

Administrative Assumptions in Top-Down Selection: A Test in Graduate School Admission Decisions

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Although top-down selection is the gold standard for making personnel decisions, several *administrative* assumptions must be met for it to be effective. We discuss three of these assumptions and test two of them: (1) top applicants will accept an offer, and (2) the time organisations give applicants to consider an offer will not influence the availability of next-tier applicants. We also examine the effectiveness of top-down selection by comparing it to an administratively simpler procedure, random selection above a threshold. Using archival admissions data from three university graduate psychology programs, we found that top applicants were *less* likely to accept an offer; however, waiting time did not influence applicant availability. In comparing the quality of applicants actually selected (with a top-down procedure) with the quality of applicants selected at random (from above five progressively stringent thresholds), we found that at higher admission thresholds, random selection resulted in better or equal quality applicants as top-down selection, depending on the criteria. We discuss implications for future research and practice.

INTRODUCTION

Top-down selection is the gold standard for making university admissions and personnel selection decisions. Because the relationship between valid predictors and performance is usually linear, applicants with higher predictor scores are likely to perform better than those with lower predictor scores (Gatewood & Field, 2001; Society for Industrial and Organizational Psychology [SIOP], 2003). This is true even when selecting applicants ranked only slightly above others—small increments in test scores compound over many applicants to increase expected utility. Top-down selection typically operates as follows. Once applicants' qualifications (e.g. test

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scores, grades, recommendations) are combined into a total score, applicants are ranked from best to worst. Then a cutoff is typically established, below which no candidates would be given an offer. Applicants above the cutoff are often referred to as being on the “short-list”. Selection decisions are made by first offering admission to the top applicant on the short-list; if the top applicant turns down the offer, the second-ranked applicant is offered admission, and so on down the list as necessary. If more than one position (x) is available, then offers would typically be made to the top x applicants; applicants below them would only be made offers (sequentially based on rank) when any of the initial top candidates turn down an offer.

While psychometric issues (e.g. test validity) have held a prominent place in the literature on selection decision-making (Guion & Highhouse, 2006; Schmidt, 1991), there is a dearth of research on how administrative procedures influence the effectiveness of decision-making strategies. What are the administrative assumptions in top-down selection? How frequently are these administrative assumptions violated in practice? Are they robust? What are the effects of assumption violations on the effectiveness of top-down selection? The objectives of this study are to examine administrative assumptions in top-down selection, the extent to which they are violated in practice, and the effectiveness of top-down selection compared to an administratively simpler decision-making strategy. We begin by discussing three administrative assumptions in top-down selection and how they are likely to influence its effectiveness. We argue that when these three assumptions are violated, top-down selection will not be an optimal strategy. We use archival admissions data from three university graduate psychology programs to test two of these assumptions and to compare the effectiveness of top-down selection with an administratively simpler procedure, random selection above a threshold.¹

An advantage to using admission data from US graduate psychology programs is that policies and procedures for these programs are fairly standardised (www.apa.org/ed/accept, 2008). Most graduate psychology programs use Graduate Record Examination (GRE) scores and undergraduate grade point average (GPA) as measures of quality. The GRE is a standardised test used by many graduate schools in the United States. At the time this study was conducted, the GRE consisted of two multiple-choice sections, verbal and quantitative. The verbal section included reading comprehension and analogies, and the quantitative section included problem-solving and mathematics (e.g. algebra, geometry). Scores on each section could range from a low of 200 to a high of 800. A verbal score of 740 would be in the 99th

¹ The nature of our data would not allow us to test all three assumptions.

percentile, while a quantitative score of 740 would be in the 82nd percentile; a verbal score of 480 and a quantitative score of 600 would be in the 55th and 49th percentiles, respectively (Educational Testing Service, 2007). Most US universities assign course grades on the following scale: “A” signifies outstanding work, “B” above average, “C” average, “D” below average, and “F” failing. Grade point averages are typically calculated by assigning a 4 to an A, 3 to a B, 2 to a C, 1 to a D, and 0 to an F (e.g. a 3.5 would be a B+ average). Most graduate programs accept students for autumn admissions; application deadlines are typically in January; and most graduate programs allow applicants until 15 April to make a final decision.

Administrative Assumptions

At least three administrative assumptions are fundamental to top-down selection. The first and second assumptions involve the probability that applicants will accept an offer, and the third involves the time allowed to consider an offer. While traditional variables, such as the selection ratio and predictive validity of selection tests, are often considered when evaluating effectiveness of selection systems, the impact of probability of applicants’ acceptance and time to consider an offer are rarely taken into consideration (Arvey, Gordon, Massengill, & Mussio, 1975; Hogarth & Einhorn, 1976).

The first assumption is that top applicants will accept admission offers. Why start from the top unless one expects that top applicants will accept an offer? Murphy (1986), however, argues that this assumption is often unjustified. For example, some top scoring applicants may receive better offers from competing institutions. Applicants typically apply for multiple positions, and highly qualified applicants tend to be the top (or close to the top) choices of multiple organisations (Smith & Rupp, 2004). An applicant who has high GRE scores and a high undergraduate GPA will probably be a top choice of many university graduate programs. Because this applicant will have more offers than lesser qualified applicants, he or she will also be more likely to turn down more offers (see Stoup & Benjamin, 1982).² Surprisingly, we could locate little empirical research to support this common sense idea. One study (Bowen & Bok, 1998) found that applicants to selective US undergraduate institutions with the highest Scholastic Aptitude Test (SAT) scores (99th percentile) had approximately a 63 per cent probability of admission to each school, whereas those with scores at about the

² Indeed, top applicants may be the *most* likely to reject offers because they should have the most options.

77th percentile had approximately a 31 per cent probability of admission.³ A second assumption, which is a corollary of the first, is that applicants are likely to accept offers in a descending interval sequence: if the top applicant rejects an offer, then there is a non-trivial probability that the second-ranked applicant is likely to accept an offer; if the second-ranked applicant rejects an offer, then the third-ranked applicants is likely to accept and offer and so on. This assumption may not always be met. Second-ranked applicants are also likely to have applied elsewhere and be desirable to multiple organisations. The closer applicants are to the top of the ranking, the more options they should have, and the less likely that they would accept any one offer (see Becker, 1993).

The third assumption is that the time organisations give their top-tier applicants to consider an offer does not significantly influence the availability of next-tier applicants. Descriptions of top-down selection that we have reviewed do not mention time as an important factor (e.g. Gatewood & Field, 2001; SIOP, 2003), or they mention it only in passing (Guion, 1998; Ryan & Tippins, 2004). However, time delays can influence selection outcomes when offers are made sequentially (Arvey et al., 1975). If an organisation allows the top choice a certain period of time to consider an offer, it is inadvertently providing applicants ranked below the top choice *more* time to consider other offers (the time given to the top-ranked applicant plus the time they are allowed, if they are given an offer). For example, if the top choice has a week to make a decision and the second choice will not get an offer until the top choice rejects the offer, the second choice may use that week (plus whatever time he or she has to make a decision) to consider offers he or she has from other organisations. If the second choice is offered another job during the time that the first choice is deliberating, it may be to his or her advantage to accept it because it is not certain that an offer from the first organisation will be forthcoming. If all of the applicants close to the top accept other offers while the top choice is deliberating *and* if the top choice rejects the organisation's offer, then the next available applicants will be ranked much lower.

Some researchers have examined potential effects of assumption violations with simulated data. Hogarth and Einhorn (1976) compared conditions where (1) applicants were certain to accept an offer, (2) all applicants had the same probability of accepting an offer, or (3) higher scoring applicants were less likely to accept an offer. Their results indicated that—in addition to test validity and selection ratios—it was beneficial to take into

³ At the time that Bowen and Bok (1998) gathered their data, the SAT consisted of two sub-tests: verbal and mathematics. Each test could range from 200 to 800. As an estimate of the meaning of these scores (in 1998) a combined score of 1,500 would be in the 99th percentile; a combined score of 1,000 would be in the 77th percentile.

account the probability of applicants accepting offers. Moreover, in cases where the probabilities of applicants accepting offers are uncertain, alternatives to top-down selection may in fact result in more efficient decision-making.

Murphy (1986) pointed out that the selection utility literature has erroneously assumed that applicants with the highest test scores will accept job or university admissions offers. He shows that utility models substantially overestimate economic gains when they do not include parameters for applicants rejecting job offers. Conventional utility analysis of selection decisions takes into account the number of jobs to be filled, the correlation between test scores and job performance, the standard deviation of performance, and the average test score among those selected. Acceptance rate is not typically taken into account, but it has an important effect. For instance, assuming a normal distribution of ability, being turned down by the top 50 of 1,000 applicants for 100 job openings and thereby successfully acquiring candidates ranked 51–151 results in an approximate 35 per cent reduction in ability (Murphy, 1986). These analyses show the importance of accounting for applicants rejecting job offers. What we need now are empirical investigations of the extent to which these assumptions are actually met or violated in the real world.

The first purpose of this study is to examine whether the first and third assumptions are violated in real-world selection practice (the nature of our data set did not allow us to test the second assumption). The second is to compare top-down selection with an administratively simpler procedure, random selection above a threshold. We use admissions data from three graduate psychology programs in the US. These programs use a modified top-down selection decision procedure. The admissions procedure in these programs should be reasonably representative of most graduate psychology programs in the US because graduate admissions criteria and, as noted earlier, procedures for graduate admissions are fairly standardised (www.apa.org/ed/accept, 2008). In addition, graduate programs typically have more applicants than openings, and most programs—even the top programs—do not always get their top choices.

We tested for violations of the first assumption (top applicants will accept admission offers) by correlating offer acceptance with applicant quality. For the third assumption (the time organisations give their top-tier applicants to consider an offer should not significantly influence the availability of next-tier applicants), we compared the rate of initial offer acceptance with acceptance rates after a time delay. To examine the effectiveness of top-down selection, we compared the quality of applicants who were admitted and enrolled in graduate programs with the quality of applicants who would have been admitted by selecting applicants at random from above a minimally acceptable cut-score. If random selection results in admitted students of the

same as or better quality than top-down selection, this would suggest that the effects of assumption violation on applicant quality are consequential, indicating that top-down selection may not always be more effective than random selection above a threshold.

METHOD

Participants

Participants were applicants to (masters and doctoral) graduate programs in experimental psychology, clinical psychology, and industrial/organisational psychology at a regional university located in the United States. We began with 1,750 applicant records for the years 1998 to 2008. However, we only included records in our initial data set for which data were not systematically missing by program or by year. This gave us our initial archival data set of 1,230 applicant records (submitted between 1998 and 2008). After excluding individual records that did not have sufficient information, a total of 976 usable cases remained (79%). Of these, 623 were rejected, 352 were offered admission, 220 declined admission offers, 132 enrolled, and one withdrew. These numbers included the final disposition of 63 applicants who were initially placed on the wait-list. Of those placed on the wait-list, 30 were subsequently rejected and 33 were offered admission; of the wait-listed applicants who were offered admission, 24 declined admission offers and nine enrolled.

Data and Procedure

Data on applicant quality included verbal and quantitative GRE scores and undergraduate GPA. We used the combined verbal and quantitative GRE score, which ranges from 400 (low) to 1,600 (high). GPAs range from 0 (low) to 4.0 (high). GPA and GRE scores correlated modestly ($r = .17$, $n = 977$, $p < .01$; see also Dawis, 1971; Kuncel, Hezlett, & Ones, 2001).

All of the programs used a top-down decision-making model for ranking applicants. Typically, faculty on admission committees ranked applicants based on GRE scores and undergraduate grades. This is an approach that is conventional in college admissions within the United States at both the undergraduate and graduate levels. Applicants are rank-ordered according to scores on standardised tests, combined with previous academic performance (e.g. GPA). Numerous studies have demonstrated the predictive validity of combined test scores and academic performance (e.g. Burton & Ramist, 2001). Selection committees may also use various other predictors such as letters of recommendation, personal statements of career interest and biographical history, and extracurricular or community service activi-

ties, but these variables typically receive less weight than GRE scores and GPA. Rankings provided by individual faculty were averaged to determine the final ranking of applicants. Applicants were then placed into one of three categories: accept, wait-list, or reject. Those on the wait-list typically waited from one to three weeks before being notified that they were either accepted or rejected. Aside from specific legal requirements that are afforded to protected classes, there are not any standard requirements in the procedural aspects of college admissions.

We tested the first assumption, that top applicants will accept admission offers, by correlating ability scores with acceptance of an offer. The third assumption, the time organisations give their top-tier applicants to consider an offer should not significantly influence the availability of next-tier applicants, was tested using two procedures: (1) we compared the rates at which applicants accepted admissions offers and (2) we compared the scores of wait-listed applicants who declined an offer with the scores of wait-listed applicants who accepted an offer. If the waiting period resulted in the loss of better applicants, then the scores of wait-listed applicants who declined offers should be higher than those who accepted offers.

To examine the effect of assumption violations on the utility of top-down selection, we compared the GPA and GRE scores of applicants who accepted offers (and enrolled) with applicants drawn at random from among all applicants who had been admitted. That is, we randomly selected applicants from above the cutoff score below which no applicants had actually been given offers. However, to make a fair comparison between random selection and the actual applicants who were selected and enrolled, we needed to estimate and then include the probabilities that randomly selected applicants would accept an offer.

To do this, we created descending bands for each of the two measures of applicant ability (GPA and GRE). We assigned applicants to bands based on their scores. Within each band we calculated two percentages: (1) the percent of applicants who were offered admission and enrolled out of the total number of applicants within the band and (2) the percent of applicants who were offered admission and enrolled out of the total number of applicants who enrolled. Using a bootstrapping program, we drew 100 samples of the latter percent at random from each band and then calculated the mean and standard deviation for each sample. We calculated the mean of these 100 means and standard deviations to determine the average GRE and GPA scores for the number of incumbents enrolled if they were randomly selected from each band. We weighted these scores by the percentage of the incumbent population from each band. For example, 17 applicants fell in the GRE band of 1,440–1,390; two of these applicants (11.8%) enrolled. This group composed 1.6 per cent of the total number (134) of applicants who enrolled. Taking 100 random samples of 11.8 per

cent of applicants within this band yielded a mean GRE score of 1,141.3. This was multiplied by 1.6 and added to the randomly sampled mean multiplied by the incumbent percentage for each of the bands (see Appendices A and B).

RESULTS

Table 1 lists the GRE and GPAs of all applicants and for various categories of applicants (e.g. rejected applicants, applicants who were offered admission and declined, applicants offered admission and accepted). The GPA and GRE scores of applicants who were offered admission but turned it down (coded "1") were significantly higher than the scores of those who eventually enrolled (coded "0"). GRE scores correlated positively with turning down an admissions offer ($r = .25$, $n = 352$, $p < .01$), as did GPA ($r = .16$, $n = 352$, $p < .01$); the results using logistic regression, where we regressed acceptance of admission offer on GPA [$\chi^2(1, n = 352) = 8.83$, $p < .01$, $B = .005$, odds ratio = 1.005] and on GRE [$\chi^2(1, n = 352) = 22.73$, $p < .01$, $B = .004$, odds ratio = 1.004], were also both significant. Thus, higher ability applicants were less likely to accept an offer, indicating that the first assumption was violated.

To examine the third assumption, that the time organisations give applicants to consider an offer is not a significant factor in the effectiveness of top-down selection, we compared the rates at which initial and wait-listed applicants accepted a decision. The percentage of applicants accepting an offer decreased from 38 per cent for initial offers to 27 per cent for offers made to wait-listed applicants, $\chi^2(1, n = 352) = 1.63$, $p = .2$. Although this was

TABLE 1
Descriptive Statistics of GPA and GRE of Applicants by Enrollment and Acceptance Decision

<i>Applicants</i>	<i>n</i>	<i>GPA</i>	<i>SD</i>	<i>GRE</i>	<i>SD</i>
All Applicants	976	3.40	0.37	1082.0	166.63
Rejected	624	3.32	0.37	1033.0	165.70
Offered Admission	352	3.54 ^{ns}	0.33	1169.0	128.64
Turned Down Offer	220	3.58 ^{ns}	0.31	1194.0	118.46
Enrolled	132	3.47	0.34	1127.3	134.44
Withdrew	1	3.96	—	1320.0	—
Wait-Listed, Offered Admission	33	3.42 ^{ns}	0.37	1201.1 ^{ns}	108.35
Wait-Listed, Turned Down Offer	24	3.47 ^{ns}	0.37	1201.5 ^{ns}	107.39
Wait-Listed, Enrolled	9	3.28 ^{ns}	0.36	1200.0 ^{ns}	117.47

Note: All tests of mean difference are significant at $p < .05$ for GPA and GRE scores except where noted by an "ns"; that is, all means within a column with the "ns" superscript are not significantly different from one another. Exact *t*- and *p*-values for all comparisons are available from the authors.

in the expected direction, it was not significant. The scores of wait-listed applicants who declined an offer of admission were contrasted with the scores of wait-listed applicants who accepted an offer of admission. Wait-listed applicants who declined an offer had higher GPAs and GREs than those who accepted offers; however, neither difference was statistically significant.

Using random selection, we created 13 separate bands for both GRE and GPA scores, allowing an equal number of bands to be chosen for inclusion for each cut off score (Appendices A and B). One-sample *t*-tests revealed that when the cutoff scores were a GRE score greater than 910 and a GPA greater than 2.81, the differences between top-down selection scores and random selection scores were significantly different in both groups, so we used these cutoff scores as a starting point. We calculated an average of the bootstrap means and standard deviations for all bands above the cutoff score. Sample size was calculated by multiplying the number of applicants in the band (*n_i*) by the percent in the band that enrolled. These values were then summed and used as the sample size in the *t*-tests. The two bands immediately preceding our initial cutoff score and the two bands immediately following our initial cutoff score were chosen to examine any patterns of mean differences between top-down selection and random selection for GRE and GPA scores.

To examine the effectiveness of top-down selection, we compared the quality of applicants selected at random with the quality of applicants who actually enrolled. Table 2 compares the mean GRE and GPA scores of enrolled applicants when top-down selection was used with the hypothetical scores of enrolled applicants if applicants were admitted through random selection at five different cutoff scores.

We used a one-sample *t*-test for comparing the differences between means, using the random selection means as the hypothetical means. For the mean

TABLE 2
GPA and GRE Scores by Selection Type

<i>Selection type</i>	<i>GPA</i>	<i>GRE</i>
Top-Down Selection (<i>n</i> = 132)	3.47	1127.3
Random Weighted Selection by Cutoff Band		
GRE > 1030 (<i>n</i> = 108), GPA > 3.05 (<i>n</i> = 118)	3.53	1233.2 ^a
GRE > 970 (<i>n</i> = 117), GPA > 2.93 (<i>n</i> = 122)	3.47	1203.7 ^a
GRE > 910 (<i>n</i> = 126), GPA > 2.81 (<i>n</i> = 127)	3.41 ^a	1174.1 ^a
GRE > 850 (<i>n</i> = 129), GPA > 2.69 (<i>n</i> = 132)	3.35 ^a	1144.8
GRE > 790 (<i>n</i> = 132), GPA > 2.57 (<i>n</i> = 133)	3.29 ^a	1115.3

Note: GPA and GRE means in the random sample that are significantly different (*p* < .05.) from means in the top-down selection are denoted by an “a”.

GRE scores, applicants selected at random from the three highest cutoff scores had significantly higher GRE scores than those selected by top-down selection; there were no significant differences at the lowest two cutoff scores. For mean GPAs, there were no differences between top-down and random selection at the two top cuts for random selection; at the three lowest cuts, random selection resulted in lower GPAs than top-down selection.

DISCUSSION

We described three administrative assumptions of a top-down personnel admission and selection strategy: (1) there is a non-trivial likelihood that the top choice will accept a job offer; (2) applicants are likely to accept offers in a descending sequence; (3) the time organisations give applicants to consider an offer does not significantly influence the availability of lower-tier applicants. We tested for violations of the first and third assumptions using archival admissions data. This, to our knowledge, is the first study to test these assumptions using real-world selection data. We found a clear violation of the first assumption—the highest quality applicants were the most likely to turn down an organisation's offer. The time delay in giving offers to second-tier applicants did not significantly influence the availability of applicants accepting an offer, nor did it affect the quality of those applicants.

We then examined the effectiveness of top-down selection by comparing the quality of applicants actually selected (with a top-down procedure) with the quality of applicants selected at random (from above five progressively stringent thresholds), after adjusting for the probability that higher scoring applicants would be less likely to enroll. Our results indicate that at the two highest thresholds, random selection resulted in better or equal quality applicants as top-down selection, depending on the criteria.

Limitations

Since relatively little research has been conducted on administrative assumptions and the effects of administrative assumptions on top-down selection, these results should be interpreted cautiously. We were unable to directly test the second assumption. In addition, admission occurred with only three rankings: admit, wait-list, or reject. Although our data and results are probably representative of admissions data in university graduate programs in the US, admission practices still vary somewhat from program to program—such as the criteria for ranking applicants and the processes by which applicants are ranked. It is also probably the case in our sample, as in most graduate programs, that fit with faculty interests may moderate the relationship

between objective measures of applicant quality (GRE scores and GPA) and rank.⁴

The generalisability of our results may also be limited by the nature of the sample, i.e. applicants to university graduate programs in the US. For example, graduate programs in Europe, the UK, and Asia have somewhat different admission procedures and policies. In addition, our results may not necessarily generalise to undergraduate admissions in the US. Undergraduate admissions procedures are somewhat less standardised. Some undergraduate institutions use ACT (American College Testing) test scores, while others use the SAT;⁵ some offer rolling admissions, while others do not. Also, generalisations to work organisations may be problematic. They probably vary more broadly than universities in their selection contexts, the administration of their selection procedures, and decision rules.

Another possible limitation is the degree to which these results generalise across institutions of differing prestige. For example, with high-prestige institutions, a greater percentage of applicants may accept offers than with lower-prestige institutions. The university from which we collected our data would be considered of average prestige among US universities. Finally, low power due to the limited sample size (particularly within some applicant categories) may have contributed to statistical non-significance of some comparisons.

Implications

This research is one of a handful of studies that provide empirical evidence about the assumptions and effectiveness of the top-down decision strategy used in admissions and selection decisions. Thus, more research is needed on how selection decisions occur in organisations, the constraints they are under, and how they vary by context. How often, in fact, is top-down selection used? In what kind of organisations? How often are its assumptions violated? Under what conditions are they most likely to be violated? For example, are assumptions violated to the same degree in elite institutions, which tend to be highly desirable to applicants? Or do all institutions face similar pressures to get their top choices, because applicants tend to apply to organisations that are generally compatible with their abilities (see Wilk, Desmarais, & Sackett, 1995). Similarly, how might market conditions (e.g.

⁴ This may explain why there was a modest relationship between objective measures of quality (GRE scores and GPA) and admission offers. For example, although 20 applicants had a GRE score between 1,400 and 1,500, only 11 of these applicants received an offer of admission.

⁵ In the past (before the test was renamed the SAT Reasoning test), the letters (SAT) stood for "Scholastic Aptitude Test" and later "Scholastic Assessment Test".

supply of applicants, number of openings) influence assumption violations, and the effectiveness of top-down selection, across and among different types of organisations?

What additional effects might assumption violations have? For example, when top choices turn down admission offers the selection ratio changes. With each rejection, the number of applicants decreases and the selection ratio becomes larger. This has an implication for the utility of selection practices: as the selection ratio increases, the utility of a selection test decreases (Taylor & Russell, 1939). The results of this study also emphasise importance of applicant reactions to testing procedures and of contextual factors that may improve applicant reactions. Negative reactions may increase the number of top choices who turn down an organisation's offer (Hausknecht, Day, & Thomas, 2004).

Future research could also look at the cost implications of top-down selection. When is it economical to use top-down selection? For example, when the cost of ranking applicants is minimal (as might be the case when ranking is done mechanically by an algorithm), and when other conditions are favorable, then top-down selection should be an economical strategy. However, when ranking applicants is costly (e.g. when ranking involves extensive discussion and judgments by decision-makers, whose time is expensive), then the cost of ranking applicants might outweigh its benefits.

One practical implication of this research is that those involved in selection should examine the degree of assumption violations when they are using a top-down approach to selection decisions. The subjective expected utility (SEU; Edwards, 1954) model provides a conceptual and computational framework that could be used to estimate the utility of making an offer to an applicant. Given that applicants differ in quality and have different probabilities of accepting a job offer, an SEU framework could be used to determine the utility of making an offer to an applicant, with the goal of identifying the most qualified applicant *likely to accept an offer*. Following Edwards' general model, a preliminary equation for estimating the subjective expected utility of making an offer to an applicant is:

$$SEU_i = (P_i Q_i) - C_i$$

Where: P = the probability of an applicant accepting a job offer; Q = the quality of an applicant; and C = the cost of ranking the applicant. For example, if there is a low probability that a top-ranked applicant would accept an offer, then there may be a lower utility associated with offering that individual a position. Instead, it might be more efficient to extend an offer to a second- or third-ranked applicant because they may be more likely to accept. If there are significant assumption violations, then it may be advisable to examine how the selection process could be altered to operate more

efficiently. We are *not* arguing against top-down selection as an ideal or for its use when conditions are optimal. What we are suggesting is that other strategies may be more effective than top-down selection *when conditions are not optimal for top-down selection*. When conditions are optimal, top-down remains the best strategy.

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APPENDIX A

<i>GRE score</i>	<i>n_i</i>	<i>Percent in band who enrolled</i>	<i>Percent of total who enrolled</i>	<i>Bootstrap mean</i>	
				<i>M</i>	<i>SD</i>
1500–1450	7	0%	0%	–	–
1440–1390	17	11.8	1.6	1411.3	13.0
1380–1330	43	11.6	3.7	1349.0	12.7
1320–1270	50	28.0	10.4	1293.2	5.5
1260–1210	86	16.3	10.4	1233.5	7.0
1200–1150	147	16.3	17.9	1175.7	4.5
1140–1090	165	20.6	25.4	1115.6	4.2
1080–1030	131	11.5	11.2	1054.2	6.2
1020–970	114	7.9	6.7	997.1	8.3
960–910	96	9.4	6.7	937.5	7.6
900–850	45	6.7	2.2	880.4	13.8
840–790	34	8.8	2.2	821.0	13.7
780–730	24	8.3	1.5	759.5	15.33

Note: *n_i* = Number of applicants in the band.

APPENDIX B

<i>GPA</i>	<i>n_i</i>	<i>Percent in band who enrolled</i>	<i>Percent of total who enrolled</i>	<i>Bootstrap mean</i>	
				<i>M</i>	<i>SD</i>
4.0–3.89	83	22.9	14.2	3.95	0.01
3.88–3.77	83	7.2	4.5	3.82	0.03
3.76–3.65	113	18.6	15.7	3.71	0.01
3.64–3.53	113	13.3	11.2	3.59	0.01
3.52–3.41	133	14.3	14.2	3.47	0.01
3.40–3.29	104	16.3	12.7	3.35	0.01
3.28–3.17	85	14.1	9.0	3.23	0.01
3.16–3.05	90	10.0	6.7	3.11	0.02
3.04–2.93	67	6.0	3.0	3.00	0.02
2.92–2.81	35	14.3	3.7	2.88	0.02
2.80–2.69	27	18.5	3.7	2.74	0.02
2.68–2.57	10	10.0	0.7	2.63	0.03
2.56–2.45	18	5.6	0.7	2.51	0.04

Note: *n_i* = Number of applicants in the band.