde{x}), 0 \leq R_B \leq \min(x - A_B, \tilde{a}_A)\Big). \end{aligned}$$

9) Integrate over all possible $\{\tilde{a}_A, \tilde{r}_A\}$ to calculate the ex-ante payoff of school A, $\pi_A(X_{1A} = \tilde{x}, X_{1B} = x)$. Note that we should use conditional probabilities in integration.

10) Iterate over all possible $\tilde{x}$. If none of the $\tilde{x}$ constitutes a profitable deviation such that $\pi_A(X_{1A} = \tilde{x}, X_{1B} = x) > \pi_A(X_{1A} = x, X_{1B} = x)$, then we find out a symmetric pure strategy equilibrium when $p_A = p_B = 0.5$, with x as the round 1 strategy and σ^*_{2s}, σ^*_{3s} as the round 2 strategies.