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More Applicants or More Applications per Applicant? A Big Question When Pools Are Small

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Two aspects of many real-world hiring situations affect hiring success in ways that are not well understood. One is that many applicant pools are relatively small, with perhaps fewer than 20 and sometimes fewer than 10 applicants. The other is that job seekers are likely to apply for more than one job at a time. Despite calls for more research that would be relevant to the small-scale hiring situation, scholars have given little attention to expected new-hire quality in small-pool hiring in general and even less to more specific questions of how that expected quality is affected if applicants apply for multiple jobs simultaneously. Most currently accepted methods linking expected new-hire quality to the selection ratio (or hiring rate) are based on the properties of large pools. The authors argue that those methods are based on the inherent, but dubious, assumption that all job seekers in a given applicant pool are pursuing that particular job and no other jobs. In the small-pool context, these factors have significant, and previously unrealized, negative effects on the expected quality of new hires when job seekers apply for multiple jobs at once. The authors present a conceptual development of a method, based on averages of order statistics, for estimating correct values of expected new-hire quality when pools are small and job seekers tend to apply for multiple jobs simultaneously. A series of simulations support the conclusion that the method yields accurate estimates.

Keywords: *personnel selection; small applicant pools; hiring rate; order statistics*

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Cascio and Boudreau lament the scarcity of "rigorous, logical, and principles-based frameworks for understanding the connections between human capital and organizational success" (2008: 2). We share their concern but find encouragement in the considerable progress that has been made toward a rigorous framework of that sort in the area of personnel selection. Over the past 75 years, researchers (e.g., Brogden, 1949; Cronbach & Gleser, 1965; Naylor & Shine, 1965; Schmidt, Hunter, McKenzie, & Muldrow, 1979; Taylor & Russell, 1939) have developed techniques for estimating the impact of personnel selection practices on organizational success in terms of productivity and financial return on investment.

Unfortunately, however, we believe that two aspects of many real-world hiring situations affect hiring success in ways that are not well understood. One concerns the sizes of applicant pools. It seems likely that many are relatively small. There could be a number of reasons for this. The job might be located in a sparsely populated area where applicants are not plentiful. It could be set in an unattractive physical environment (e.g., climate, working conditions). The nature of the work could be unappealing to many people (e.g., monotonous, working alone), or it might require training or licensure that few people have. Tight labor markets might also restrict the sizes of applicant pools. Another reason why many applicant pools are small is that the overwhelming majority of employers in the United States are small firms, with over 5 million having fewer than five workers (Bobko & Potosky, 2011). Small businesses have done approximately 65% of the hiring in the United States over the past 15 years (Headd, 2010). Although it is not necessarily true that small employers attract small applicant pools, Bobko and Potosky suggest that this might often be the case. For all of these reasons, relatively small applicant pools appear to be more the rule than the exception—but small-pool hiring has not been studied in much depth.

The other real-world consideration is that some (probably most) job seekers apply for more than one job at a time. People who need a job might well apply for several to enhance their chances of getting one. We will discuss two related consequences of people applying for multiple jobs at the same time. One is that this makes applicant pools larger than they would be if people applied for only one job at a time. The other is that it causes various employers' applicant pools to overlap, which almost necessarily means that some job offers will be rejected.

Although the multiple-applications-per-applicant issue would affect hiring success in pools of any size, we focus on its effects in small pools. We show that traditional and other more recently proposed techniques for calculating the expected benefit of a valid personnel selection system (i.e., the expected quality of new hires the system will yield) can significantly overestimate the true values.

These concerns are important for a variety of reasons. The small-pool and the multiple-applications-per-applicant situations are common, but our current theoretical understanding in both of these regards is incomplete at best. Past selection research has focused almost entirely on large organizations (Bobko & Potosky, 2011; Wyatt, Pathak, & Zibarras, 2010) and large-pool hiring. Heneman, Tansky, and Camp note that "scholars are lamenting the dearth of information about human resource practices in [small and medium-sized enterprises]" (2000: 11). Heneman et al., as well as Bobko and Potosky, urge researchers to examine the generalizability of large-scale selection research findings to the small-scale context. We will argue that large-pool methods translate poorly to the small-pool environment.

De Corte (1999, 2000) laid important foundations for small-pool selection research. We review his work in the next section, but for now we simply point out that he did not explore the effects of multiple applications per applicant or the effects of overlapping applicant pools. Currently, little is known about either of those.

Purpose

This article's title reflects two ways pool sizes can grow. More people can enter the job market (more applicants), or people who are already in the job market can increase the numbers of jobs they apply for (more applications per applicant). One of our basic purposes is to demonstrate that there are meaningful differences between these two in terms of the quality of new hires that can be expected, especially when pools are small.

We will show that proper estimates of expected new-hire quality are based not just on how large applicant pools are but also on why they are those sizes. If, for example, 1 applicant will be hired from a pool of 20, quality-of-hire expectations are quite different (and higher) if those 20 people are in this applicant pool, and not in any other pools, than they would be if people in general choose to apply for several jobs at the same time. To our knowledge, this phenomenon has received no attention from researchers.

Another question that has not been studied in the small-pool context is whether expectations are different either (a) when high-quality applicants apply for more jobs than do low-quality applicants or (b) when low-quality applicants apply for more jobs than do high-quality applicants. We address this question and the others we have raised and provide a means for understanding how to answer them.

In the next section, we briefly examine typical methods for estimating new-hire predictor scores in large pools. We emphasize that it is *predictor,* not criterion, scores that we examine. The methods we introduce are well suited to working with predictor scores, which can be converted easily to expected criterion scores if a selection system's criterion-related validity is known. If predictor and criterion scores are standardized in the population, the expected criterion score associated with a given predictor score is the product of the validity coefficient and that predictor score (Brogden, 1949). However, the realities of hiring in small organizations and in other small-pool situations may be different than in large-scale hiring. For example, when the number of incumbents is relatively small, their job duties may be more broadly defined and the desired qualifications may therefore be harder to specify (Bobko & Potosky, 2011). Also, in at least some cases, small-scale selection systems may be less rigorous than their large-scale counterparts. In addition, meaningful validation studies may be difficult, if not impossible, to conduct in small-scale hiring situations (Sackett & Arvey, 1993). Therefore, relatively little is known about validity coefficients for typical selection systems of this sort. For those reasons, we frame our presentation around predictor scores.

We look at De Corte's (1999, 2000) framework for assessing expected scores in smaller pools. We continue with a conceptual argument for how De Corte's methods can be extended to model the effects of inflated applicant pools and rejected offers. We then describe the simulations we used to test first our general conceptual approach and then the effects of inflated applicant pools, offer rejections, and various relationships between applicant quality and number of applications per applicant. Although we provide a substantial amount of simulated data, it would be impossible to cover all possibilities and imprudent for us to claim that our results capture all of the subtleties of real-life hiring in small-pool situations. Our goals are more modest—to call attention to phenomena that affect hiring in these situations and to illustrate general principles that help explain them.

Current Methods for Estimating Expected New-Hire Predictor Scores

At least until recently, most researchers (e.g., Murphy, 1986; Schmidt et al., 1979) have used the selection ratio in the estimation of new-hire predictor scores. If the selection ratio is, for example, 10%, and if predictor scores are standardized, the average score across all applicants in the top 10% of the applicant population can be computed (Cronbach & Gleser, 1965: Appendix 1) as the ordinate (height) of the standard normal curve at the 90th percentile divided by the selection ratio. The calculation in this case is 0.175/0.10 = 1.75, indicating that the average standardized predictor score across all applicants in the top 10% of the applicant population is 1.75. We refer to this approach as the *selection ratio method*.

The selection ratio method has been criticized as conceptually inappropriate because it estimates the expected predictor score across a complete segment (e.g., all applicants in the top 10%) of the *population* of possible applicants, rather than just the actual hires from a finite *sample* of applicants (Alexander, Barrett, & Doverspike, 1983; De Corte, 1999, 2000). We thank an anonymous reviewer for an example that provides an intuitive explanation of the rationale for that criticism. Suppose we had 100 job seekers and selected the 5 highest scorers among them. Then suppose the same 100 were randomly divided into five subgroups of 20, and we selected the highest scorer in each subgroup. Would we expect the same 5 people to be selected in the second scenario as in the first? No, because it is unlikely that the top 5 applicants overall would all be in different subgroups. This means that 1 or more people not in the top 5 overall would be among the 5 selected in the smaller subgroups scenario. This also illustrates why the effect is more pronounced in small samples. If we divided 100,000 applicants into five subgroups, choosing the top 100 out of each subgroup of 20,000 will yield results similar to choosing the top 500 out of 100,000. Alexander et al. contend that because applicant pools are, in effect, samples taken from the population of possible applicants, estimates of predictor scores should be sample based rather than population based. This is especially true when pools are small.

Alexander et al. distinguished between the terms *selection ratio* and *hiring rate;* they defined hiring rate as "the percentage of total applicants hired" and contrasted that with the selection ratio, which is "the proportion of the identified population scoring above [a chosen] cutting score" (1983: 342). Although the two terms are often used interchangeably, Alexander et al. advocated using *hiring rate* in situations where selections are made from a finite applicant pool. Like De Corte (1999, 2000), we follow Alexander et al. and use *hiring rate* to refer to the percentage of applicants hired from a particular pool. Although Alexander et al. argued that the expected predictor score for a hiring rate of 10% is less than the value implied by a selection ratio of 10%, they did not quantify the difference.

Years later, De Corte (1999, 2000) did quantify that difference using order statistics. Order statistics is a branch of statistics that may be unfamiliar to many organizational researchers. Briefly, the *k*th order statistic of a sample is the *k*th largest[1] value in that sample. If one were to draw 10 observations at random from a given distribution, the first (or second) order statistic for that sample would be the largest (or second largest) of the 10 observations. If the parameters of a population are known, the expected value can be determined for any order statistic in a sample of any size drawn from that population. In the case of the standard normal distribution, published tables (e.g., Harter, 1961) provide expected values for all order statistics in samples of various sizes. Further details of order statistics theory are available in many statistics texts (e.g., Wackerly, Mendenhall, & Schaeffer, 2008).

De Corte (1999, 2000) argued that if an applicant pool size is known, and if the pool is considered a random sample from a population of potential applicants, then the expected standardized predictor scores of the applicants in that pool are given by the expected values of the standardized order statistics for samples of that size. In a pool of 10, the top-ranked applicant's expected predictor score is the expected value of the first order statistic in a sample of 10 drawn from a standard normal population. We call this method of determining expected predictor scores the *order statistic method*. Before continuing, we call attention to the idea that in our treatment of this topic (as in De Corte's) applicants' predictor scores represent their standardized positions in the applicant population, not in a particular applicant pool. Thus, they are population-based Z scores, with a mean of 0 and a standard deviation of 1.

To illustrate the difference in estimates between the selection ratio and order statistic approaches, we consider again the case where 1 applicant is selected from a pool of 10—a hiring rate of 10%. Order statistics tables indicate that that the expected value of the first order statistic in a sample of 10 is 1.54. We contrast that with 1.75, the value computed earlier by the selection ratio method. The selection ratio method estimate is considerably (i.e., 13.6%) larger than the order statistic method estimate. In fact, it has been proven mathematically (Gillett, 1991) that order statistic estimates are always smaller than the corresponding selection ratio method estimates and that the smaller the applicant pool, the greater the difference between the two types of estimates. Thus, the size of the pool is an important consideration.

Rejected offers is the other issue we raise that affects estimated predictor scores. Researchers (e.g., Hogarth & Einhorn, 1976; Murphy, 1986) have been interested for years in the problem of how rejections affect the expected quality of new hires. Murphy uses the selection ratio method to assess the effects of rejected job offers and showed that rejections substantially reduce expected new-hire predictor scores.

Murphy (1986) and De Corte (1999, 2000) both conclude that traditional methods overestimate expected predictor scores, but for different reasons. De Corte points to Gillett's (1991) proof that the selection ratio method always overestimates expected scores, especially in small pools, and argues that order statistics is the conceptually correct approach. Murphy uses the selection ratio method to show that rejected offers have a more significant negative effect on expectations than has been realized previously. We contend that a conceptually appropriate approach to studying the effects of multiple applications per applicant in small-pool environments must incorporate both types of effects. In the next section, we begin to outline our approach for doing so.

Effects of Multiple Applications per Applicant in Small Pools

Having more applications per applicant leads to larger applicant pools, and this creates an inflated impression of selectivity. Consider an example in which there are 10 organizations, each seeking 1 person, and there are 20 people seeking those jobs. If each person applies for 1 job, there are 20 applications in total. For simplicity, we temporarily assume that the 20 applications are spread evenly among the 10 employers so that each employer receives 2. Order statistics tables indicate that the expected predictor score for the top applicant in a pool of 2 is 0.56. But what if each of the 20 people had applied for 3 jobs rather than 1 job? Then there would have been 60 applications in total, enough for each employer to receive 6. The expected predictor score for the top applicant in a pool of 6 is 1.27. If each person applied for 5 jobs, the pools would have 10 candidates apiece. The top applicant in a pool of 10 has an expected score of 1.54.

If 10 organizations hire from an overall pool of 20 applicants, is it reasonable to conclude that the expected value is 0.56 if each applicant applies for 1 job but that this rises to 1.27 if each applies for 3 jobs and to 1.54 if each applies for 5 jobs?

Before answering that question, we observe that it is the same 20 people who comprise the overall pool of candidates, regardless of how many jobs each applies for or the sizes of the resulting applicant pools. The quality of the overall pool does not improve simply because each of them applies for more jobs. Therefore, it is not reasonable to conclude that employers can hire much better candidates if their pools are of size 10 (expected value 1.54) than if their pools are of size 2 (expected value 0.56).

The order statistic method correctly estimates the expected predictor score of each applicant (by rank-order position) in a pool of a particular size. The expected values of the top scores in pools of 2, 6, and 10 really are 0.56, 1.27, and 1.54, respectively—but those are not the expected scores of the *hires* from those pools. As people apply for more jobs, the pools get larger and the expected value of the highest score per pool increases. At the same time, however, more applications per applicant cause increasing amounts of overlap between pools. High-scoring applicants might be offered multiple jobs, but they can accept only one. Their other offers will be rejected, and those employers will have to hire less desirable candidates. Hence, the expected scores of the hires are less than the expected scores of the highest scoring candidates.

We need a way to account for the effects (on the expected scores of new *hires*) that occur when job offers are rejected. As mentioned earlier, Murphy (1986) offered a method for assessing the effects of rejections on expected values, and other researchers (e.g., Schmitt, 2007; Sturman, 2000) have argued that it is important to use a technique such as Murphy's to account for the effects of rejections. We agree that it is important to account for the effects of rejections, but we do not believe that Murphy's technique is appropriate when applicant pools are small. Murphy modeled a problem where there was one large pool (1,000 applicants) from which 100 were hired. He showed the effects of losing 50 of the top 100 applicants and replacing them with others ranked from 101st to 150th.

The small-pool problem is different. We are considering situations akin to what expectations would be if there were 100 different employers, each seeking to hire 1 person from its own pool of 10 applicants. Like Murphy's (1986), our situation starts with a total of 1,000 applications and ends with 100 people being hired. But as Gillett (1991) has shown, the expected value among the top 100 out of 1,000 (approximately 1.75) is greater than the expected value among the 100 hires that would result from hiring 1 candidate from each of 100 pools of 10 (approximately 1.54). Therefore, Murphy's selection-ratio-based (and population-based) method is not the best way to assess the effects of offer rejections in the small-pool context.

An Improved Method

A better way to determine expected scores for new hires (i.e., not the highest score in each pool but the score of the person actually hired) when pools are small involves thinking of that expected score as the average value across all organizations' new hires and using order statistics to compute that average. To illustrate, we continue with the example of 20 people pursuing 10 jobs and each person applying for 1, 3, or 5 of them. Recall that we are temporarily assuming that each employer receives the same number of applications (2, 6, or 10, respectively).

Because 50% (i.e., 10/20) of the overall pool of applicants will get 1 of the jobs, we expect that, on average, 50% of an organization's applicants will be among the 50% overall who will get jobs. So if an organization received 2 (or 6 or 10) applications, we expect that 1 (or 3 or 5) of those applications came from people who will get 1 of the jobs.

In the case where each applicant applied for 1 job and each organization had an applicant pool of 2, we first note that the applicant pools are mutually exclusive. If every applicant applies for only 1 job, the pools cannot overlap and no employer will lose its first choice to another employer. The expected value of the first order statistic in a pool of 2 is 0.56. Since there is no competition for new hires, the average (expected) value across hires and organizations must also be 0.56. Expected new-hire values match the first order statistic when applicants apply for 1 job only.

When each applicant applied for 3 jobs, the pools were of size 6. Let's say Organization *Y* has one of those pools. Its pool of 6 is expected to include 3 who will be hired somewhere. The first three order statistics in samples of 6 have expected values of 1.27, 0.64, and 0.20, respectively. Some organization (perhaps *Y,* but perhaps not) will hire the top candidate in *Y'*s pool, the candidate with the expected score of 1.27. We expect that another organization (again, maybe or maybe not *Y*) will hire the second-ranked person (expected score 0.64), and still another will hire the candidate with the expected score of 0.20. The expected predictor score across all of those hired is the average of the three expected order statistics, (1.27 + 0.64 + 0.20)/3 = 0.70. If Organization *Z* is in the scenario where each applicant applied for 5 jobs and each pool included 10 applicants, we assume that *Z* has 5 applicants who will be hired somewhere and that *Z* will get 1 of them. The expected values of the top five order statistics from samples of 10 are 1.54, 1.00, 0.65, 0.38, and 0.12, and the average of those is 0.74.

When each person applies for 1 job (and each pool is completely unique), the first order statistic (0.56) gives the correct expected value for the new hire. But when applicants apply for multiple jobs, the first order statistics are significantly higher than the true new-hire expected values, 1.27 versus 0.70 for 3 applications per person, and 1.54 versus 0.74 for 5 applications per person. The first order statistic overestimates the expected value of the actual new-hire predictor score by 81% and 108% in those two cases. If pool sizes increase because people are applying for more jobs (rather than because there are more people seeking jobs), expected values of the first order statistics can be very inaccurate estimates of expected new hire scores. The inflation in pool sizes caused by the additional applications per applicant must be considered.

It is interesting to note, however, that the expected new-hire score did increase (from 0.56 to 0.70 to 0.74) as people submitted more applications (1, 3, and 5, respectively) and the pools got larger (2, 6, and 10), even though there was no change in the composition or the size of the overall pool of applicants. This happens because as the better applicants submit more applications, it becomes less likely that they will fail to get a job because they are "stuck" behind another applicant who is better still. Or from the employer's perspective, when people submit applications to more employers, it becomes more likely that the employer will receive one or more applications from the better applicants. So the larger pools created when people apply for more jobs do mean higher expected new-hire predictor scores. However, our example shows that the increases in expected scores are much smaller than what the first order statistics would suggest.

We are arguing that order statistics can be used to estimate predictor scores of applicants hired from pools of any size by averaging expected order statistics values. In the example we have been using, half of the overall pool of applicants would be hired by some organization, so the number of statistics to be averaged was half of the size of the applicant pools. If the portion of the overall pool that will be hired had been different (e.g., 25%), then the number of order statistics to be averaged would have varied correspondingly (i.e., the top 25% of the order statistics for a sample equal in size to the applicant pool). In the next section, we make a general case for this technique.

A general case for the improved method. Let us assume that there are a total of J jobs to be filled (i.e., that there are J employers and each wants to hire 1 person) and a total of P persons who want one of the J jobs. Let us also assume that each person applies, on average, for $\overline{A}_p$ of those jobs. Thus, the total number of applications (A) in the system is $A = P \times \overline{A}_p$. The total number of applications can also be written as $A = J \times \overline{A}_J$, where $\overline{A}_J$ is the average number of applications per job (i.e., the average size of an applicant pool).

If all J jobs are filled from the pool of P persons, then the overall or aggregate hiring rate is J/P. This rate is low (or high) when the number of jobs available is low (or high) relative to the number of people seeking jobs. But it is important to realize that the overall hiring rate is completely independent of the number of jobs for which the typical applicant applies. In other words, J/P is strictly the ratio of the number of jobs available to the number of people who want a job. It is not affected by the number of applications per applicant. But note that the size of the average applicant pool is very much affected by the number of applications each applicant submits. If applicants were to apply on average for twice as many jobs, the average pool size would double—but this would have no effect on the quality of the overall pool of job seekers.

If J and P were known, the average of the first J order statistics for samples of size P would be a fairly good estimate of the expected predictor score of new hires. That estimate, however, would be only approximate because the P persons would not comprise one large pool from which J of them would be selected. Instead, there would be J applicant pools, averaging $\bar{A}_J$ in size, and one applicant would be selected from each pool. The apparent hiring rate from a pool of average size would be $1/\bar{A}_J$, especially if the organization was able to hire its first choice, but this is not the effective hiring rate.

If applicants submit multiple applications, the apparent hiring rates in the various pools are not the same as the effective (aggregate) hiring rate. That is, J/P and $1/\bar{A}_J$ are not equal. In fact, $J/P = \bar{A}_P/\bar{A}_J$. This can be seen by comparing cross products ($A = P \times \bar{A}_P = J \times \bar{A}_J =$ the total number of applications). Thus, it is $\bar{A}_P/\bar{A}_J$, and not $1/\bar{A}_J$, that is proportional to J/P. That is, J/P represents the actual hiring rate in the aggregate, and $\bar{A}_P/\bar{A}_J$ expresses that same rate at the level of the individual applicant pool. So for organizations with average-sized pools, the effective hiring rate (in terms of its leading to an accurate estimate of the expected predictor score of new hires) is not "one over the size of the applicant pool." It is $\bar{A}_P/\bar{A}_J$, the ratio of the average number of applications per applicant to the size of the average applicant pool.

Does this theoretical method work? We have presented a logical case for our method, but we have so far made two simplifying assumptions, neither of which is probably ever true in real-world hiring situations.

1. Applications are distributed evenly across organizations, creating applicant pools of equal size for all organizations.
2. Every applicant submits the same number of applications.

It is important to determine whether our method yields viable estimates of new-hire predictor scores if these assumptions are invalid. We use simulations to do so.

Method

We first developed a set of theoretically derived values based on the method described above. Then we did a series of simulations, first to confirm the viability of the general approach and then to test the effects of relaxing the simplifying assumptions that we incorporated into the first simulation.

Theoretical Values

We computed expected values for new hires from order statistics tables by averaging a number of the top expected order statistics from samples of a given size. For each situation we considered, the number of order statistics we averaged was the number of applications per applicant, and the sample size was the size of the pool. So, for example, to compute the expected value of the predictor score if there are 4 applications per applicant and the pool size is 10, we averaged the top four expected order statistics for samples of 10. We also computed the apparent and the effective hiring rates. Apparent hiring rates are "one over the pool size," $1/\bar{A}_J$. Effective hiring rates are the number of applications per person divided by the pool size, $\bar{A}_P/\bar{A}_J$.

Simulations

For the sake of continuity, we first describe what each of the simulations was designed to do, and then we outline the more technical aspects of the simulation process itself. Unless indicated otherwise, we simulated 1,000 sets of 50 applicant pools in each condition. Thus, except in situations where some of the jobs remained unfilled, each of the expected values we report in the next section is an average across 50,000 hires per condition.

Simplest case. In the first simulation, both of the previously mentioned assumptions were maintained. In a given condition, all applicants applied for the same number of jobs and applications were distributed evenly across employers. We computed expected values as the observed averages of predictor scores for new hires. Effective hiring rates were computed as the percentage of applicants in a given hiring situation who were actually hired.

Unequal pool sizes. In the second simulation, we relaxed the assumption that applications are spread evenly across employers. All applicants in a given condition submitted the same number of applications, but they were allowed to apply for any of the jobs in that condition (i.e., applicants were randomly assigned to applicant pools, with equal probability per job). The average pool size was controlled, but pool sizes varied across employers.

Unequal numbers of applications per applicant. In this simulation, we also relaxed the assumption that all applicants apply for the same number of jobs. We are not aware of empirical data concerning the number of jobs applicants typically apply for, and we suspect that this number varies across job types and that it changes as labor market conditions change. Nonetheless, a reasonable case could be made that there is a relationship between employee quality and the number of jobs applied for. To examine the possible effects of relationships of that sort, we created four types of distributions of applications.

In bottom-loaded distributions, the poorest candidates applied for the most jobs and the best candidates applied for the fewest. In top-loaded distributions, that relationship was reversed. In middle-loaded distributions, applicants at the top and bottom ends of the distribution applied for relatively few jobs and those in the middle applied for the most. In balanced distributions, all applicants applied for the same number of jobs. We simulated each of these four distributions at three different levels of average number of applications per applicant (3.5, 7, and 14). We also simulated hiring rates of 10%, 20%, 25%, 33%, and 50% (hiring on average 1 out of 10, 5, 4, 3, and 2 applicants, respectively) for each combination of distribution and number of applications per applicant. (See the Table 5 note for specific details of these distributions.)

Expected values for top choices. The fourth simulation addressed the question of what should be expected in cases where employers are able to hire their first choice, that is, where their hiring is not affected by offer rejections. We computed the average predictor scores for only those new hires who were ranked first in their applicant pools. Top-ranked applicants who were not hired by a particular employer (because they were hired elsewhere) were not included in these calculations, nor were new hires who were not the employer's first choice.

Simulation process. The algorithm used for the simulation was programmed using ActionScript, the object-oriented language for Flash. The result was a flexible simulator that can be posted on a webpage. The simulator allows the experimenter to set the number of jobs, the number of candidates, the number of applications per candidate, and the average pool size.

The pseudocode for the Monte Carlo algorithm is shown in Table 1. The algorithm proceeds through two loops. In the first loop all of the candidates are generated and assigned to employers' applicant pools. In the second loop each employer selects the best available candidate, if any. The predictor scores are generated from a standard normal distribution. The assignment of candidates to applicant pools is effected by randomly selecting a position for each application made by each applicant. The simulator allows for both the case where each position must receive the same number of applicants and for the case where this is not required.

The second loop of the algorithm determines which candidate, if any, is hired from each pool and then cumulates statistics. This is performed in four steps for each position. First the available candidates are sorted by predictor scores. Then the highest ranked candidate is selected for the position and the predictor score is recorded. Finally, the selected candidate is removed from the pools of all other positions to which that candidate has applied.

Results

Theoretical Values

Table 2 presents theoretically derived results. Apparent hiring rates are $\frac{1}{\textit{Pool Size}}$. These indicate what the hiring rate would seem to be, especially if an employer hired its top choice. The upper entry in each row of Table 2 is the expected value of a new-hire predictor score. The lower entry is the effective hiring rate, $\frac{\textit{Applications per Applicant}}{\textit{Pool Size}}$ (i.e., $\bar{A}_P / \bar{A}_J$), which is proportional to J/P. Comparisons across columns within any row show how expected predictor scores and effective hiring rates differ, for a given applicant pool size, when people apply for more jobs on average. This table shows, for example, that the expected predictor score of a hire from a pool of 8 could be as high as 1.42 (i.e., 1.42 standard deviations above the mean in the population of potential applicants) if applicants apply for only 1 job each. If they apply for 2 (or 3) jobs each, the expectation falls to 1.14 (or 0.92). If they apply for more than 3 jobs each, the expected value falls further.

Effective hiring rates reflect the overall or aggregate hiring rate in each condition. Interesting comparisons can be made by locating different conditions with the same effective

Table 1
Pseudocode for One Run of the Simulations

```
Loop 1—Fill applicant pools with candidates
    For each candidate
        Generate a predictor score
        For each application of the candidate
            If equal pool sizes is not required
                Randomly choose (apply for) a position from list of all positions
            Else (equal pool sizes is required)
                Randomly choose (apply for) a position from those whose pools are not yet filled
Loop 2—Select best available candidate in each pool
    For each position
        Sort candidates by predictor score
        Select highest ranked available candidate
        Cumulate statistics
        Remove the selected candidate from this and all other pools
```

Table 2
Theoretically Derived Expected Values of New-Hire Predictor Scores and Effective Hiring Rates

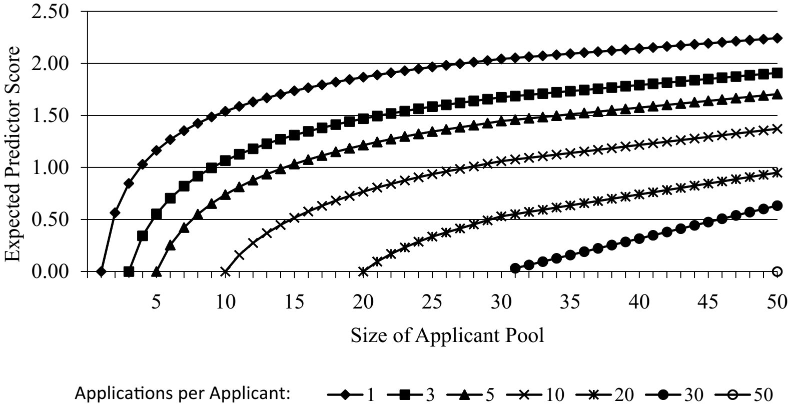
		Number of Applications per Applicant										
Pool Size	Apparent Hiring Rate	1	2	3	4	5	6	8	10	15	25	50
2	50%	0.56 50%	0.00[a] 100%	0.00[b] 100%	0.00[b] 100%	0.00[b] 100%	0.00[b] 100%	0.00[b] 100%	0.00[b] 100%	0.00[b] 100%	0.00[b] 100%	0.00[b] 100%
3	33%	0.85 33%	0.42 67%	0.00[a] 100%	0.00[b] 100%	0.00[b] 100%	0.00[b] 100%	0.00[b] 100%	0.00[b] 100%	0.00[b] 100%	0.00[b] 100%	0.00[b] 100%
4	25%	1.03 25%	0.66 50%	0.34 75%	0.00[a] 100%	0.00[b] 100%	0.00[b] 100%	0.00[b] 100%	0.00[b] 100%	0.00[b] 100%	0.00[b] 100%	0.00[b] 100%
5	20%	1.16 20%	0.83 40%	0.55 60%	0.29 80%	0.00[a] 80%	0.00[b] 80%	0.00[b] 100%	0.00[b] 100%	0.00[b] 100%	0.00[b] 100%	0.00[b] 100%
6	17%	1.27 17%	0.95 33%	0.70 50%	0.48 67%	0.25 83%	0.00[a] 100%	0.00[b] 100%	0.00[b] 100%	0.00[b] 100%	0.00[b] 100%	0.00[b] 100%
8	13%	1.42 13%	1.14 25%	0.92 38%	0.73 50%	0.55 63%	0.38 75%	0.00[a] 100%	0.00[b] 100%	0.00[b] 100%	0.00[b] 100%	0.00[b] 100%
10	10%	1.54 10%	1.27 20%	1.07 30%	0.89 40%	0.74 50%	0.60 60%	0.32 80%	0.00[a] 100%	0.00[b] 100%	0.00[b] 100%	0.00[b] 100%
15	7%	1.73 7%	1.49 13%	1.31 20%	1.16 27%	1.03 33%	0.92 40%	0.71 53%	0.52 67%	0.00[a] 100%	0.00[b] 100%	0.00[b] 100%
25	4%	1.97 4%	1.74 8%	1.58 12%	1.45 16%	1.34 20%	1.25 24%	1.08 32%	0.94 40%	0.62 60%	0.00[a] 100%	0.00[b] 100%
50	2%	2.25 2%	2.05 4%	1.91 6%	1.80 8%	1.71 10%	1.62 12%	1.49 16%	1.37 20%	1.14 30%	0.79 50%	0.00[a] 100%

Note: The upper entry in each cell is the expected value of a new-hire predictor score. The lower entry in each cell is the effective hiring rate. Entries in this table are based on the assumptions that all applicants apply for the same number of jobs and that applications are spread evenly across organizations so that all organizations' applicant pools are the same size.

a. This cell refers to a situation in which the number of jobs and the number of people are equal. Thus, all of the jobs can be filled and all of the people can get jobs. If all people get jobs, the expected value of the standardized predictor score for new hires is 0.00 and 100% of the applicants are hired.

b. This cell refers to a labor shortage, where there are more jobs than people. If all people get jobs, the expected value of the standardized predictor score for new hires is 0.00 and 100% of the applicants are hired.

Figure 1
Expected Standardized Predictor Scores of New Hires, According to the Number of Applications Submitted per Applicant



Note: Expected predictor scores assume 1 hire per organization.

hiring rate. For example, 1 application per applicant in pools of 5 has an effective hiring rate of 20%, as do 2 per candidate in pools of 10, 3 per candidate in pools of 15, and 10 per candidate in pools of 50. The respective expected values in those conditions are 1.16, 1.27, 1.31, and 1.37. This shows that as applicants apply for more jobs, expected values rise due to increasing likelihoods that the better candidates will be hired somewhere. However, the increase in these expected values for actual hires is much smaller than the increase in the corresponding first order statistics (1.16, 1.54, 1.73, and 2.25) for pools of those sizes, once again showing that the first order statistic is a poor estimator of expected new-hire scores, unless it is true that job seekers apply for only one job at a time.

Figure 1 illustrates this effect. The top curve represents expected predictor scores for new hires, assuming that all applicants apply for just 1 job and that there is 1 hire per organization. These are identical to the estimates produced by the order statistic method as outlined by De Corte (1999, 2000). The lower curves show expected scores when applicants apply for multiple jobs. It is clear that if job seekers submit even just a few applications each, expected predictor scores for new hires are significantly lower than those suggested by the order statistic method.

Simulations

Simplest case. This simulation (Table 3) began the testing of our theoretical results. It maintained the simplifying assumptions (all applicants apply for the same number of jobs, and all employers receive the same number of applications) discussed previously.

A comparison of the simulated values in Table 3 to the theoretically derived values in Table 2 shows that corresponding values below the diagonals are identical or very nearly so,

Table 3
Simulated Values of Expected New-Hire Predictor Scores With Applications Distributed Evenly Across Applicant Pools

	Number of Applications per Applicant										
Pool Size	1	2	3	4	5	6	8	10	15	25	50
2	0.56 50%	0.14 87%	0.02 98%								
3	0.85 33%	0.42 65%	0.15 88%	0.03 97%	0.01 99%						
4	1.02 25%	0.66 50%	0.34 73%	0.13 90%	0.04 97%	0.01 99%					
5	1.17 20%	0.83 40%	0.55 60%	0.29 78%	0.12 91%	0.03 98%	0.01 99%				
6	1.26 17%	0.96 33%	0.71 50%	0.47 66%	0.27 81%	0.11 92%	0.00 99%				
8	1.42 13%	1.15 25%	0.93 38%	0.74 50%	0.55 62%	0.37 75%	0.09 94%	0.01 99%			
10	1.54 10%	1.29 20%	1.09 30%	0.91 40%	0.75 50%	0.60 60%	0.31 80%	0.08 95%			
15	1.74 7%	1.52 13%	1.34 20%	1.18 27%	1.05 33%	0.94 40%	0.72 54%	0.52 67%	0.06 97%		
25	1.96 4%	1.77 8%	1.61 12%	1.47 16%	1.37 20%	1.27 24%	1.10 32%	0.95 40%	0.63 60%	0.04 98%	
50	2.25 2%	2.07 4%	1.93 6%	1.82 8%	1.73 10%	1.65 12%	1.51 16%	1.39 20%	1.14 30%	0.79 50%	

Note: The upper entry in each cell is the expected value of a new-hire predictor score. The lower entry in each cell is the effective hiring rate. Entries in this table are under the assumptions that all applicants apply for the same number of jobs and that applications are spread evenly across organizations so that all organizations' applicant pools are the same size. The number of jobs available was 50 in all cases. All omitted entries are 0.00 ± 0.01 with effective hiring rates of 100%.

but entries on or above the diagonals diverge somewhat. We refer to the diagonal as the set of entries where the number of applications per applicant and the pool size are equal. Note that all omitted entries in Table 3 have expected values of 0.00 and hiring rates of 100%.

We look first at the on- and above-diagonal cases, where results differ between the tables. Recall from our earlier discussion that $J/P = \bar{A}_P / \bar{A}_J$. For entries on the diagonal, pool size ($\bar{A}_J$) equals the number of applications per applicant ($\bar{A}_p$), so it must also be true that the number of jobs (J) equals the number of people (P). Thus, it would be possible in these situations for all jobs to be filled and for all people to get jobs. Entries above the diagonal (number of applications per applicant is larger than the pool size) are situations where J is greater than P. There are more jobs than people. This represents a labor shortage. It would be possible in these situations for all people to get jobs, but it is not possible to fill all the jobs. If all people get jobs, the expected value of the standardized predictor score for new hires must be 0.00 and the hiring rate must be 100%, both as indicated in Table 2.

But the simulated entries on (and some above) the diagonal in Table 3 show positive (not 0) expected values, and the effective hiring rates are lower than the corresponding theoretical values in Table 2. This reflects the fact that, in the simulation, employers were sometimes unable to hire anyone because all of the applicants in their pools had been previously hired elsewhere. In the perfect theoretical world of Table 2, unhired applicants and unfilled jobs are essentially matched until either the supply of applicants or the supply of jobs is exhausted. Thus, theoretical expected values for the new hires are 0.00 and hiring rates are 100%. In the somewhat more realistic world of Table 3, where some applicants are not hired and some jobs are not filled, the expected values for new-hire scores are positive because the people who *are* hired are more likely than those who are not hired to be above-average applicants. Because not all are hired, the effective (actual) hiring rates are less than 100%.

The most practically important parts of these tables are the parts below the diagonals, where the number of people seeking jobs is greater than the number of jobs available. This is the typical situation where some applicants will not get any of the jobs. Thus, hiring rates are less than 100%. We note that entries in this section agree closely across Tables 2 and 3. The largest absolute difference between corresponding entries is 0.03, and the mean absolute difference is just over 0.01. This suggests that our theoretical method accurately predicts simulated results. However, the assumptions inherent in the Table 3 results are admittedly unrealistic.

Unequal pool sizes. This simulation (Table 4) relaxes the assumption that applications are spread evenly across employers. As a result, the number of applications (pool size) varies from one employer to the next. Comparing Table 4 to Table 3, it is clear that having unequal pool sizes leads to reductions in some expected values. The effect is most noticeable in the smallest pools and where there is 1 application per applicant. This was not unexpected. When pools vary in size, it is always true that some pools are smaller than average and others are larger. When pools are small, differences in expectations between successive pool sizes are relatively large. This can be seen clearly in Table 2. For example, the differences in expected values between pools of 2 and 3 is greater than the differences between pools of 3 and 4, and so on. So when the average pool is small, the smaller-than-average individual pools reduce the expected values more than they do when pools are larger.

The mean absolute below-diagonal difference in corresponding entries in Tables 2 and 4 is just over 0.02. In the 1-application-per-applicant column, the average difference is about 0.05, with simulated values lower than the theoretically derived values. In columns where there are multiple applications per applicant, the mean absolute difference is less than 0.02. Thus, outside of the smallest pools in the 1-application-per-applicant situation, the theoretical values in Table 2 are close estimates of the values in Table 4. Most of the differences between corresponding entries in those tables are 0.05 or less, which is rather inconsequential in a practical sense. If it is true that real applicants generally tend to apply for more than 1 job at a time, then discrepancies between the 1-application-per-applicant columns in Tables 2 and 4 are irrelevant.

Table 4
Simulated Values of Expected New-Hire Predictor Scores and Effective Hiring Rates With Applications Distributed Unevenly Across Applicant Pools

	Number of Applications per Applicant										
Average Pool Size	1	2	3	4	5	6	8	10	15	25	50
2	0.53	0.23	0.07	0.01	0.01						
	43%	77%	94%	99%	99%						
3	0.75	0.43	0.19	0.05	0.02						
	32%	61%	83%	95%	99%						
4	0.94	0.62	0.36	0.17	0.05	0.01					
	25%	48%	70%	87%	96%	99%					
5	1.09	0.78	0.53	0.30	0.15	0.04	0.01				
	20%	40%	59%	76%	89%	97%	99%				
6	1.20	0.92	0.69	0.47	0.28	0.13	0.01				
	17%	32%	50%	65%	80%	91%	99%				
8	1.38	1.12	0.90	0.71	0.55	0.36	0.11	0.01			
	13%	25%	38%	50%	62%	75%	93%	99%			
10	1.51	1.26	1.06	0.89	0.74	0.58	0.31	0.09			
	10%	20%	30%	40%	50%	60%	80%	94%			
15	1.72	1.50	1.33	1.18	1.05	0.93	0.71	0.52	0.06		
	7%	13%	20%	27%	33%	40%	54%	67%	97%		
25	1.95	1.76	1.60	1.47	1.37	1.27	1.10	0.95	0.63	0.04	
	4%	8%	12%	16%	20%	24%	32%	40%	60%	98%	
50	2.24	2.07	1.93	1.82	1.73	1.64	1.50	1.39	1.14	0.79	
	2%	4%	6%	8%	10%	12%	16%	20%	30%	50%	

Note: The upper entry in each cell is the expected value of a new-hire predictor score. The lower entry in each cell is the effective hiring rate. The number of jobs available was 50 in all cases. Entries in this table are under the assumption that all applicants apply for the same number of jobs, but the applications are distributed randomly and with equal probability across organizations. All omitted entries are 0.00 ± 0.01 with effective hiring rates of 100%.

Unequal numbers of applications per applicant. This simulation also relaxed the assumption that all applicants in a given condition apply for the same number of jobs. Table 5 shows that expected values increase as the number of applications per applicant increases and as the hiring rate decreases. This is consistent with other results we have presented. The important comparison in Table 5 is between the distributions, that is, between the columns. In any row of that table, differences across the distributions are generally minor. The largest within-row difference is 1.72 – 1.64 = 0.08 when the hiring rate is 10% and average number of applications per applicant is 3.5. It might be somewhat surprising that differences in the distribution of applications tend to have small effects on expectations, but this does suggest

Table 5
Expected New-Hire Scores With Different Distributions of Applications Across Qualities of Applicants

Number of Applications	Hiring Rate	Average Pool Size	Bottom Loaded[a]	Middle Loaded[b]	Top Loaded[c]	Balanced[d]
3.5 per Applicant[e]						
	10%	35	1.64	1.68	1.72	1.70
	20%	17.5	1.29	1.33	1.36	1.34
	25%	14	1.16	1.20	1.22	1.20
	33%	10.5	0.98	1.02	1.03	1.01
	50%	7	0.68	0.68	0.72	0.70
7 per Applicant[e]						
	10%	70	1.71	1.70	1.74	1.73
	20%	35	1.36	1.36	1.39	1.38
	25%	28	1.24	1.23	1.25	1.25
	33%	21	1.05	1.06	1.07	1.06
	50%	14	0.76	0.78	0.77	0.76
14 per Applicant[e]						
	10%	140	1.74	1.74	1.75	1.75
	20%	70	1.39	1.38	1.39	1.39
	25%	56	1.26	1.26	1.26	1.26
	33%	42	1.07	1.08	1.08	1.08
	50%	28	0.79	0.78	0.79	0.79

Note: All entries are based on 50 jobs. Applications were distributed randomly and with equal probability across employers.

a. In the bottom-loaded distribution, with an average of *3.5 applications per applicant,* all applicants that were 2 or more standard deviations below the mean applied for 6 jobs; applicants 1 to 2 standard deviations below the mean applied for 5 jobs; applicants 0 to 1 standard deviation below the mean applied for 4 jobs; applicants 0 to 1 standard deviation above the mean applied for 3 jobs; applicants 1 to 2 standard deviations above the mean applied for 2 jobs; and applicants more than 2 standard deviations above the mean applied for 1 job. This results in an average of 3.5 applications per applicant. The numbers of applications for each of those groups is doubled in the *7 applications per applicant* distribution and quadrupled in the *14 applications per applicant* distribution.

b. In the middle-loaded distribution with *3.5 applications per applicant,* all applicants who are 2 or more standard deviations away from the mean (above or below) applied for 1 job; applicants 1 to 2 standard deviations above or below the mean applied for 3 jobs; applicants 0 to 1 standard deviation above or below the mean applied for 4 jobs. In the *7 applications per applicant* middle-loaded distribution, all applicants who are 2 or more standard deviations away from the mean (above or below) applied for 2 jobs; applicants 1 to 2 standard deviations above or below the mean applied for 6 jobs; applicants 0 to 1 standard deviation above or below the mean applied for 8 jobs. In the *14 applications per applicant* middle-loaded distribution, all applicants who are 2 or more standard deviations away from the mean (above or below) applied for 4 jobs; applicants 1 to 2 standard deviations above or below the mean applied for 6 jobs; applicants 0 to 1 standard deviation above or below the mean applied for 18 jobs.

c. The top-loaded distributions are the reverses of the respective bottom-loaded distributions. For example, in the top-loaded distribution with *3.5 applications per applicant,* all applicants who are 2 or more standard deviations above the mean applied for 6 jobs; applicants 1 to 2 standard deviations above the mean applied for 5 jobs; applicants 0 to 1 standard deviation above the mean applied for 4 jobs; applicants 0 to 1 standard deviation below the mean applied for 3 jobs; applicants 1 to 2 standard deviations below the mean applied for 2 jobs; and applicants more than 2 standard deviations below the mean applied for 1 job.

d. In the balanced distributions, all applicants applied for the same number of jobs. To accomplish this in the *3.5 applications per applicant* condition, we simulated 3 applications per applicant and 4 applications per applicant and then averaged the results.

e. The actual numbers of applications per applicant in the middle-loaded distributions were 3.63, 7.05, and 14.10, respectively, in the 3.5, 7, and 14 applications-per-applicant conditions.

that the theoretical model is rather robust to variations in the relationship between applicant quality and the number of applications per applicant. Regardless of whether the distributions were bottom loaded, top loaded, or something in between, differences in expected values are small. Therefore, the theoretical values in Table 2 appear to be good estimates of expected values, even if the equal-number-of-applications-per-applicant and the equal-number-of-applications-per-pool assumptions are both violated.

This is illustrated by comparing entries with similar effective hiring rates and pool sizes in Tables 2 and 5. For example, Table 2 indicates that in pools of 15 (or 25 or 50), a 20% hiring rate theoretically results in expected new-hire scores of 1.31 (or 1.34 or 1.37). Very similarly, the top panel (3.5 applications per applicant) in Table 5 shows that a 20% hiring rate is associated with an average pool size of 17.5 and an expected predictor score between 1.29 and 1.36. Hiring rates of 20% for 7 and 14 applications per applicant show expected predictor scores of 1.36 to 1.39 and 1.38 to 1.39, respectively, again very much in line with the theoretical results in Table 2. For any *effective* hiring rate from Table 2, the associated expected predictor scores are very similar to the corresponding scores in Table 5, especially if the pools are also of comparable size.

Expected values for top choices. We turn next to consider a question that has gotten very little attention. We have shown that rejected job offers lower expectations about new-hire quality. But what happens if an employer's first offer is accepted, that is, when there are no rejected offers to lower the expectations? Is it reasonable to expect that in this case the first order statistic gives the correct expected value for the new hire? Perhaps unexpectedly, the answer is no, especially if there has been more than 1 application per applicant (Table 6).

When there is 1 application per applicant, the entries in Table 6 essentially match those in Table 4. In both of those tables, applications are distributed randomly across employers, so pool sizes are unequal. As we have mentioned, when there is just 1 application per applicant, there can be no overlap between pools, and every simulated employer is able to hire its first choice. Thus, we should expect this column in Table 6 to match the corresponding column in Table 4. These values are a bit less than the first order statistics (provided in Table 6) for the reasons mentioned in our discussion of Table 4.

But when there is more than 1 application per applicant, the expected values of the first-choice hires are significantly lower than the first order statistics. For example, with 3 applications per applicant and a pool of 8, the expected value of a first-choice hire is 1.17, versus a first order statistic of 1.42. Why would the first order statistic be an inflated estimate of the new-hire predictor score if the organization succeeds in hiring its first choice? The reason is as follows: The first order statistic is the average of the highest scores across all pools of 8. But some of those pools will have the same person ranked at the top, so in effect, the scores of people who are at the tops of multiple pools are counted multiple times when the top scores are averaged. But since those people can be hired by only one firm, their scores count only once when the first-choice hires' scores are averaged. Thus, the average for first-choice *hires* must be lower than the average of the *top scores* across all pools (i.e., the first order statistic).

This again shows that the order statistic method provides inaccurate estimates of expected new-hire predictor scores, especially when there is more than 1 application per candidate. We

Table 6
Simulated Expected Predictor Scores for New Hires Who Were Ranked First in Their Applicant Pools

		Number of Applications per Applicant										
Pool Size	First Order Statistic	1	2	3	4	5	6	8	10	15	25	50
2	0.56	0.53	0.37	0.32	0.30	0.31	0.30	0.31	0.36	0.37	0.40	0.55
3	0.85	0.75	0.59	0.51	0.48	0.49	0.49	0.50	0.57	0.60	0.60	0.88
4	1.03	0.94	0.78	0.70	0.67	0.67	0.66	0.71	0.74	0.75	0.82	1.04
5	1.16	1.09	0.93	0.85	0.81	0.81	0.81	0.85	0.87	0.88	1.00	1.17
6	1.27	1.20	1.07	1.01	0.97	0.95	0.95	0.97	0.98	1.02	1.09	1.27
8	1.42	1.38	1.25	1.17	1.16	1.14	1.15	1.16	1.18	1.18	1.25	1.43
10	1.54	1.51	1.39	1.32	1.29	1.28	1.29	1.30	1.31	1.34	1.40	1.53
15	1.74	1.72	1.61	1.56	1.53	1.52	1.51	1.52	1.53	1.56	1.61	1.72
25	1.97	1.95	1.86	1.81	1.78	1.78	1.77	1.77	1.78	1.81	1.85	1.93
50	2.25	2.24	2.16	2.11	2.09	2.08	2.08	2.08	2.10	2.10	2.15	2.23

Note: These are the average scores of the top-ranked applicants who were actually hired. In each of these cases, each applicant applied for the same number of jobs, but applications were distributed randomly and with equal probability across employers. The number of jobs available was 50 in all cases.

reemphasize that the 1.17 value just discussed does not reflect the overall expected value of a hire from a pool of 8 when there are 3 applications per applicant; it is the average of just those cases where the employer got its first choice. Table 4 indicates that the overall expectation, considering all hires, in this situation is 0.90. Thus, the first order statistic overestimates, by about 21%, even the expectation among first-choice hires in this scenario. It overestimates the correct overall expectation by about 58%. We note again, however, that our theoretically derived estimate (Table 2) for this situation is 0.92, very similar to the Table 4 simulated value of 0.90.

The simulations we have reported support our theoretically derived means for various combinations of pool sizes and numbers of applications per applicant, but the amount of variation that should be expected around the means is also an important consideration in hiring. We are referring to the variation in predictor scores among individuals hired in a given condition. For example, if pool size is again 8 and applicants have applied on average for 3 jobs, the expected predictor score for a new hire is 0.92 (Table 2)—but if many hires were made under that circumstance, what would be the expected standard deviation of the predictor scores of those hires? We now address that question.

Individual variation around means. Table 7 provides simulated estimates of the standard deviations of the predictor scores in each of our conditions. We emphasize that these are not the standard errors of the means presented previously; they are standard deviations of the predictor scores of the individuals hired in each situation. With the means, they provide in each case a sense of how new-hire predictor scores would be distributed. Because the applicant pools we have examined are small, significant variability was expected. The standard deviations in Table 7 range from 0.47 to 1.02.

Table 7
Simulated Values of Standard Deviations of Expected New-Hire Predictor Scores

	Number of Applications per Applicant										
Average Pool Size	1	2	3	4	5	6	8	10	15	25	50
2	0.86	1.01	1.00	1.01	1.01						
	43%	77%	94%	99%	99%						
3	0.74	0.88	0.98	1.00	1.01						
	32%	61%	83%	95%	99%						
4	0.71	0.83	0.94	1.01	1.03	0.98					
	25%	48%	70%	87%	96%	99%					
5	0.69	0.77	0.86	0.93	1.01	1.02	0.99				
	20%	40%	59%	76%	89%	97%	99%				
6	0.64	0.75	0.82	0.87	0.94	1.00	0.97				
	17%	32%	50%	65%	80%	91%	99%				
8	0.61	0.69	0.76	0.80	0.87	0.91	0.99	0.97			
	13%	25%	38%	50%	62%	75%	93%	99%			
10	0.60	0.65	0.70	0.80	0.78	0.86	0.93	1.02			
	10%	20%	30%	40%	50%	60%	80%	94%			
15	0.54	0.61	0.66	0.72	0.74	0.80	0.81	0.88	0.98		
	7%	13%	20%	27%	33%	40%	54%	67%	97%		
25	0.51	0.56	0.61	0.65	0.67	0.71	0.75	0.80	0.88	1.00	
	4%	8%	12%	16%	20%	24%	32%	40%	60%	98%	
50	0.47	0.51	0.53	0.57	0.61	0.63	0.67	0.68	0.74	0.82	
	2%	4%	6%	8%	10%	12%	16%	20%	30%	50%	

Note: The upper entry in each cell is the standard deviation of the simulated individual hires in each condition. The lower entry in each cell is the effective hiring rate. The number of jobs available was 50 in all cases. Entries in this table are under the assumption that all applicants apply for the same number of jobs, but the applications are distributed randomly and with equal probability across organizations. All omitted entries are 1.00 ± 0.02 with effective hiring rates of 100%.

The smallest standard deviations occur where the pool sizes are largest and the numbers of applications per applicant are smallest. Consistent with sampling theory, the standard deviations increase as pool sizes decrease. In other words, the smallest pools exhibit the greatest variability. The standard deviations also increase within rows as the number of applications per applicant increases. This reflects the associated increases in effective hiring rates (also presented in Table 7). Increases in effective hiring rates mean that larger portions of the overall pool of applicants are being hired. As the effective hiring rate approaches 100%, the standard deviations of the new hires approaches its population value of 1.00.

Interesting comparisons can again be made by comparing Table 7 entries that have the same or comparable effective hiring rates. We again use 20% as an example. This happens where pool sizes are 5, 10, 15, 25, or 50 and applications per applicant are 1, 2, 3, 5, or 10, respectively. Our tabled standard deviations for these conditions are very similar—0.69, 0.65, 0.66, 0.67, and 0.68. Other effective hiring rates exhibit similar degrees of consistency across specific conditions.

These standard deviations can be used to construct confidence intervals around expected new-hire values. Using Tables 4 and 7, when pool size is 10 and applications-per-person is 2, the 90% confidence interval is $1.26 \pm (1.645 \times 0.65) = 0.19$ to 2.33. This is a wide range of values for new hires. Confidence intervals around other expected values in our tables would also be wide. In fact, those with standard deviations larger than 0.65 would be wider than this one. We point out, however, that the wide confidence intervals are a consequence of the small sizes of the pools. They are not due to a lack of precision in our estimates of the expected (i.e., average) values. Nonetheless, it should be recognized that individual cases can vary widely around the expected values.

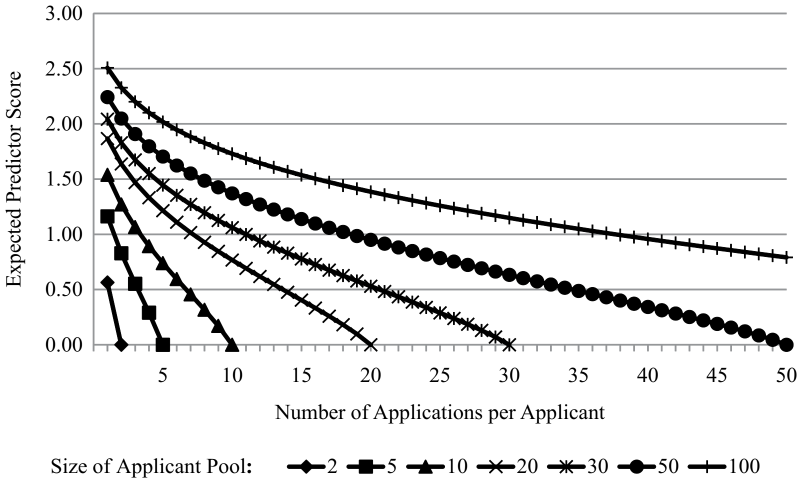
Discussion

We have shown that if people apply for more than one job at a time, expected predictor scores for new hires are significantly lower than those suggested by the order statistic method and that this is true even when the employer's first choice is hired. The underlying reason is that actual expected predictor scores are driven primarily by the aggregate or system-wide hiring rate, and not by the size or the apparent hiring rate of any one organization's applicant pool. It is the overall ratio of *applicants* to job openings, not the number of *applications* per job opening (i.e., pool size), that mostly determines expected predictor scores. The ratio of applicants to openings equals the number of applications per opening only if each applicant applies for exactly one job.

Figure 1 illustrates how expected predictor scores are affected if job seekers submit multiple applications. It also useful for determining approximately how large an applicant pool would have to be, given a certain number of applications per applicant, to reach a given expected score. For example, when there is 1 application per applicant, a pool of 10 yields an expected predictor score of about 1.50 for the top-ranked candidate. If job seekers submit 3 or 5 applications apiece, then pools of about 20 or 30, respectively, are required to reach an expected score of 1.50. A pool of over 60 is required to reach that same expected predictor score if the number of applications per applicant is 10. This illustrates again that the number of applications per applicant has a major, and until now unrecognized, impact on expected predictor scores.

Figure 2 shows that the negative effect of additional applications per applicant on expected predictor scores is much greater when pools are small than they are when pools are large. That is, the slopes of the declines in expected scores as the number of applications per person increases are more severe in the smaller pools than in the larger pools. Thus, expectations for hires from relatively small pools of applicants will be impacted to a much greater degree by multiple applications per applicant than hires from larger pools will be.

Figure 2
Expected Standardized Predictor Scores of New Hires, According to the Size of the Applicant Pool



Note: Expected predictor scores assume 1 hire per organization.

Limitations

Due to space limitations, we have not addressed reliability, across organizations, of applicants' predictor scores. Our presentation has effectively assumed that all organizations arrive at the same judgment of a given applicant, that is, that interemployer reliability is perfect. We investigated the effects of this assumption by conducting additional analyses in which a unique error term was introduced into each applicant's score at each organization to which he or she applied. This simulated a degree of interemployer unreliability in assessing candidates. Observed predictor scores (true score plus organization-specific error plus random error) were used to rank applicants for hiring decisions, but then true scores were used to compute expected values for new hires. The patterns of results were identical to those we have presented, but the magnitudes of the expected scores were reduced. A more complete description of this simulation is available from the first author.

A related possibility is that differences across organizations in the predictor score for a particular applicant reflect, in part, true differences across those organizations in person–organization fit (Kristof-Brown, Zimmerman, & Johnson, 2005) rather than random measurement error. Research (e.g., Schneider, 1987; Schneider, Goldstein, & Smith, 1995) suggests that all organizations have unique characteristics that affect the types of candidates who will be attracted to the organization, as well as the criteria the organization uses in its selection process. We conducted an additional simulation to test possible effects of this sort.

A randomly chosen fit score was added to each applicant's score at each employer to which he or she applied (to represent true differences in fit for a given employee across employers). A random error score was added to each score as well. Again, observed predictor scores (true score plus fit score plus error) were used to make hiring decisions, but expected scores were based on true score plus fit score. Results were once again as expected. The addition of fit scores tended to raise expected predictor scores (organizations were better able to hire people with both high true scores and high fit scores), but error scores tended to lower them. Due to space limitations, as well as a lack of empirically based data to suggest the true relative magnitudes of these sorts of true and errors scores, we do not present those results here. More detailed descriptions of this simulation process and results are also available from the first author.

Another possible criticism is that our simulations treat jobs and applicants at one point in time and not as a dynamic process in which jobs open and close at different times. The simulations, like other studies of this general phenomenon, also assume that the best available candidate always accepts a job offer. Similarly, all of the applicants in our simulations were active job seekers. Thus, the effects of passive candidates on these expected values are not assessed.

A final limitation of this research is that our evidence was based on simulated data, and all simulations are imperfect representations of reality. Assumptions must be made and specific values must be chosen for the parameters in the simulation models. All of the simulations we have reported, for example, were based on 50 jobs being available system-wide. It is reasonable to question whether results would have been similar if larger or smaller numbers of jobs had been modeled. We reran our simulations with 10 and then with 100 system-wide jobs. Results were very similar to the 50-jobs simulations. This tends to confirm our position that it is not the absolute numbers of jobs and job seekers that drive these results; it is their sizes relative to each other. We indicated earlier that $J/P = \bar{A}_P / \bar{A}_J$ is the key relationship. That is, the ratio of total jobs to total people is reflected in the ratio of applications per person to applications per job (pool size), and it is the latter ratio that is the basis for our method. We cannot claim that our methods would always accurately predict actual hiring results, especially given our previous discussion of the widths of the confidence intervals for individual hires. But we do argue that our results provide strong support for our conclusions about the general nature of the phenomena we have described.

Conclusion

Situations involving small applicant pools are a common and important part of the hiring landscape, but very little research has been directed toward small pools (Heneman et al., 2000). We agree with De Corte (1999, 2000) that order statistics are an appropriate tool for modeling small-pool hiring. But we also contend that the order statistic approach must be adjusted to account for the heretofore unrecognized effects of multiple applications per applicant. It is clear that those effects have significant implications for expected predictor scores. Hiring rates in inflated pools appear to be lower than what the effective or aggregate hiring rate really is. This means that selectivity is overestimated and that true expectations for new-hire quality are lower than what they might appear to be. Overlap among pools will likely result in rejected offers, which, in turn, will mean that the actual quality of hires will be further reduced.

Our average order statistic method provides a means for understanding the phenomena we have identified. We indicated in our introduction that current theory in the small-pool and multiple-applications-per-applicant situation is incomplete at best. Heneman et al. (2000) argued that the study of human resource issues in the small-business context should be strongly encouraged. Similarly, Bobko and Potosky argued that traditional methods for computing the utility of selection systems, which have been developed and applied in large-scale hiring contexts, should be reconsidered when small-scale hiring is of interest; they added that "current formulas may need re-thinking if they are applied to smaller firms" (2011: 79). We suggest that their point applies not just to small employers but to any hiring situation that involves small applicant pools. Our work represents the academic community's first step toward understanding the real underlying dynamics of what is surely a very common hiring situation.

Our results demonstrate clearly that it makes a big difference whether applicant pools grow because more people choose to enter the job market or because the people already in the job market choose to apply for greater numbers of jobs. We hope that an improved understanding of these phenomena will foster further research in this area and be a foundation for the development of theory and tools that will be of value to scholars and to "practitioners [who] may be unaware of practical issues they should be conscious of that can be identified and explained through academic research" (Heneman et al., 2000: 12).

Note

1. Often, the *k*th order statistic is defined as the *k*th *smallest* value in a sample rather than the *k*th largest. However, because this article concerns top-down hiring, and because applicant pools vary in size, it is simpler to rank the order statistics from highest to lowest. Then, the first order statistic is always the largest observation, regardless of the size of the pool.

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